On Psycho-physiological Player-centric Game Experiences

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On Psycho-physiological Player-centric Game Experiences

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Abstract

Computer games continue to receive increasing attention in industry and academia as a new kind of media, a new research focal point, a new art-form and an influential cultural force. However, compared to the significant economic and cultural impact and maturity of the game industry, the academic entertainment and serious game research field is in its infancy. This is particularly noteworthy when compared with the history of classic game theory studies.

Currently, the game industry appears to rely heavily upon heuristics, craft and experience to inform design and production decisions, with little guidance from formal theory. However, the current renaissance in new multi-disciplinary game-based fields, including: game-based learning, positive impact games, social reality games, serious games and gamification, increases the necessity for a theory of player experience in interactive entertainment-oriented game play. Such a theory is far from trivial, as we first need to understand the fundamental challenges that occur at the interface between players and games during game play. This thesis will focus on understanding these challenges, using psycho-physiological data as a means to interface human players with games.

Thus, the focal research question in this thesis is 'What are the main challenges faced when using psycho- physiological data as a mediator for player-experience in a computer game?'

Both playing and non-playing analysis have been performed in this thesis to answer this question. Three experiments were conducted, in the context of the game 'Snake', the board game 'Go' and interactive problem solving to distil the challenges. Games, human game experience, and the interaction between human players and games as game play have been analysed and defined. Game information, human information, game performance and psycho-physiological data, including electroencephalographic data during game play were collected to facilitate the analysis. The fundamental results reinforce the literature that psycho-physiological signals during game play do encode the game experience of human players, and electroencephalographic signals could also be used as an input channel for games during game play.

The main challenges recognised in using psycho-physiological data to facilitate player experience lie in the multiple factors that need to be considered when analysing

the human game experience and game play interaction. From the perspective of human game experience, an ensemble of indicators is needed to make an accurate judgement of the human game experience. This appears an inherent requirement because of the multi-faceted view of what an experience of game play is. Any game experience model must, of necessity, be game and context-dependent due to the complexity and variation of each game. From the perspective of game play interaction, electroencephalographic signals can act as a bridge between human players and games to facilitate game design. However, to design optimal game experiences for human players, the bridge needs more factors to be considered, including the game context and the individual human experience model.

In summary, the studies presented in this thesis concern the use of psychophysiological data to mediate player experience. They show the potential of these signals in adaptive game design to optimise a player's game experience, while also clearly demonstrating a number of core challenges that need to be overcome before an overarching theory for player-experience can be fully established.

Keywords

Game, Computer Game, Game Research, Game Design, Psycho-physiological Data, Human Experience, Game Play, Player Experience, Electroencephalographic Data, Challenge, Human-Game Interface

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Shen Ren
Canberra, Australia

Certificate of Originality

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person, nor material which to a substantial extent has been accepted for the award of any other degree or diploma at UNSW or any other educational institution, except where due acknowledgement is made in the thesis. Any contribution made to the research by colleagues, with whom I have worked at UNSW or elsewhere, during my candidature, is fully acknowledged.

I also declare that the intellectual content of this thesis is the product of my own work, except to the extent that assistance from others in the project's design and conception or in style, presentation and linguistic expression is acknowledged.

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List of Acronyms

ADHD	Attention Deficit Hyperactivity Disorder
AI	Artificial Intelligence
ANS	Automatic Nervous System
BCI	Brain-Computer Interface
BVP	Blood Volume Pulse
CEMG	Corrugator Electromyography
DLPFC	Dorsolateral Pre-Frontal Cortex
EEG	Electroencephalographic
EMG	Electromyography
ERP	Event Evoked Potentials
EvC	Evolutionary Computation
FFT	Fast Fourier Transform
fMRI	functional Magnetic Resonance Imaging
GA	Genetic Algorithm
HCI	Human-Computer Interaction
HRV	Heart Rate Variability
IBI	Inter-Beat Interval
IEC	Interactive Evolutionary Computation
LIP	Lateral Intraparietal
MANOVA	Multivariate Analysis of Variance
PET	Positron Emission Topography
Resp	Respiration
RMS	Root Mean Square
RR	Respiration Rate
SC	Skin Conductance
sEMG	Surface Electromyography
SR	Skin Resistance
ST	Skin Temperature
STFT	Short Time Fourier Transform
SVM	Support Vector Machine
SWB	Subjective Wellbeing
TBR	Theta/Beta Ratio
UNSW	University of New South Wales
ZEMG	Zygomatic Electromyography

List of Publications

Peer-reviewed publications arising from research work conducted in this thesis are listed chronologically below (latest to earliest):

1. Ren S., Tang J., Barlow M. and Abbass H.A. (2014) An Interactive Evolutionary Framework Controlled via EEG Signals, IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), Beijing, China.

2. Ren S., Barlow M. and Abbass H.A. (2012) Frontal Cortex Neural Activities Shift Cognitive Resources Away from Facial Activities, 19th International Conference on Neural Information Processing (ICONIP2012), LNCS766, 132-139, Springer.

Chapter 1

Overview

Everything in the future online is going to look like a multi- player game.

Eric Schmidt (CEO of Google)

This opening quotation is part of what Mr. Schmidt said to the international audience at the G-20 council for international economic cooperation in Pittsburgh, 2009. 'If I were 15 years old, that's what I would be doing right now', he continued.

Games are powerful. The first documented records of games can be found in Herodotus' masterpiece *The Histories*. About 3000 years ago, the ancient Lydians, from Lydia in Asia Minor, were said to have invented the dice, sheep's knuckle-bones, the ball and other common games to encourage a starving population to forget about famine for 18 years [235]. The strategy they adopted was to engage in games for one day to forget the craving for food, and to eat the next day without games at all. Though the accuracy of *The Histories* has been doubted to some extent, the power of games was recognised (or at least believed in) by people living in the Archaic period of Greece: it could be used to fight against the most important and elementary physiological needs of human beings.

Games today are more powerful than ever. Annual sales of computer and video game in the United States (US) reached 9.5 billion USD in 2007, 11.7 billion in 2008, 10.5 billion in 2009 [25], and 20.77 billion in 2012 [26], according to the Entertainment

Software Association's report, the most respectable and in-depth game industry report of its kind in the US. This deep penetration of popular culture is sweeping much of the world, not just the US. At the end of 2013, 17% of the world's population played games [222]. It is estimated there are 184 million video game players in US [26], 180 million in China, 75 million in India, 140 million in other Asia Pacific Areas, 145 million in the Middle East, 115 million in Latin America, 120 million in Eastern Europe, 180 million in Western Europe, and 85 million in Korea, Japan and Oceania [222]. Humans are devoting some three billion hours per week as a planet on game playing [207], and the number is increasing each year.

In 2013, the average age of game players in the US was 30, and the average number of years players had been playing video games was 13 [26]. Meanwhile, five million hard core gamers are spending more than 40 hours a week playing games [207]. The ancient Lydians played games to escape from reality, but contemporary players play games for more significant reasons: they appreciate computer game as a brand-new art medium, enjoy the storylines and music, build up their social networks, experience alternative virtual lives, learn new skills, improve their problem solving and decision making and motor abilities, and help improving their attention spans by training their working memory. However, games have long been considered trivial and have a negative stereotype: merely for fun, wasting time, and distracting from real life. However, there is nothing trivial about fun and about feeling better that could be experienced from games and game-based serious applications.

Games are powerful. We must envisage, study, and respect this power in order to utilise it. That is the primary motivation of this thesis.

1.1 Motivations

Alongside the significant economic and cultural impact and maturity of the game industry, the current academic entertainment and serious game research field is still in its infancy. While computer games have existed approximately as long as the popularity of computers and personal computers [166], academic computer game research is a recent development in the last two decades. This may due to: 1) The field has long been seen as 'low-brow' by negative media because of its entertainment-oriented nature and because of its great economic success as an industry. 2) The field is difficult to investigate as games can be simulations: in principle, computer games could portray any phenomena, and in principle no field could be excluded from this rich and diverse multi-discipline [13]. The richness of computer game research has increased the difficulty of investigation but has also provided a great number of opportunities for scholars in multiple fields.

The difference between the academic game research discussed within the frame of this thesis and the computational games or game theory in classical game theoretical research is notable. Compared with the classic game theoretical studies in mathematics, focusing on computational models of games and decision making (which has a much longer history, sophisticated theories and mythologies), the game studies in this thesis focusing on games as artistic media providing enjoyable game play and experience for human players, is only seriously studied within the recent two decades.

Meanwhile, games as the best sources to enjoyable user experience have been more and more recognised as a subject for scientific research by scholars. If the mechanics of game systems could be understood, inspiring people to voluntarily participate in these activities with joy, these mechanics could be applied to other serious domains beyond entertainment. This idea leads to many current fruitful game-related research areas including: game-based learning, positive impact games, social reality games, and serious games.

Further, in a broader sense, games involve activities far beyond video games, including sports, tabletop board and card games, outdoor game activities and real-world simulations in vast amount of serious domains including military, business, health, education, management, transport and decision making. In this thesis, the computer-based video game activities are mainly focussed on within this scope. However, the significance of the thesis is beyond entertainment and could also impact other serious game applications. Still, games can be simulations built upon the abstractions of the real world. If the process of game design could be reversed instead, to design elements of the real world as much as the design of good games, we are one step closer to Aristotle's dream: to enjoy the pleasure of a job and to make perfection of work. This movement from the virtual to the real world is what current gamification scientists are thrilled about and struggling to achieve using game design methods and game mechanics in non-game contexts.

The lack of formal game play related theories and game experience research is crippling the development of game-based enjoyable and serious domains including entertainment and serious games. In the current game industry, game design and production decisions appear to rely heavily upon heuristics, craft and experience, with little formal theory for guidance. Prototyping and playtesting as software evaluation skills are widely used to facilitate early game design; most game designers, especially early in the twentieth century, were programmers. However, the contents of games are far beyond software that serves a specified goal or interfaces for accessing computer resources, an unpleasant game experience arising from a boring storyline is completely different from game experience of an unintuitive interface. While evaluating the success of games is still left as an open challenge, generally, game play should be considered as an experience-oriented activity, evaluated from a user experience perspective, instead of a usability perspective, which will be further explained in Section 3.2. A limited amount of formal studies using this approach has been addressed in literature.

While the current game industry relies on heuristics and experience in game design and evaluation, academic game research also lacks proper formal theories to guide it. To address this problem, scholars in the game domain have been seeking ideas and inspirations from multiple relevant fields, including human-computer interaction (HCI), psychology, sociology, education, cognitive science, aesthetics, business and economy, art, media studies. However, due to the great variations in games, none of these disciplines could cover the context of game research in their existing knowledge and theories. The reason may be due to the omni-potential of games, and the details will be further explained in Chapter 2.

As none of the current established disciplines could cover game research as a sub-domain, game research should be recognised as an independent research discipline. However, the field is still in a nascent state. There is no consensus in this field on fundamental questions such as 'what is a game",“what is game play' and 'what is game experience'. The qualitative and quantitative analysis of games, game play and game experience is still lacking, even though billions of people worldwide are involved in game activities. To address these problems, this thesis will focus on the challenges faced by current game research, especially in game play interaction and the game experience of players.

All these inspirations and limitations of current academic game research come together as my motivations for undertaking research in this new area.

1. Games are powerful and pervasive yesterday, today, and tomorrow.
2. Games are not for pure entertainment. They can, and should, be applied to serious domains.
3. Games are not intrinsically virtual. Real world elements may be designed based upon studies of game mechanics to add more enjoyment to 'spice' up life.
4. From the perspective of the game industry, the current game design and evaluation processes are still underdeveloped.
5. From the perspective of the nascent academic game research, a well-proposed well-recognised game play and game experience theory is still lacking.
6. Referring to multiple relevant fields, currently none of the well-defined disciplines could solely incorporate game research as a sub-field.

These motivations drive me to understand the challenges faced by current experience-oriented player-centric game research. This thesis will focus on understanding the challenges in game play and game experience, within the scope of using psycho-physiological data to interface human players with games. By fulfilling this goal, both playing and non-playing analysis before, after and during game play will have been performed. Self-reports used to be considered the best way in psychology to understand people's mental states. However, continuously presenting self-assessment tests to players during game play is not only impractical, but also interrupts the game experience. Inspired by cognitive science, HCI, brain-computer interaction, and the current development of wearable medical devices, psycho-physiological data to interface between human players and games has been particularly assessed in this thesis.

This study, in understanding challenges in game research by using psycho-physiological data, will not only benefit game research in different directions, but will also be important to HCI and enjoyable interface design. The paradigm of game playing provides a perfect environment to understand user experience; the contribution of this thesis could be far more significant than just the entertainment applications of games.

1.2 Problem Statement

Inspired by the motivations discussed in Section 1.1 in this thesis, the main problem to be addressed is to understand the human game experience by studying the interaction between humans and games, using psycho-physiological data to explore the dynamics of this interaction. In this case, the three main subjects of human-game interaction — games, human game experience — and the interaction between human players and games as game play need to be analysed and defined.

The thesis attempts to address this problem by using playing and non-playing analysis based on game information, human information, game performance and psycho-physiological data, including electroencephalographic data collected before, after and during game play interaction. Three experiments are conducted in the context of the 'Snake' game, the Asian board game 'Go' and an interactive problem solving process, with each experiment having a particular focus.

1.3 Research Questions and Hypotheses

Focusing on the psycho-physiological data derived from players during game play, as a means to interact between games and players, the focal research question in this thesis is:

Research Question

RQ1: What are the main challenges faced when using psycho-physiological data as a mediator for player experience in a computer game?

Within the above research question, the player experience is defined as 'all aspects of the human player experience when interacting with games as interfaces and environments'; this will be specifically explained in Chapter 3, Section 3.1. 'Mediator' is defined as 'intermediate medium to reflect players' game experiences in game play'.

Corresponding to the research question, the main hypothesis of the thesis becomes:

Main Hypothesis

H1: Psycho-physiological data could be used as a mediator for player experience in a computer game.

This main hypothesis could be decomposed into three sub-hypotheses.

First, as the game play interaction and human game experience are the focus of this thesis, there is the experience hypothesis.

Experience Hypothesis:

H1.1: Game play interactions between human players and computer games would impact human game experiences.

The Experience Hypothesis indicates that: 1) game playing is an interactive activity between human players and computer games; 2) there will be changes in regard to game experience before and after play; and 3) the experience change is mainly due to the game play interaction. The experience hypothesis will be justified in Chapter 3, with experiments detailed in Chapters 4 and 5.

Psycho-physiological data collected from human players during game play has been mainly assessed in terms of interaction between human players and computers, so that the second measurable hypothesis is proposed accordingly.

Measurable Hypothesis:

H1.2: The game experience of human players during game play could be reflected by psycho-physiological data collected by current sensory technologies.

The Measurable Hypothesis proposes that the human game experience is inferable by observing and analysing optical and electrical signals generated from activities in central and peripheral nervous systems under current technologies, upon which, the game experience could be evaluated. This measurable hypothesis will be justified in Chapters 4 and 5.

By utilising psycho-physiological responses in changing game applications to interact between human players and computers, the final hypothesis called 'adaptable' is proposed.

Adaptable Hypothesis:

H1.3: Games could be designed in real-time at a system level to respond to changes of brain activities reflected by psycho-physiological data.

The Adaptable Hypothesis is proposed to test the feasibility of using psycho-physiological data from players as input channels to games, which will be justified in Chapter 6.

All these three sub-hypotheses come together to support the main hypothesis that psycho-physiological data could act as a bridge to interface between human players and computer games.

To answer the main research question, the main challenges faced by academic game research in using psycho-physiological data to facilitate player-game interaction have been analysed from three perspectives, as follows.

- **Sub-question 1 (RQ1.1)** What are the player-centric models of interaction in game play?

- **Sub-question 2 (RQ1.2)** Could psycho-physiological data, especially electroencephalographic (EEG) data, encode the game experience of human players?

- **Sub-question 3 (RQ1.3)** Could EEG data be used as an input channel to control simplified games?

The first sub-question addresses the general models of games and human players to support the use of psycho-physiological data in analysing game experience, and in designing the three conducted experiments presented in Chapters 4, 5 and 6. This sub-question is answered in Chapters 2 and 3.

The second sub-question focuses on the use of psycho-physiological data, especially EEG data, in reflecting human player experience during actual game play. The data has been analysed together with subjective self-reports of players and the objective game context and game performance. This sub-question is answered in Chapters 4 and 5.

The third sub-question utilises the EEG data collected from human players in real-time, which is recognised as being the most informative among collected psycho-physiological signals, to control game applications. This sub-question is answered in Chapter 6.

1.4 Contributions

The main contributions of this thesis are in response to the research question proposed in Section 1.3, which are listed with three aspects.

- **Contribution 1**: Player-centric models of what is a game, game play, and game experience are proposed based on an analysis of, and identified weaknesses in the existing literature (Chapters 2 and 3). Compared with the existing literature in game research, which has generally addressed models from game designers' perspectives, the models in this thesis are fully player-centric to target the main subject of game play interaction with players, instead of designers. Compared with the existing literature on usability and user experience of products and software, this thesis focuses on the context of computer games, which have great richness in their content, wide variations in their genres, and a profound significance in their applications in entertainment and serious areas as enjoyable, encouraging and engaging interfaces.

- **Contribution 2**: Psycho-physiological signals during game play are proven to encode the game experience of human players during game play (Chapters 4 and 5). Two experiments based on designed games have been conducted to collect psycho-physiological data in analysing game interaction and experience. Though a considerable number of psycho-physiological studies have been conducted on indexing cognitive processes, the corresponding research in the context of computer games — especially in real complete game playing instead of imposing game elements (video, picture, audio) or game events to the players — is still rare. Meanwhile, due to a lack of theoretical studies in game backgrounds, as discussed earlier, and the lack of consistency in psycho-physiological studies in different domains, research using psycho-physiological data as a bridge between games and players to reflect game experience is still a gap to be filled.

- **Contribution 3**: EEG signals collected from human players could act as an input channel to interface between human players and games (Chapter 6). Though real-time EEG has been studied as a communication channel between human brains and computer systems by HCI and virtual reality communities, research to use the signals in game problem solving does not exist in the literature. Further, the use of EEG signals in brain-computer interface (BCI) usually requires extended training for particular participants; this problem, which inhibits the application of BCIs, has also been addressed in this thesis.

The challenges recognised in using psycho-physiological data to facilitate game interaction and player experience mainly lie in the multitude of factors that need to be considered when analysing the human game experience and game play interaction. These findings of this thesis are listed as follows.

- **Finding 1**: An ensemble of indicators is needed to make an accurate judgement of the human game experience, which may be because of the multi-faceted view of what a game experience is.
- **Finding 2**: Any game experience model must, of necessity, be game and context-dependent, due to the complexity and variation of each game.
- **Finding 3**: EEG signals can act as a bridge between human players and games to facilitate game design. However, to design optimal game experiences for human players, the bridge needs more factors to be considered, including the game context and the individual human experience model.

1.5 Thesis Structure

This thesis proceeds as follows.

- **Chapter 1**: The overview of the entire thesis. The chapter starts with the motivations that inspired this thesis, followed by a problem statement, research questions, hypotheses and the contributions. The thesis structure and the conclusion of this chapter are presented at the end.
- **Chapter 2**: The analysis of games and humans as players, from the perspective of multiple domains, including: game design, game research, psychology, cognitive science, neural science, medical science, HCI, physiology, education, sociology, business, is presented in this chapter. Further, the psycho-physiological measures used in this thesis, with corresponding signal processing methods, are presented.

- **Chapter 3**: Games, game play and game experience models are defined and analysed from a player's perspective in this chapter. Evaluation methods are proposed using both subjective and objective indicators derived from multiple information collected before, after and during game play, including: game information, human self-report information, psycho-physiological response data and game actions as performance. Real game play scenarios are proposed to test the proposed models and the evaluation methodologies.

- **Chapter 4**: The first game play scenario — the game of 'Snake' — is designed to analyse game experience of human players in playing casual action games which provides simple physical challenges and requires no special skills to play, and to evaluate the general game play and game experience models proposed in Chapter 3. This experiment is designed to focus on the kind of game with a simple problem space but requiring rapid mental and motor responses. Game information and player information, including psycho-physiological data collected during game play, are analysed to see how this information encodes the game experience of players during 'Snake' game playing.

- **Chapter 5**: The second game play scenario — the Asian board game of 'Go' — is used to analyse game play and game experience of human players in playing against computer 'Go' programs. The 'Go' game is one of the most complex games. This experiment is designed to analyse game play that requires a high degree of cognitive workload, strategic problem solving skills, learning, experience, and speciality of players during game play under this 'Go' game context. Game information and player information, including psycho-physiological data, are again collected for analysis from both professional and amateur 'Go' game players. Results of the 'Snake' game experiment and 'Go' game experiment provide evidence that psycho-physiological data, especially EEG, could be used as a mediator between games and human players to reflect game experience.

- **Chapter 6**: The third experiment is designed to evaluate if EEG data collected from human players could be used as a bridge to communicate between games and players. For this purpose, a simplified game scenario that is fully understood and fully in control is used, which is presented as an interactive problem solving scenario using evolutionary computation. The exploration and exploitation processes of this problem solving are controlled by analysis of EEG signals collected from players under designed mental tasks, which have well-established EEG features as a new communication channel. The experimental results confirm that EEG signals could work as an input channel to interface between games and players.

- **Chapter 7**: Conclusion and future directions are presented in this final chapter. The main contributions and findings of this thesis are addressed, which show the potential of psycho-physiological signals in designing optimal game experiences for human players during game play. However, due to the richness of games and human experience, there are still significant challenges to be overcome in my future work to improve both player experience and enjoyable interface design.

1.6 Conclusion

Games are not trivial. As a new addition to the field of games, computer games are currently a new media, a new research field, a new art-form and an important cultural force that are showing their importance, power and prosperity in great variety of fields. They have begun to be seriously researched in universities, institutions and organisations around the world.

In this thesis, I would like to present my work in understanding the major challenges within the scope of using psycho-physiological data to interface human players with games, which hopefully adds another element to the nascent field of academic game research. Psycho-physiological signals — especially EEG signals — are indicators for human game experience and a bridge to interface between human players and computers. A number of core challenges that need to be overcome to design optimal player experience in game play have also been identified; I expect to address those challenges in my future work.

Chapter 2

Games and Human Players Analysis

When it comes to exploring the mind in the framework of cognitive neuroscience, the maximal yield of data comes from integrating what a person experiences — the first person — with what the measurements show — the third person.

Daniel Goleman [122]

As the psychologist Daniel Goleman pointed out in his interview [122], the exploration of a person's subjective experiences should be integrated with objective measurements for analysis in cognitive neuroscience. However, this view is not only limited to cognitive science. According to the Webster's New World Collegiate Dictionary, subjective means 'of, affected by, or produced by the mind or a particular state of mind; of or resulting from the feelings or temperament of the subject, or person thinking'. Objective means 'of, relating to, or being an object, phenomenon, or condition in the realm of sensible experience independent of individual thought and perceptible by all observers' [134]. From these definitions, scientific methods in all fields require objective evaluation of subjective perceived phenomenon. As in the realm of this study in game play and game experience, there are three main entities to be analysed and objectively tested: game, game play interaction, and human experience. Among these the first two could be considered objective, as an object and a phenomenon to be observed, and the last one as subjective, resulting from mental state, feelings and thoughts during game play interaction, not directly tangible, but possibly reflected in objective measures. The feasibility of using objective measures to indicate human subjective feelings and thoughts is discussed in this chapter. In particular, psycho-physiological response signals including blood volume pulse (BVP), skin conductance (SC), skin temperature (ST), respiration (Resp), EEG and electromyography (EMG) are evaluated in detail.

In this chapter, the main subjects involved in the activity of game play — games and human players — are analysed from variety of fields. First, games, including the definition of games, the fun in games, the designed experience of games, and the importance of games, are presented in Sections 2.1 and 2.2. The three main entities involved in game play are reviewed and discussed, mainly from the designers' perspective, which exists in the literature, and game design heuristics. The human players are then discussed in Section 2.3, with the information processing of humans and objective evaluation techniques focussed on this thesis explained in detail.

2.1 Games

As mentioned in the beginning of Chapter 1, games are powerful and have never been so powerful as today. Why are games so powerful? Are games powerful because we players can obtain some extrinsic reward from playing them? Or because Atys the king of Lydia forced his people to play them? Or is there some magic power hidden in the little dice 3000 years ago and in game disks now?

Clearly, there is nothing magic in a dice made from sheep's knuckles. Society would not reward any fame, fortune, or power to game players for doing well in games (except for some professional game players). People play games because they 'want' to play them. They are playing them from their own intrinsic motivations, playing for its own sake. As illustrated by Johan Huizinga in his book 'Homo Ludens', play is a necessary element to the generation of culture [152]. According to the motivational spectrum in self-determination theory [82] (in psychology), intrinsic motivation — pursuing interest/enjoyment and inherent satisfaction — is the most important and pervasive motivation to fulfil a task, with the best positive experience [246].

Before digging into the mechanisms and attributes of games as good autotelic and self-rewarding systems, 'what a game actually is' needs to be first defined.

2.1.1 What is a Game?

The question 'what is a game?' seems easy, but it turns out to be a very deep philosophical question. The famous philosopher Ludwig Wittgenstein actually believes that the word 'game' does not have a definition, and do not need to have one because the word is used successfully without a definition. Further, we do not need one as we use the word successfully without a definition [312]. This question is not a dead end. Today most people are more likely to adopt the view of another philosopher — Bernard Suits — that 'playing a game is the voluntary attempt to overcome unnecessary obstacles' and that a game itself has three important concepts: pre-lusory goal, constitutive rules and lusory attitude [280]. Still, many people in diverse fields, including anthropology, psychology, philosophy and game design have provided vast numbers of definitions over the years, as reviewed by Katie Salen and Eric Zimmerman in their book *Rules of Play* [248] and Raph Koster in his *Theory of Fun for Game Design* [174]. Specifically, some are cited here:

'A game is a series of meaningful choices.'

– Sid Meier (Sidney K. Meier, the creator of several remarkable game classics including the Civilization series)

A game is 'a system in which players engage in an artificial conflict, defined by rules, that results in a quantifiable outcome.'

– Katie Salen and Eric Zimmerman, Rules of Play: Game Design Foundamentals [248]

'A game is a problem-solving activity, approached with a playful attitude.'

– Jesse Schell, CEO of Schell Games [258, 259]

Here we will not confuse ourselves with philosophical questions. The definition of a game that I have determined is an amalgam of the above definitions, that a game is:

a system governed by rules involving problem solving and is designed to be fun

Accordingly, a game play is:

A voluntary problem-solving process that is bound by rules and is fun.

While this definition lacks complete rigour and leaves undefined such a 'slippery term as fun, it will suffice for this work.

From all the above definitions, it is easy to raise the question of why people voluntarily take on the troubles of dealing with unnecessary obstacles, to solve problems and to impose artificial conflicts on themselves? It is not the irrational behaviours of one single person, or a small group of persons, but more than one billion members of the world's population. It is estimated that every week players devote three billion hours (about 342,000 years) to video game playing [207]; that is almost the entire duration since the first human being left his or her mark on this planet.

2.1.2 The Fun in Game

This attraction of games might be because playing games is fun.

It seems to be quite obvious that playing a game is fun. Usually it should not be 'fun', in appearance. As defined, game play is a voluntary problem-solving process. However, problem-solving in general is not usually considered to be fun. In other words, what is fun in overcoming 'unnecessary obstacles'?

2.1.2.1 The Theory of Fun

First, what is 'fun' in general?

Games are defined by their play. Actually we do not distinguish between the two words 'play' and 'game' in many languages, including Spanish, German, Greek, Bulgarian, Polish and Japanese. In English, the *Oxford Dictionary* defines the word 'play' as to: 'engage in activity for enjoyment and recreation rather than a serious or practical purpose', and 'fun' as 'enjoyment, amusement, or light-hearted pleasure' [86]. Both of these show that 'fun' is 'enjoyment, amusement and recreation' in essence. Interestingly, in Chinese, the word fun, 'Qu', originated from a poem in the book of *Shijing*, about twelfth century BC, with its original meaning of 'eager to walk towards something' [316], which vividly depicts the extrinsic behaviour when human beings are pursuing something fun.

Generally, fun is 'a source of enjoyment' [174]. It is about feeling good. Enjoyment itself is a composite concept. Easy success, accumulating wealth, and complete relaxation can be enjoyable, but triumph after struggling, sharing with others, hard-working, or even conflict, sorrow and sympathy can be enjoyable too in some circumstances. By performing a field study of over 2000 observations from people playing different kinds of games, Nicole Lazzaro categorised fun into four keys [183]. She also confirmed that the best selling games usually create fun in at least three of these four keys.

These four keys of fun in games are:

- Easy Fun: Games grab attention with incompleteness and ambiguity, intrigue and eagerness for exploration.
- Hard Fun: Games present challenges, which involves strategy planning and problem solving.
- People Fun: Games work as a medium for creating social experience.
- Serious Fun: Games provide values and meanings, to make a difference to the player in the real world.

This is not the only study on fun in games. Game designer Marc LeBlanc identified eight kinds of fun as: sensation, fantasy, narrative, challenge, fellowship, discovery, expression and submission [153]. Raph Koster defined four clusters of emotions that would make people feel good in games, but did not combine them as 'fun'. These are: mentally mastering problems, aesthetic appreciation, visceral reactions and social status maneuvers [174].

In anatomy and physiology, our brains reward ourselves by the release of various chemicals, including endorphines, dopamine, oxytocin and serotonin to keep us in happiness during various situations, including the experience of fun [43]. In contrast, depression has been proved as linked to the disrupted signalling of the dopamine neuromodulatory system [105]. Attention-deficit hyperactivity disorder (ADHD) is also believed associated with the decreased injection of dopamine [178]. Dopamine is an important neurotransmitter, which is injected into the system to make us happy. It is also involved in addiction mechanisms in the human brain [261]. For the discovery of dopamine, the Swedish scientist Arvid Carlsson was awarded the Noble Prize in physiology or medicine in 2000 [31].

In cognitive science and evolutionary psychology, fun in games is often associated with a concept known as 'flow'.

2.1.2.2 The Optimal Experience — Flow

In Brian Sutton-Smith's play theory, the opposite of fun is not work, but boredom [283]. On the other hand, if the task is too hard, such that it induces anxiety, it is not fun at all. In 1975, Mihaly Csikszentmihalyi proposed a notion called 'flow' to depict an optimal experience during tasks that is neither boring or anxious. In his work, flow is described as a subtle mental state with complete involvement. Flow is defined as 'being completely involved in an activity for its own sake. The ego falls away. Time flies. Every action, movement, and thought follows inevitably from the previous one, like playing jazz. Your whole being is involved, and you're using your skills to the utmost' [114]. Flow is also what the psychology literature calls 'autotelic experience', in which no external goals or rewards are needed [73]. It is the optimal state of positive experience.

As Csikszentmihalyi pointed out, if the skills are larger than the opportunities for using them, the state of boredom occurs. By contrast, if the challenge is too demanding compared to the skills, the state of worry results. Only in the middle, when an individual perceives that challenge perfectly matches the individual's capabilities, will flow occur. Hence, to construct a flow activity is to offer the optimal experience by providing optimal challenges geared towards the relevant skill level [73].

From another perspective, fun is 'the emotional response to learning' [72]. In this view, the flow state could be considered as the balance between perceived information for learning and a person's learning capacity. The learning capacity of humans to process the number of chunks of information in working memory has been examined by several researchers in psychology. The results range from seven [210], to the range of five to seven [266], and to the range of three to four [46]. Later on, different models of working memory were proposed, but it has been generally well accepted that the information processing capacity of humans is limited. For example, in attempting to process more information than the capacity, information overload (or what is called sensory overload) occurs, which results in anxiety. In contrast, people are creatures that constantly seek information. If this desire is not satisfied, the information deficit causes boredom. Right in the middle, that is flow.

Where can we find flow? How do we pursue flow? According to the research of Csikszentmihalyi, 'Games are an obvious source of flow, and play is the flow experience parexcellence' [76]. Flow experience could be best produced by a specific combination of self-chosen goals, optimal designed obstacles and instant feedback; these in turn are the three elements that form an engagement loop in game design [303].

A recent branch of psychology, 'positive psychology' or the science of happiness, also proposed by Martin Seligman and Mihaly Csikszentmihalyi in 1998, has proposed a 'sustainable happiness model' [198], in which the factors that determine subjective wellbeing (SWB) — happiness — are classified as set-point, circumstances and intentional activities. The set-point is determined by genetics (e.g., unchanging personality and temperament) that is the extent to which the up/down range of happiness an vary for a person. The term 'circumstances' are related to an SWB demographic profile including income, health, marital status, religion and belief, but their affect on happiness is short-lived and small. 'Intentional' activities are activities people are pursuing, and are considered to be the factor with the highest potential for bringing people to the upper end of their set range. By analysing this model, Sonja Lyubomirsky pointed out that the way to pursue happiness is to take work (the practice of intentional activities), which fits into one's intrinsic motives, but feels like play [263]. In other words, as described earlier, such work is an autotelic fun system pursued in a playful attitude, that is, a game.

2.1.2.3 The Worst Experience — Quit

Though there are some well-designed life-long games (e.g., World of Warcraft), most game products have a life cycle of several months or years. Even within this process, usually a particular player will not stay in for long: they will first have a try, become engaged for a period, and then leave for a new one. If the concept of flow could be used as the best optimal experience during game play, stopping playing a game could be a sign of a worst game experience for a particular player.

So when would the player choose to quit?

From an evolutionary perspective, human beings have not evolved to be within flow at all times. Dopamine release only occurs when people are several steps away from reward. This mechanism has evolved to stimulate humans to take action to promote survival in natural selection. A brain that is always in happiness will not take survival actions, and will be pushed out from the gene pool [43]. In general, we need 'downs' to have 'ups'. In game cycles, if the player can not obtain an optimal flow experience from the game (either bored or anxious), they quit, even with the most well-designed games. There are also plenty of 'bad' games on the market, and people get in and out from them quickly.

From a psychological perspective, as Raph Koster pointed out, human brains are great pattern-recognition machines [174]. Brains 'eat up' chunks of information, process them, and then adopt the patterns. Once the patterns have been adopted, it becomes a routine that people do not need to be conscious when seeing and applying. Once our brain iconifies all the patterns that a game can offer, we become bored by the autopilot process of playing and then quit.

In other words, game playing uses the same process as learning. Once players grasp all patterns, even the most engaging game can become boring. At this time we quit, because our brains need something new to learn.

So generally, players choose to quit due to the lack of a good game experience. This may happen because: 1) there are too many or too few information chunks designed for players at any stage of the games; 2) there is a decrease in new information chunks over time. This has been tested in Chapter 4 when the game is very easy or lacks variations, the player chose to hit the wall to 'die' quickly in order to quit the game.

The reasons discussed above could lead to a conclusion that - game play can be fun, but it is not inherently fun. The fun in games can be designed, and should be well-designed to achieve the best player experience.

2.1.3 A Designed Experience in Game Play

Game design, both conventional and video, is not trivial. As Katie Salen and Eric Zimmerman have pointed out, there is a vast gulf between the game interface and its actual meaning [248]. Take one of the most basic and well-known games: Tic-Tac-Toe. The game design is not about the symbols of 'X' and 'O' and the nine-square layout. It is about capturing certain squares and its correspondence to the game conditions of 'win' and 'lose'. Game design is a sub-set of design, just like film design, architectural design or graphic design. The rules for problem solving in games should be designed, and should be designed to be fun: that is the task of game design.

Game design is not game development, though a game designer for a video game before 1970s used to be the chief programmer (or the only programmer) of the game, due to the nature of this early phase of this industry. Now a great number of highly recognised universities have opened up game design majors, or provide game and game design lectures. The content of these lectures usually has its roots in computer and information technology, but simultaneously explore the artistic, narrative, dramatic and psychological elements of game design. This interdisciplinary field has drawn more and more attention in both industry and academia.

2.1.3.1 Game Play Models from a Designer's Perspective

Game design is the most important feature that makes the difference between good games and bad games, long-engaging games and short engaging games. Jenova Chen, a Chinese game designer who developed a series of award-wining games including one called 'Flow' itself, had his own idea about game flow and the design of game flow. As he believed, an enduring enjoyable game should be designed as: 1) matching the concept of flow; 2) keeping the game-play experience in the flow zone; 3) offering player-centric choices to allow different players to enjoy their flows in their own ways; and 4) embedding the choices in the main activities to prevent interruption of flow [60].

However, he did not provide details on how to keep the game experience in the flow zone. In order to generalise game experience scheme from the designers' perspective, Daniel Cook's skill atom in games [69], shown in Figure 2.1, is first discussed, in which player action, simulation in games, feedback and updating the mental models in the brain form a closed-loop cycle.

In his proposed model, a player first starts with a game action (e.g., press a button). This action stimulates a simulation in game (e.g., the light of the room may be on). This simulation provides feedback to the player (e.g., the graphic scene in game is brighter). At last, the player updates his or her mental model based on the

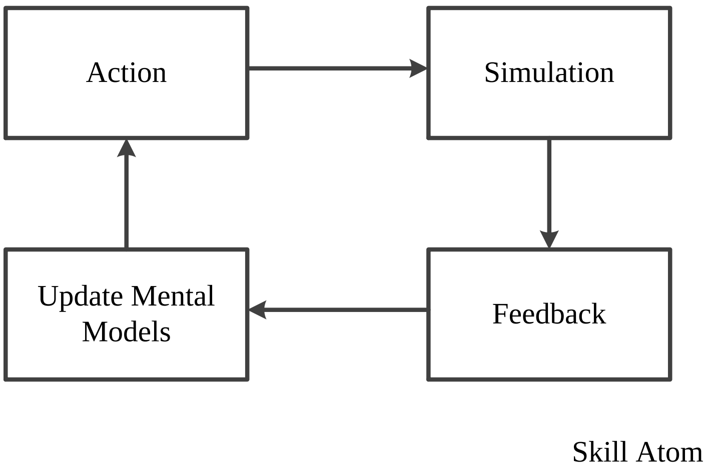


Figure 2.1: Daniel Cook's Skill Atom [69]

feedback (e.g., once a particular button is pressed, the light of a room in game will be on). The skill atom of game design describes the basic unit of interaction between a human player and the game as game play. He assumes that if the game action of the player results in making progress (when updating his/her mental model), the game experience is positive. Otherwise if the game action is in vain, the experience is negative, expressed as boredom or frustration [69].

However, the game action of a player is not generated randomly. In order to produce a game action, a player as a rational human being would first observe the problem presented by the game, and would then produce game action based on his or her own goals to be achieved. In order to address the player goals and problems of the game, another two components — problem observation and motivation — are added into this loop, and arrive at what I call an 'engagement loop', as in Figure 2.2. The engagement loop simulates a single problem solving action in game play interaction. The human player observes the problem, forms a motivation to solve the problem, takes action to try to solve it, simulates the action in the game environment, gets feedback, updates a mental model about the problem, then observes the problem to form a new motivation. From a designers' perspective, the fluent processing of this engagement loop, during which the game is constantly providing positive feedback such as making progress or gaining new skills, would stimulate positive game experience to players.

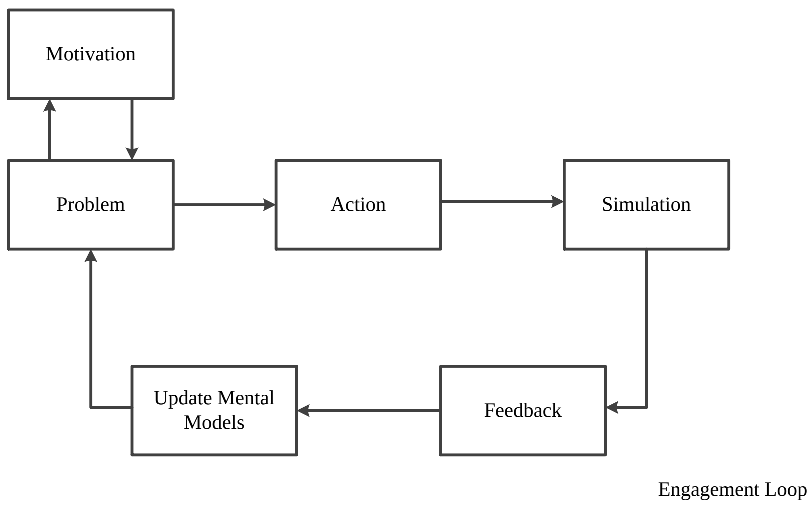


Figure 2.2: Engagement Loop

Still, most games are not only composed of a single problem. Instead, a game is usually a large problem space with quests followed by more quests. The engagement loop in Figure 2.2 shows the game play interaction in a micro-frame as the problem solving process of a single problem. In a macro-frame, which defines the game play process in general with multiple problems linked like a chain, another game play model needs to be proposed. As Amy Jo Kim believed, the fun of any particular game decreases over time [164]. To ensure the success of game design, game designers should not hypothesise that the game experience is static, as the players are learning skills. Take the example again used in the engagement loop, pressing a button would result in light up a room in game. After the player's mental model updates, although pressing the button again and again would still result in positive feedback from games (the room is brighter), the player would not consider it as making progress or gaining skills, and the game experience might be negative. As players construct more and more mental models in their brains to autopilot the process, a progression loop needs to be proposed from the designer's perspective to provide a positive game experience.

The progression loop can then built based on an evaluation of skill levels and resources gained from the game of players. The problems provided by the game are adjusted to fit the increase of player skills, as shown in Figure 2.3.

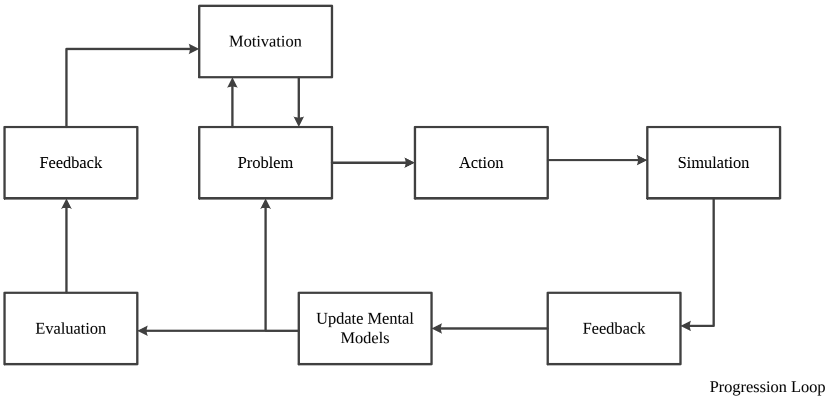


Figure 2.3: Progression Loop

In the proposed progression loop, a human player would start with the observation of a problem, form motivations, produce game actions, and at last update his or her mental model based on the game feedback. A game would provide a problem space to the player, get stimulation based on the game actions, provide feedback to the players, monitor the game actions as performance and resources obtained from the games, and at last adjust the problem space based on the evaluation. From a game designers' perspective, if a game is providing problems as a chain that perfectly fits a human player's skill level and resources, the player would obtain a positive experience from the game play interaction.

The proposed game play loops have been widely applied intuitively in many successful commercial games on the market. 'Plants vs. Zombies', a popular tower defence video game that has been nominated for multiple interactive achievement awards, is one good example. The game is designed such that players must plant different kinds of plants with their own special attacking or defending skills in their virtual backyards to stop zombie attacks across a range of increasingly complex levels. At first, the player has a limited choice of plants and a small amount of space to defend. Later on, more plants are 'unlocked' and more powerful zombies are attacking as opponents. Before unlocking a new set of scenes(night time, pool, rooftop, etc.) as 'backyards' to defend, there is usually a much more difficult level, considered the same as the 'boss fight' in other games. The game integrates both the engagement loop in the micro-frame and the progression loop in the macro-frame. Another example is a Japanese role-playing action game named 'Dark Souls'. This game will automatically update the strength and the toughness of all opponents once the player 'clears' the game and restarts it. The maximum adaptation will be achieved after the player clears and restarts the game ten times. This progression design drives the hard-core players to repeat the game to challenge the more difficult opponents, while most other role-playing games would be dropped by players after they experience the whole storyline once.

2.1.3.2 Designing Game Experience

In designing game experience, the major element to be designed is the 'problems' component involved in both the engagement loop and progression loop, representing game play interaction in micro-frame and macro-frame. According to the previous discussion, from a designers' perspective, game problems should be designed to make players feel they are 'making progress' or 'gaining skills' to ensure a positive experience for players. However, this goal is not easy to achieve. The design of the game problems is the most important, complex and subtle part of the game design.

Just as different people have different learning approaches (e.g., there are 7 forms of intelligence [112]), different people approach problems in different ways. There is no universal prototype of fun or problem design technique that could be adopted in games that would mean enjoyment for every player. One game design rule is that 'it is not possible to design an ideal game that pleases everyone, because everyone does not enjoy the same thing' [17].

To attract as many varieties of players as possible, besides the method of designing a game that entertains in a variety of ways, one of the prerequisites before game designing is to study the targeted players. Usually, game designers categorise their players by background information including gender, age and educational level, or by more sophisticated personality models like the multiple forms of intelligence [112], Myer-Briggs personality types [219] and Big Five model [206]. By studying these groups, they translate these motivations defined by different models into decisions in game design, and hypothesise that players in the same group (e.g., in the same age group) behave in a certain way. This approach has actually achieved great success in the game market [294].

However, this approach is not without flaws. 'We are all equal in the fact that we are all different. We are all the same in the fact that we will never be the same' [159]. Humans are much more complex than psychological models. Neither do people always act as they are supposed to. It is similar to purchasing a suit by buying an off-the-rank item of a fixed size. The suit will fit somewhat, but will likely not fit perfectly. It is designed to fit an average shape in that size, but not a particular person. For tailoring options, the bespoke suit is the best, as it is customised to fit the particular customer. However, as the customer changes his or her shape over years, even a bespoke suit will not remain perfect.

The same thing happens in game design. There is no established universal human categorisation that could be used to depict every particular person as [player. Even if there were, as players are involved in game play interaction, the adoption of new skills as a learning process will also change the pre-defined models even before playing. Thus, in order to design an optimal game experience, three factors need to be considered: 1) the feelings of human players need to be understood, but not be anticipated from designers' perspectives; 2) the feelings of human players need to be analysed individually, but not generally; and 3) the feelings of human players need to be analysed in real-time as the game play progresses, but not assumed to be static.

According to this discussion, under current techniques, one possible solution for analysing individual human feelings during tasks in real-time would be psycho-physiological measurements; this thesis focusses on this area.

2.2 Not Just Games

So far, games have been discussed from several aspects: 1) they are powerful and have a long history; 2) they are the best autotelic system and require no extrinsic incentives, offering players no fame, fortune or power in the real world; 3) according to scholars in multiple fields (autonomy, neuroscience, cognitive science, evolutionary psychology, game and game design), they are fun and even addictive.

Just as economist Edward Castronova pointed out, the exodus of people from engagement with the real world to the game world has now created great social change that makes global warming a tempest in a teacup [56]. While game players are cheering for their golden age, the moral debate over games has not ended. On the one hand, game industries are achieving great success and accumulating great wealth from this boom; on the other hand, the news of adolescents and young adults sudden death in front of screens with games still on have been reported in different countries [215, 243]. For a lot of non-players, including worried parents, concerned educators and politicians, games are just 'digital heroin', and playing games is nothing more than a waste of time. Even gameers sometimes feel that they have neglected other important things in their lives after engaging in games for protracted periods; this is called 'gamer regret', according to technology journalist Clive Thompson [65].

Thus, it is easy to raise this question. Games seem to be non-productive and addictive: why should game and game play be studied? Why should game experience be designed?

This question could be answered quickly: because fun experiences in games matter.

2.2.1 The Importance of Fun

Games seem to be useless, or at least non-productive. As discussed in Section 2.1, games are self-contained, closed-loop and autotelic systems that do not have, and yet do not need, external rewards such as money, power or prestige. In other words, playing games would directly reward us with nothing more than emotional contentment and pleasure. Officially, the virtual goods and virtual currency obtained in the virtual game world can not be exchanged for real money. Although there are professional gamers who build up teams to compete in professional video game competitions for cash prizes, in most cases, their names on the leader boards rewards the player with nothing more than a 'wow' in the world channel. Even a player who has explored every corner of the Continent of Azeroth can not be a geographer in the real world based on this knowledge. Also in our society, there is ingrained cultural bias regarding games. Even the word 'game' itself has a negative meaning of 'manipulate, typically in a way that is unfair or unscrupulous' [86].

Are they really useless?

Besides the fact that positive psychologists already believed that long-lasting happiness does not lie in extrinsic rewards like wealth, fame and beauty, but in internal contentment [197], there are also numerous benefits from game playing, according to the research of evolutionary psychologists. Video game players outweigh non-game players in endogenous control of attention [126, 127] and task-dependent executive control [33]. Playing certain casual video games has a positive impact on stress related disease, including depression and anxiety [245]. Video-game play may provide important principles for treating amblyopia [187]. Games such as 'Sudoku', can also benefit working memory [20]. Thus, according to all these benefits, games have been researched and designed as possible training methods for brains to deal with untrained real-world complex tasks [98]. Some game accessories, like the Nintendo Wii balance board, have also been studied regarding their utility to facilitate balance training for Parkinson's disease [99].

Fun initially seems useless too. It seems like fun is nothing serious; one antonym for fun is actually 'serious'. However, the feeling of fun can be found in any of the most serious domains. The Dutch graphic artist M.C.Escher considered his work as 'a game, a very serious game'. Aristotle believed 'pleasure in the job puts perfection in the work'. Fun matters. The feeling of fun in serious domains, as Winston Churchill stated, 'is the one class distinction in the world worth striving for' [63]. Fun is the best internal driver to pursue anything in any domain. Accordingly, games, as the best carriers of fun, have been more and more recognised as a subject for scientific research by scholars. This idea has led to many of the current fruitful game-related research areas including: game-based learning, positive impact game, social reality game, serious game and gamification.

2.2.2 From Entertainment to Serious

I am truly the Grasshopper; that is, an adumbration of the ideal of existence, just as the games we play in our non-Utopian lives are intimations of things to come. For even now it is games which give us something to do when there is nothing to do. We thus call games 'pastimes', and regard them as trifling fillers of the interstices in our lives. But they are much more important than that. They are clues to the future. Their serious cultivation now is perhaps our only salvation. That, if you like, is the metaphysics of leisure time.

Bernard Suits [23]

The first attempt to move games from entertainment to more serious areas is called game-based learning.

According to the research of Edward L. Deci and Richard M. Ryan in self-determination theory, humans — as well as other species — in their healthiest states, are by nature active, inquisitive, curious and playful creatures [82]. They are happy to engage in explorative, playful and curiosity-driven behaviours, even without external reinforcement or reward [305]. These playful behaviours, especially when the creatures are young, are identified as processes of learning in a natural way.

Accordingly, games can be viewed as learning tools [174]. As noted in game play models from a designer's perspective in Section 2.1.3, players develop their skills while the game progresses — this phenomenon could be simply interpreted as a learning process. The progression loop designed for players could be recognised as 'teaching in accordance to their abilities'.

Multimedia development has provided game-based learning with a great number of incentives and resources, leading to a lot of recent successful applications including FAA-certified 'Flight Simulator' (for aviation training) [173], 'Quest Atlantis' (a 3D game-based learning environment for children ages from 9 to 15) [30], and 'Quest to Learn' (a middle and high public school built upon the model of game-based learning in Manhattan, New York, by Katie Salen) [247].

After games were tested as effective learning tools, scholars began to wonder if educational games could be extended to much broader areas — not only as mediums of knowledge, but also providing help for personal behaviour change and habit formation. This idea has initiated successful products, including 'NIKE+ series' (a series of personal health management games on PCs, mobiles, and kinect for players to keep fit) [255], 'Plantville' by Siemens (inspired by the popularity of Zynga's 'Farmville', this game provides knowledge and training for a plant manager, as well as promoting their brand and their industrial products), and the 'Superbetter' (a web-based platform developed by the game researcher Jane McGonigal, which uses game elements to motivate players in fulfilling their goals. I have used this platform to fight against procrastination during my thesis writing) [207].

Games have also been researched for the 'greater good', so that the influence of games has extended from personal change to social change. This 'Games for Change' movement emerged in 2004 to serve humanitarian and educational efforts. This resulted in a non-profit organisation, G4C, and hundreds of game applications, including 'Free Rice' (play games to donate rice on a web-based game platform), 'Fold It' (an online puzzle game to fold protein for science), and 'EVOKE' (an online social network game to encourage players to deal with world problems after next ten years, including poverty, hunger, disease and climate change).

Serious use of serious games have been widely developed in a vast amount of areas besides entertainment and education, including military, economics, health, training and decision making. Dating back 4000 years ago in China, the playing of 'Weiqi' (also called the Game of 'Go' in Japan) has already been intuitively adopted as a training method for strategic planning in ancient wars [191, 208]. Game technology provides low-cost military simulations that have many advantages than traditional training methods, including the improvement of hand-eye coordination and the ability to work in a team [208]. Among the current serious game applications in military, the most widely used and successful one up to date is 'America's Army' developed by U.S. military, which serves as a recruiting tool for new soldiers [188]. In business and economics, games can be used as training tools for employees to develop general and job-specific skills. They can also be developed as simulations of the real economic processes. In health care, besides games and gamification applications for developing physical fitness (including 'NIKE+ series' and 'superbetter'), serious games also draw attention in recovery, rehabilitation, diagnosis and treatment of both physical and mental illness [281]. Serious games have also been developed for surgical training and decision making in recent years [125].

2.2.3 From the Virtual to the Real World

As mentioned in Section 2.1, games, especially good games, have well-designed structures to achieve positive experiences for players. However, the real world may not be structured this way. The real world does not seem to be intrinsically designed from the bottom up to make us happy [207].

Games can be simulations abstracted from the real world. Thus, by reversing the process of game design, elements of the real world can be studied for design, as much as the design of good games. Studies of games would not only benefit the 'virtual' world, including software, interfaces and virtual environments, but could be potentially important in the physical world.

2.2.3.1 Games in the Real World

Games have always been connected to the real world. The use of game rules, game elements and game structures in non-game contexts did not begin with the definition of 'gamification' in 2002 [203]. Further, it did not start from the development of game theory in the 1940s. Actually, archaeologists assume that in the age of the pyramids about 2500 B.C, worker gangs were competing against each other in building the great pyramids and left the names of their teams as graffiti, just like today's leader boards in games [217]. This might probably be the very first application of game elements in the real world.

Besides its military use, in the Earlier Song Dynasty around the eleventh century in China, the game of 'Go' also served as an inspiration for permutation in mathematics by Shen Kuo in his 'Dream Pool Essays' [177]. He also calculated the possible moves on a 5×5 game board as $3^{25} = 847,288,609,443$.

In the 1940s, John von Neumann founded the mathematical discipline of game theory, based on the considerations of the behaviour of rational decision-makers in zero-sum games [220]. game theory has now been widely applied in economics, business, psychology, philosophy, political science, biology and computer science.

Before the term 'gamification' was coined, some video game elements, including points, badges and leader boards, which are familiar to all gamers, had already been intuitively adopted in a vast amount of real world fields as rewards or incentives: from the flower-shape stamps in kindergartens to the performance table of the salesmen, from toys in a snack to a free cup of coffee after ten purchases in Starbucks, from frequent flyer programs to platinum awards credit cards.

Based on the rich tradition in HCI of designing enjoyable interfaces from games [200], along with the development of game technologies, 3D visual effects, digital music, virtual reality, and so many other technologies that we deploy in today's video games, the use of games and game elements in the real world has drawn more and more attention from researchers in numerous fields over recent years. The boom has led to a series of interesting and successful applications and several promising research areas, including serious games, detailed in Section 2.2.2, pervasive games, gamification and playful interaction.

2.2.3.2 The Future of Games in the Real World

In religious scholar James P. Carse's book 'Finite and Infinite Games' [54], life itself could be viewed as a series of finite and infinite games, that people play them either to bring the games to an end, or play them for the purpose of continuing the games. Now there are already successful gamified applications across a diverse range of topics: business, health management, finance, power saving, and habit formation. Despite the examples discussed in the former sections, there are many more not mentioned. For instance, 'Foursquare', a location-based social network application that is 'fun' to find places to be with friends, had reached 45 million users worldwide by the end of January, 2014 [1]. 'Shape up', a gamified online system for personal health management, has engaged their members to reduce over one million pounds of weight in total [3]. 'Mint.com', a personal financial management application, has attracted 10 million users to manage more than 80 billion USD in credits and debits and nearly one trillion USD in loans and assets [5]. 'OPower', an energy usage comparison application to help reduce the use of energy, has led to tens of millions of dollars reduction in users' energy bills and more than a billion tons of carbon dioxide decreased into the atmosphere [2].

In summary, games, game play and game experience are important enough to be studied and researched seriously, to benefit entertainment and serious domains, virtual worlds as well as the real world.

2.3 Human Players

In this section, human players, as another subject involved in game play interaction, are analysed. As discussed in Section 2.1.3, games could be objectively defined and designed by game designers, but the game play interaction and the game experience should be analysed from a human player's perspective. To achieve this, the information processing of players as human beings is first discussed in Section 2.3.1. The game experience model proposed in Chapter 3 is later presented based on the discussion of this section. The psycho-physiological measures that could be used to monitor human information processing in real time are then discussed in Section 2.3.2.

2.3.1 Human Information Processing Systems

Human players, discussed within this thesis, are human beings in a healthy physical and mental states. During game play, interaction requires both mental activities in problem solving and physical activities in producing game actions. Computer games using traditional input methods (keyboards and mouse) are the focus in this thesis. In this sense, the mental functions of human players are the significant focus.

The information processing of humans is the central executive control, which greatly contributes to performance during tasks. There are three approaches in which human information processing systems have been treated in the psychology field. The classic information processing approach, named as an open-loop stage-based approach, was first introduced by psychological researchers [45, 216, 231, 274]. This approach views information processing as an open-loop control system passing through different processing stages. During this process, different sources of the workload may have different influences on the different stages[308], and the different stages may also cause qualitatively different kinds of errors [236]. From this view, resources influence the performance of the human operator by influencing the different stages of information processing.

The second approach is called the ecological approach. It focuses heavily on the modelling of environment disturbance and the integrated flow interacting between the human operator and the environment [103, 118, 137]. The operator aims to meet the goals of a particular task by adapting to the environment, so that information processing is viewed as a close-loop representation in contrast to the open-loop one [250]. Human operator is considered as an element of a close-loop control system. The gap between physiological sensory devices and the executive function is controlled by mechanical linkage, which is driven by resources allocated to each parts of the human body.

The final approach is called cognitive engineering or cognitive ergonomics [234, 296], which is a hybrid of the former two. It focuses both on the understanding and modelling the knowledge structures human operators have of the domains in which they must work and the knowledge structure of computer agents in the system [250].

2.3.1.1 The Resource Theory

The resource theory is a theory of resource limitation in human information processing system. No matter which model they are proposing, there is a consensus among researchers on the characteristics of information processing: the operator must perceive information using sensory devices, must transform that information into different forms using the computational and executive processing unit, take action on both the transformed and original information, process the feedback from that action, and finally assess its effect on the environment [250]. During this sensing, transformation, action taking and feedback process, the capacity of working memory, the processing and control function on information transformation and action selection, the channels that transfer neural responses computed to the action unit, the energy and the mental efforts used during the entire process, all contribute to the performance and the efficiency of human information processing. From a resource theory perspective, the processing resources for all systems, including the human information processing system, are limited. When two processes use the same resources at the same time, they may interfere with each other. When several processes compete for the same sorts of resources, there will be a deterioration of performance. The deterioration could first be continuous smoothly degradation, named as 'graceful degradation'. If the required resources decrease enough, this may become an observed catastrophic failure [224].

The concept of a resource is critical in this context. A resource is first defined as a time that is non-shareable among tasks [44, 70, 302]. It is then developed into a limited but shareable capacity-limited processor [216]. By combining time and intensity factors, Hendy et al. define resource as the time pressure that is the load on the human information processing system that directly resulted from the ratio of the time necessary to process the required amount of information and the time allowed making a decision [144]. However, the time pressure and task complexity are not always correlated. Additionally, human behaviour is not always skill-based but sometimes rule-based [250], which means the behaviour is governed by a subconscious decision. According to another approach, by avoiding saying that a task interferes more due to its higher resource demand, and its resource demand is assumed to be higher because of its greater interference on other tasks, resource is defined separately as an energetic concept; it is an undifferentiated convergent commodity of the objective task characteristics (task complexity, bandwidth of information, etc.) and subjective rating measurements (rating of task load, skill level, etc.) like mental efforts [160], both limited and allocatable and used by human operator in tasks [309].

In complex dual task or multiple task performance analysis, resource as a single unitary commodity is too simplistic to define and illustrate the conflict and non-conflict situations occurring with multi-modality inputs and multi-concurrent tasks. Wickens presented another idea: that processing resources can be defined as a four dimensional structure with two levels in each dimension. Two tasks demanding one level of resources will interference with each other more than demanding different level of resources. It is not a unitary undifferentiated commodity, but is based on separate dimensions as stages of information processing (perceptual/cognition response), perceptual modalities of processing (input: visual and auditory, output: speech and manual), visual channels (focal and ambient) and codes of processing (verbal and spatial) [172, 307, 309, 310], as shown in Figure 2.4.

Even though there are many definitions of resource structures, researchers do not usually specify exactly what those resources are. At the beginning, time is identified as resource. Later on, energetical mechanisms, which are associated with

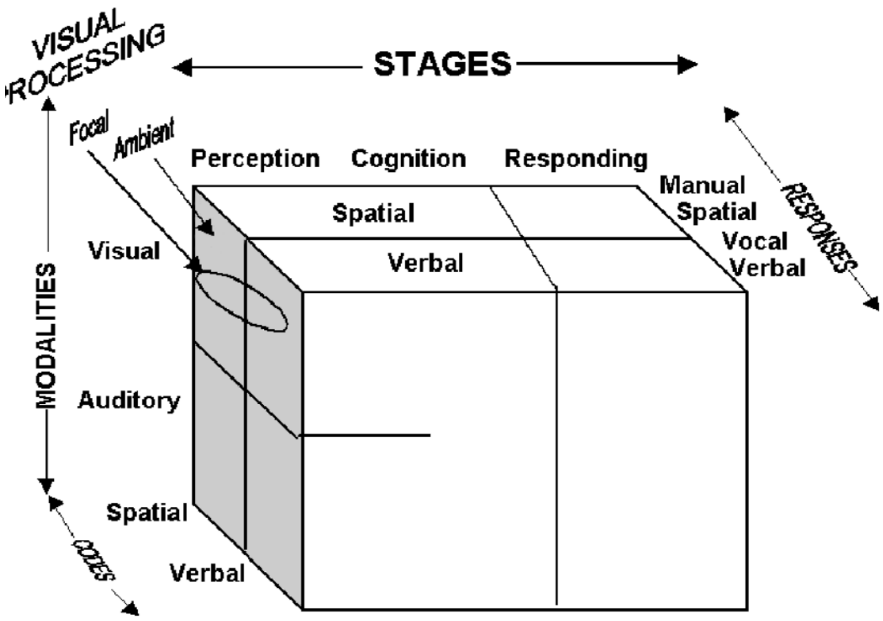


Figure 2.4: Wickens' 4-D Multiple Resource Model [310]

the activities of brain circuit, including arousal, activation and mental effort, are supposed to be resources closely related to processing stages and other typical mental state variables like mental fatigue and effects of drugs [232]. In linguistics, the resource is viewed as the limited capacity of working memory that is shared between the processing and storage demands of the different tasks to which working memory is applied [55, 77, 78]. In recent research, resources are usually conceptually defined as energetical or control systems that modulate human information processing system [172, 250]. Generally, resources definitions are categorised into three main varieties: a) a cognitive or neural substance or apparatus that could be allocated according to the requirements of tasks [145, 302]; b) a construct with both energetical and structural components [124, 224, 253]; c) a dynamic processing system that is time dependent, energy limited and structure specific [123, 249]. The actual value of the exact state depends on the available energy sources of the person, the time constraints of the performed task, and the interaction between energy sources, time constraints and processing structure [123].

There are both theoretical and practical implications with building up a resource model for the human information processing system. From the theoretical perspective, this kind of model could help understandings of the internal neurophysiologic mechanisms underlying task performance. From a practical perspective, the quantitative descriptions of these models could help estimate the performance and workloads of an operator, to increase efficiency and effectiveness of the performed tasks. Although there is former research on resource models, and there are instances in daily life that demonstrates the conflicts and limits of performance in concurrent tasks, the experimental validation of resource model is lacking to some extent.

2.3.1.2 Single Resource Model

The first idea of the resource theory is generated from the phenomena that a human operator has limited capability to deal with concurrent high requirement tasks; this is 'single channel theory'. The main idea is that the central decision mechanism of a human operator can deal with data from only one signal or group of signals at a time; delays may occur when the decision mechanism is occupied by the execution of the previous signal or feedback of the previous response [302]. This means that data from a signal arriving during the reaction time to a previous signal has to wait until the decision mechanism becomes free.

The reason for the delay is traced by the modelling of information processing. The information processing system is conventionally modelled as a filtering process with limited communication channels, connecting the central control function and the rest parts of human body [224, 309]. The filtering is assumed to be carried out by the mechanisms of human attention. Some conventional resource theories, like filter theory and bottleneck [44, 302] developed from this idea.

The first idea developed by Craik considers the human operator as an intermittent correction servo [70]. By analysing performance at tracking tasks and considering the cause of the intermittency happened between the stimuli and the response, Craik argued for two possible reasons: 1) the transmission time of nerve impulses travelling down to the sensory and motor nerves; 2) there is condensed time lag in one part of the chain. The first reason is unlikely as the incoming impulses are continuous. Thus, he considers the time lag is caused by the building up of some single computing process.

Welford conducted experiments studying the effects of discrete stimuli where a signal was arriving during the reaction time to a previous signal. The results show that the delays which lengthen the reaction time of the second stimuli are not eliminated by practice, and are due to the limitation of central function rather than the sensory functions [302]. Mental workload was measured based on a time-based assumption developed from this single channel resource theory; decisions take time, and that if this is more than the time available, responses will be delayed or omitted.

2.3.1.3 General Resource Model

Numerous experiments were conducted after the development of single channel resource theory, and researchers found that resource demand might be a more convergent concept instead of a simple bottleneck as first thought [163]. The general resource model developed out of the definition of resource as energetics concept, like the mental effort that can be characterised independently of its influence on dual task performance [146, 160]. In Kahneman's book about attention, human task performance was supported and constrained by mental efforts which could be considered as a general set of undifferentiated resources [160]. The model was also discussed earlier by Moray in 1967 [216]. Mental workload was measured according to the relation between demand for resources and the ability to supply those resources by the operator [216]. The general resource model discussed the decay of concurrent task performance due to a gradual lack of available mental efforts as resources, which was different from the single resource model that considered the human operator as an all-or-none 'bottleneck'.

2.3.1.4 Multiple Resource Model

The multiple resource model developed from the general resource model and some experiment results that indicated variance in dual task performance might not be attributed just to the quantitative resource demand of one or more component tasks, nor to the resource allocation policy between them [162, 306]. Mental efforts are not considered as a set of undifferentiated resources but as a structural concept with different levels and priorities. Series of studies have been done to explore the structure of the resource including a four dimensional multiple resource model developed by Wickens [309, 310], as shown in Figure 2.4.

The resource conflicts during concurrent tasks have later been discussed in Section 4.7.1, which was shown as a resource shift from facial activities to more significant brain functions when the difficulty of game tasks increases during consecutive playing.

2.3.2 Psycho-physiological Measures and Methods

The information processing of humans, reviewed in Section 2.3.1, captures the subjective feelings and thinkings of human players during game play. However, to evaluate the process, objective measurements can alsp be used to indicate the subjective game experience. In this thesis, questionnaires, game problems and game actions, together with psycho-physiological data collected during game play, are focused on, to evaluate proposed player-centric game experience model in Chapter 3.

The psycho- physiological data captured in the thesis could be categorised as phy- siological data (including heart rate, SC, ST, respiration data and surface electromyographic data (EMG)), and psychological data (EEG data) to facilitate analysis. Each is explained specifically in the following subsections.

2.3.2.1 Blood Volume Pulse

The heart rate (HR)/BVP signal is collected by a BVP detection sensor attached on fingertip of the subject's middle finger using an elastic strap, which is also known as photoplethysmography (PPG) sensor. This technology is a measure of the time variation of the blood flow through tissue using a photoelectric transducer, as the blood absorbs infrared light much stronger than other tissues. The output of this sensor is an electrical signal of the reflected light, which varies during each heartbeat as the blood running through tissues changes [8].

The heart pushes out blood to distribute arterial blood (oxygen-rich blood) to body and tissues, while collecting venous blood (deoxygenated blood) travels back to the heart. With every beat, it creates a wave of blood inside human body through vessels. The blood volume changes among all parts of human body are directly determined by heartbeat. Thus, the BVP can also be used as a non-invasive measure of the heart rate.

To get better radiation results, the sensor should be attached on the inner side part of the finger's first joint. Because the BVP sensor is sensitive to light and pressure, the sensor should be placed neither too loosely (the gap between the sensor and the skin will affect the result), nor too tightly (the pressure on fingertip will interfere with blood circulation) [8], as shown in Figure 2.5.

The BVP signal (BVP%) obtained is calculated from the output voltage (V) by the sensor [8], according to Equation 2.1.

$$BVP\% = 58.962V_{out} - 115.09 \tag{2.1}$$

This small finger-worn instrument could be used to collect heart rate and heart rate variability of the experiment subjects, as well as providing BVP amplitude, waveform and vasoconstriction [135]. The main indicators interested in are heart rate and heart rate variability.

The heart rate is the number of heartbeats per minute, and the heart rate

Figure 2.5: BVP Sensor

variability is the variation of the interval between heartbeats. These physiological phenomena have been investigated since the first clinical research into the human cardiovascular system. The normal resting heart rate of a healthy human ranges from 60 to 100 bpm. This variation is influenced by age, emotional stimuli, and the level of physical condition (physical activity and health). The maximum heart rate could be represented as 2.2 according to [106, 107] during heavy exercises, in which HR_{max} represents the maximum heart rate for people at a particular age:

$$HR_{max} = 220bpm - age \tag{2.2}$$

The heart rate can drop to 40bpm during sleep.

For resting conditions, the heart rate changes could be indicators of human emotional states including happiness, anger, fear, stress, frustration, relaxation, hate, grief, and reverence [66, 96].

The heart rate is a non-stationary signal. The oscillation of inter-beat interval, named as heart rate variability (HRV) is dependent on the regulation of heart rate and is a useful signal to analyse the status of the autonomous nervous system (ANS) [16]. HRV is widely used in diagnosis of myocardial infarction [52, 53], central and peripheral nervous system malfunctions [195], depression [52, 53], diabetes [304], and other diseases [16]. For healthy humans, HRV has been widely used as an indicator of stress and mental efforts, which usually decreases as the task load and mental efforts increases [242, 311], and increases if the mental efforts required exceeds the capacity of working memory [242]. Decreased HRV also has been used in showing emotional states like stress, frustration and anger [96].

The heart rate and heart rate variability are computed from the inter-beat interval (IBI), which is the time period measure of intervals between two adjacent peaks of the blood volume. The resulting smoothed IBI is the mean of 20 time intervals. When a new data point is available, the oldest one drops of the queue and the new interval is added. This smoothing method is used to reduce the impact of sensor movements and body movements, which causes noise to the signal. The heart rate is the number of peaks per minutes, which is converted from the time period IBI to a rate. The HRV is the difference between two adjacent IBI data. The signal processing is shown in Figure 2.6 and Table 2.3.2.1.

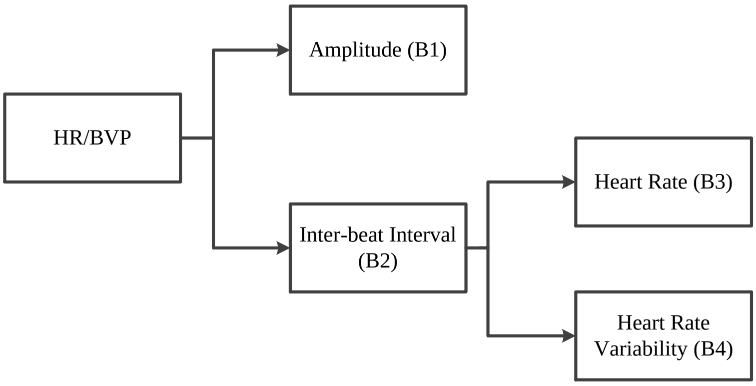


Figure 2.6: Signal Processing of BVP Data

Table 2.1: BVP Signal Processing

B1	Relative Amplitude of BVP	$\frac{d^2BVP(valley)}{dt} < 0$ $\frac{d^2BVP(peak)}{dt} > 0$ BVP$Amp = BVP(peak) - BVP(valley)$
B2	Inter-beat interval	$IBI = t(peak+1) - t(peak)$ $AverageIBI[n] = \frac{IBI[n]+IBI[n-1]+...+IBI[n-19]}{20}$
B3	Heart rate	$HR = \frac{60}{IBI}$ $SmoothedHR[n] = \frac{HR[n]+HR[n-1]+...HR[n-19]}{20}$
B4	Heart rate variability	$HRV[n] = IBI[n] - IBI[n-1]$ $SmoothedHRV[n] = \frac{HRV[n]+HRV[n-1]+...+HRV[n-19]}{20}$

The signal processing methods B1, B2, B3 and B4 listed in Table 2.3.2.1 correspond to the feature extraction of amplitude, inter-beat interval, heart rate and heart rate variability in Figure 2.6 from the collected BVP signal.

The BVPAmp in B1 method represents the relative BVP amplitude, which is calculated from the difference between peak amplitude $BVP(peak)$ and valley amplitude $BVP(valley)$. The $BVP(peak)$ and $BVP(valley)$ are correspondingly found out by the arithmetic signs of the second derivative of BVP raw signal.

The IBI in B2 method represents the inter-beat interval of heart rate, which is calculated by the time difference of different peaks found in BVP raw signal. The $averageIBI$ is the smoothed average IBI value calculated among 20 consecutive IBI results.

The HR in B3 method represents the heart rate calculated from IBI in B2 method. The $SmoothedHR$ is also the average HR value among 20 consecutive HR results.

The HRV in B4 method represents the heart rate variability which is computed by the difference between two consecutive IBI values. The HRV could also be smoothed by averaging among 20 consecutive HRV results.

2.3.2.2 Skin Conductance

The skin conductance(SC) signal is the conductance across the human skin, also named as galvanic skin response (GSR), SC response (SCR) or SC level (SCL). The measurement of SC is by sending a small amount of electrical potential through the human body and then measuring the electrodermal response between two points of the skin. The instrument to fulfil this task is called SC sensor.

The skin of a human in resting state is a high impedance resistance (low conductance). Leaving out personal differences, the conductance varies by several micro Siemens for same subject. Though this has not fully been confirmed, this variation is generally considered as relating to the sweat secreted by the skin [135], due to emotional arousal and to the number of sweat glands activated by the sympathetic nervous system. This is one of the three major part of the ANS. Due to this, the SC could be considered as the indicator of sympathetic nervous system activation and emotional arousal.

Finger SC is collected by using a SC sensor with two straps on the index and the ring fingers of the subject. To obtain better connection, the electrodes should be placed at the inner side of the second joint of finger to avoid falling off [11].

The resulting conductance is transformed from output voltage by the sensor itself using Equation 2.3. The conductance is measured in micro Siemens. The output signal ranges from -2.0V to +2.0V [11].

$$c = 24V_{out} - 49.2 \tag{2.3}$$

The SC sensor in use collects SC levels and its variations during tasks, as shown in Figure 2.7.

The SC has been generally recognised as a good indicator of emotional arousal. It is linearly correlated to arousal [181] and cognitive workload [39]. It is also considered related to different emotional states including anger, anxiety, fear, happiness and sadness [262]. It is also influenced by environmental temperature, age, sex and personal differences [39, 135].

The SC level is the raw data collected from the SC sensor. Averaging the signal within each 20 samples smooths the raw data. Skin resistance (SR) is the direct inverse of the conductance, as shown in Figure 2.8 and Table 2.2.

Table 2.2: SC Signal Processing

C1	Skin Resistance	$SR = \frac{1}{SC}$

The C1 method in Table 2.2 corresponds to the signal processing of raw skin conductance signal in Figure 2.8, in which SR is the skin resistance calculated from skin conductance SC.

2.3.2.3 Skin Temperature

The ST signal is a measure of the skin surface temperature, which normally has a mean of 32° C–35° C (89.6° F– 95°F) for a healthy human body [110, 116]. The temperature of finger skin surface is captured within the frame of the experiments in

Figure 2.7: SC Sensor

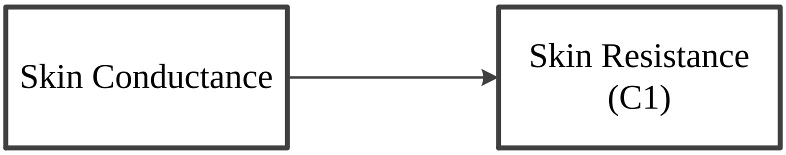


Figure 2.8: SC Signal Processing

this thesis, which usually ranges from 10°C–45°C (50°F–115°F).The ST sensor used is a thermistor together with a loop fastener to make sure solid contact between the thermistor and the finger skin [12].

Human ST is regulated by the thermoregulation system that keeps the human body temperature within certain boundaries. Though greatly influenced by the environmental temperature and blood circulation, the variations of finger ST could indicate the peripheral vasoconstriction caused by arousal.

The ST sensor should be placed firmly against the fleshy part of subject's finger using the loop fastener. To ensure better compatibility with other sensors listing above, the ring finger is recommended for both SC sensor and the temperature sensor, and should be placed there using one single loop fastener when all sensors are supposed to be placed on one hand [12].

The output temperature is transformed from the voltage (V) to the Celsius degree and the Fahrenheit degree by the sensor. The output ranges from 10°C-45°C (50°F-115°F) [12], according to Equation 2.4 and 2.5.

$$T_C = 21.34V_{out} - 32.085 \tag{2.4}$$

$$T_F = 38.415V_{out} - 25.754 \tag{2.5}$$

The ST sensor is used to collect the finger temperature and its variations during tasks, as shown in Figure 2.9.

Figure 2.9: ST Sensor

The activations of sweat glands that cause changes of SC also lead to temperature changes in the body. Finger temperature is high in a period of security, relaxation and comfort. It falls with anxiety, anger, embarrassment, humiliation, depression, guilty, fear and conflict. The degree of temperature fall is determined by the degree of stress and conflict [212]. It is also greatly affected by environmental temperature.

The ST indicator is also derived directly from the raw signal, according to Figure 2.10 and Table 2.3. The artifact is detected by calculating the signal as a percentage of 36.7°C and then computing the rate of changes within one second. If the changing rate exceeds a certain level, it is considered as noise contaminating the signal.

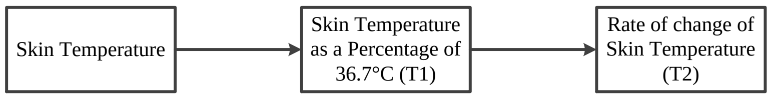


Figure 2.10: ST Signal Processing

Table 2.3: ST Signal Processing

T1	As a percentage of 36.7° C	$\mathrm{ST}Per = \frac{ST}{36.7} \times 100\%$
T2	Rate of Change	$Change[n] = \frac{STPer[n]-STPer[n-256]}{256}$

The T1 and T2 methods in Table 2.3 compute the ST percentage and the rate of change shown in Figure 2.10. The STPer represent the ST as a percentage of 36.7° C, which is average body temperature for normal healthy person. The *Change* is the rate of change of ST in one second (the ST signal is collected at 256Hz).

2.3.2.4 Respiration

The respiration sensor measures the expansion and contraction of the torso while breathing, which is shown in Figure 2.11. From the captured signal waveform, the respiration rate and depth can be calculated. One single respiration sensor placed around abdomen is used to measure the expansion of abdomen caused by breathing in and out during experiments. The sensor is a girth sensor with a loop strap made of natural rubber and a self-adhering belt, which could be worn over clothing. If the subject is allergic to rubber, this sensor could be removed.

Figure 2.11: Respiration Sensor

The variation of respiration rate and depth within the same healthy person could be indicators of emotional arousal and emotional states [37, 101].

The rubber band of the respiration sensor should be placed neither too loosely (losing contact in relaxation) or too tightly (inhibiting breath functions). It is recommended to ask the subject to breath out while attaching the sensor to make better contact. The girth sensor itself should be keeping in front [10].

The respiration elongation signal is transformed from voltage by the sensor [10], according to Equation 2.6.

$$Respiration\% = 58.923V_{out} - 115.01 \tag{2.6}$$

The respiration sensor around abdomen is used in collecting respiration rate, amplitude and period, as well as its waveform.

The main indicators interested in are the rate and the depth (amplitude) of the respiration. Average respiration rate reported in healthy human adult at rest usually ranges from 12 to 20 breaths per minute [157, 233]. It generally goes faster and deeper when the subject is excited, angry and afraid: faster and shallower when panicked or concentrated; slower and deeper in relaxation and rest; slower and shallower when the subject is withdrawn or passive [37, 135]. The respiration depth falls following this order: fear, anger, pleasure, laughter, pain, hate, wonder, disgust, normal [101].

The depth (amplitude) of respiration is a relative measure of amplitude between the adjacent peak and the valley. The respiration rate and rate variability are obtained using the same method for calculating HR and HRV from BVP signal, according to Figure 2.12 and Table 2.4.

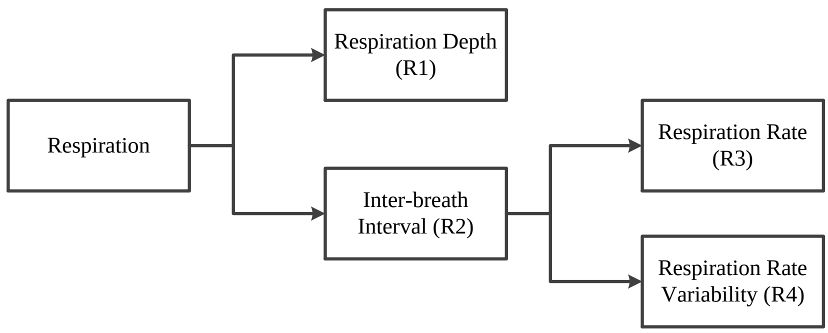


Figure 2.12: Respiration Signal Processing

The R1, R2, R3, and R4 methods shown in Table 2.4 are responses for the signal processing procedures shown in Figure 2.12. The calculations of respiration depth, inter-breath interval, respiration rate and respiration rate variability are the same with the methods used in B1, B2, B3 and B4 for heart rate features, derived from BVP signals. These include RespAmp, IBI, RR, and RRV represent respiration depth, inter-breath interval, respiration rate and respiration rate variability accordingly.

2.3.2.5 Electroencephalography

EEG is a technique of recording micro-electricity response along the human scalp. It is an effective way of measuring the electrical functions of brains. The EEG

Table 2.4: Respiration Signal Processing

R1	Respiration Depth	$\frac{d^2\mathrm{Resp}(valley)}{dt} < 0$ $\frac{d^2\mathrm{Resp}(peak)}{dt} > 0$ $RespAmp = \mathrm{Resp}(peak) - Resp(valley)$
R2	Inter-breath interval	$IBI = t(peak+1) - t(peak)$ $AverageIBI[n] = \frac{IBI[n]+IBI[n-1]+...+IBI[n-19]}{20}$
R3	Respiration rate	$\mathrm{RR} = \frac{60}{IBI}$ $SmoothedRR[n] = \frac{RR[n]+RR[n-1]+...RR[n-19]}{20}$
R4	Respiration rate variability	$RRV[n] = IBI[n] - IBI[n-1]$ $SmoothedRRV[n] = \frac{RRV[n]+RRV[n-1]+...+RRV[n-19]}{20}$

sensor is a pre-amplifier for amplifying the electrical signals collected along the scalp, which are created when electrical charges moves along the central neural system. The neurons transmit and pass information by sending electrical signals down the axon to synaptic terminals, which in turn affect relevant neurons by sending neurotransmitters into synapses [102, 287]. These electrical signals finally reach the electrodes of the scalps as differences of voltage measured and recorded over time. The EEG signal is not indicating the particular activities of a neuron, but the measurement of current that flows during excitations of dendrites of many neurons [254]. The recording is the potential between positive and negative (reference) electrodes, which varies constantly over time. The main sources are layers of cortical neurons.

Primarily, there is no single widely accepted model of how the brain works. EEG as an important parameter of brain activities has been used in clinical fields for decades. The clinical use of EEG is often recorded to distinguish dysfunctionality, seizures, or to monitor the effect of anaesthesia, or as a complementary method of measuring brain death. For research use, EEG is widely applied in neuroscience, cognitive science and brain-computer interactions.

The EEG sensors are placed according to the principal of international 10 to 20 electrodes placement system [156], which is an internationally recognised method of EEG sensor placement. It is called 10 to 20 because the electrodes are placed according to the segmentation of the distances between adjacent electrodes; they are either 10% of 20% of the total front-back or left-right distance of skull. The EEG sensor is shown in Figure 2.13.

Figure 2.13: EEG Sensor

The electrode sites are named with a capital letter and a number. The capital letter indicates which area of brain the electrode is targeting. The number is used to indicate the distance between the site and the central line along the interhemispheric fissure.

To achieve clean and effective EEG recordings, electrode preparation, scalp preparation and electrode placement are essential for every recording. The electrodes should be cleaned before use. The scalp must be prepared before fixing the electrodes by applying skin prepping gel to remove dead skin, sweat and other contaminations to the EEG signals. The electrode cups should be filled with conductive paste to fix to the prepared parts of scalp, as a positive site. Ear clips are used on both sides of the ear lobes for reference sites. Conductive paste should also be applied to the gold disc of the ear clip electrode to achieve better conduction of the reference sites [7].

The output of the EEG sensor is the voltage between positive and reference sites, named raw EEG signal, and usually measured in microvolts [7].

The EEG sensor captures the raw EEG signal, which can be filtered into different frequency bands for analysis, as well as its amplitude, waveform, power spectrum, power of the raw signal and of different bands. The correlation and coherence between different electrode sites can also be calculated.

The early clinical use of EEG was to diagnose diseases by visualising the waveform over time and inspecting the signal. The computational method of signal processing enabled a more comprehensive way of analysing EEG signal by time and frequency analysis. The most well-known classification of EEG waveform uses frequency bands, which classify EEG signal into delta (0-4Hz), theta (4-8Hz), alpha (8-13Hz), beta (13-30Hz), gamma (>30Hz) [287]. Frequency bands are usually extracted by using spectral estimation methods. The low frequency bands, including delta and theta, are usually seen in infant EEGs, or when the subject is in deep sleep, drowsiness or meditation. The alpha band is usually seen in adult relaxation [279], and the beta band in active movements, concentration and anxiety. The beta band is closely related to mental activity and engagement. The attention (arousal) is first investigated in the close-eye attenuation of EEG, especially at the alpha band [18]. The alpha band emerges when closing eyes and relaxing; it attenuates when opening eyes and mentally engaged. The beta band emerges and alpha band attenuates when paying attention. The high frequency gamma band is only related to some certain cognitive or motor functions [287], like diverse information binding, motor activity, sensory coordinating, selective attention, transient binding of cognitive features and conscious perception of visual objects [151].

The asymmetric feature of pre-frontal cortex EEG activity is widely recognised as relating to positive and negative emotions. The greater relative left than right frontal cortical activity is associated with positive affect (positive or approach in valence) [19, 67, 121, 139, 290]. Correspondingly, the greater relative right than left frontal cortical activity is associated with negative affect (negative or withdrawal in valence) [155, 257, 282, 290]. However, the latter is far less extensive than the former. This effect is usually seen in the alpha band.

Amplitude, waveform, power, and power spectrum of the raw signal, as well as its different frequency bands are indicators in this thesis.

The EEG signals are subject to noise and artifacts. During preprocessing stages, the noise in the EEGs may be estimated and mitigated using filtering techniques. EEGs capture neural information under 100Hz. Frequencies above 100Hz can simply be removed by using low pass filters. EEG signals usually contain a huge 50 or 60Hz artifacts. In this case, another notch filter is designed to reduce this artifacts.

The short-time Fourier transform is used to achieve frequency analysis of EEG signals. The EEG data has been used in clinical field for decades by visual inspection, but the first breakthrough towards digital processing of the EEG signal came with the development of fast Fourier Transform (FFT), which made the application of Fourier Transform possible. From then, Fourier Transform became the major signal processing tool for EEG, providing new information about the spectrum. However, the Fourier Transform is based on an assumption that the signal outside the window is periodic, which results in high error rates. It also lacks the information on the time evolution of the signal. Another approach, named short-time Fourier Transform (STFT), was developed to partially solve this problem. With this approach, Fourier

Transform is applied to segmented data via different windows. Then, the time evolution of the frequencies can be followed and the stationary requirements will come back to the satisfaction of the stationary requirement within the window length.

The short-time Fourier Transform (STFT), also called Gabor Transform, is a window-based Fourier Transform which multiplies the signal $f(t)$ with a window function g, and then computes the Fourier coefficient of the product gf, so that only the signal within the frame of the window is considered. This process is repeated across the time. It results in a compromise of both time-based and frequency-based views.

The mathematical presentation is shown in Equation 2.7

$$X(m,\omega) = \sum_{n=-\infty}^{\infty} x[n]\omega[n-m]e^{-j\omega n} \tag{2.7}$$

The EEG signal is generally described as the combination of rhythm activities and transient activities. The rhythm activities are usually analysed by first dividing the EEG raw signal into different frequency bands, and then analysing the features in each frequency band accordingly.

This filter is designed to filter EEG waveform into different frequency bands, as delta, theta, alpha, beta, and gamma. Equiripple band pass filters, based on the Parks-McClellan optimal FIR filter design method, are designed to achieve the optimal result between the desired frequency response and the actual frequency response.

The basic statistical features extracted directly from the EEG raw signals are the maximum, minimum, mean, median, standard deviation, skewness and kurtosis. The skewness is the measure of lack of symmetry of a data set. If the left tail is longer, the density is concentrated on the right tail; it is called negative-skewed. Otherwise it is called positive-skewed. If the data is more centred, the skewness will be close to 0. The kurtosis is the measure of whether the data is peaked or flat. The data with high kurtosis tends to have a more distinctive peak near the mean. The first and second order derivatives of the EEG signal are also calculated.

The power spectrum of EEG signal is computed by Welch method. The Welch method is a spectrum estimator that computes an averaged squared magnitude of the Fourier Transform of EEG. The absolute and relative powers (power at the percentage of total power) for delta, theta, alpha, beta and gamma bands are computed from the power spectrum according to their frequency range.

It is clear that there are interactions and collaborations among different brain regions while performing mental tasks. It is not always easy to find these relationships via visual inspection. If a time series could be predicted by another, then they are said to be causal [254]. The correlation and coherence between different EEG channels might be clues to find the interactions. The correlation coefficients could describe the global relationship between features. The coherence is a measure of the correlation between two time series at each frequency. In other words, the advantage of coherence over correlation is that it could show at which frequencies two sets of time series are coherent and at which frequencies they are not. Coherence, in EEG analysis, usually shows the functional association between two different regions.

In summary, the EEG signal processing methods and results are shown in Figure 2.14 and Table 2.5.

The E1 to E6 methods in Table 2.5 are signal processing for EEG raw signals collected from all channel sites represented in Figure 2.14.

The first E1 step is for noise reduction, low pass, band pass and notch filters are used to reduce noise and artifacts outside interested frequency bands. The upper and lower bounds are determined by the context of the experiment and analysis.

The second E2 step is to separate frequency bands using designed band pass filters discussed above. The exact upper and lower bounds of each frequency band are also determined by experimental design.

The EEG signals, after filtering into different frequency bands, are discussed within the frame of each band. Both time domain analysis and frequency domain analysis are performed. Time domain analysis is achieved by methods E4, E5 and

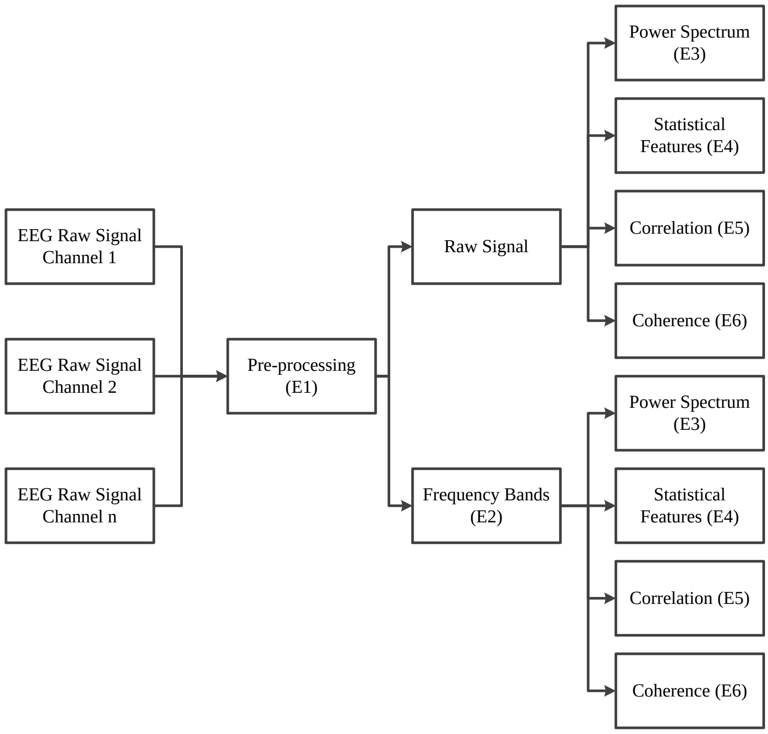


Figure 2.14: EEG Signal Processing

Table 2.5: EEG Signal Processing

E1	Noise Reduction	Low pass, band pass and notch filter
E2	Filter into different frequency bands	Band pass filter
E3	Power spectrum estimation by Welch method	$\hat{R}_{x_m}(k) = \frac{1}{M}\sum_{m=0}^{M-1}\lvert DFT_k(x_m)\rvert^2 \triangleq \{\lvert X_m(\omega_k)^2\rvert\}_m$
E4	Statistical features	maximum, minimum, mean, median, standard deviation, skewness, kurtosis, derivatives
E5	Cross correlation	$\hat{\rho}_{xy}(k) = \frac{\hat{\gamma}_{xy}(k)}{\sqrt{\hat{\gamma}_x(0)\hat{\gamma}_y(0)}}$
E6	Coherence	$\lvert R(\lambda)\rvert^2 = \frac{(Mod(f_{y,x}(\lambda)))^2}{f_{y,x}(\lambda)f_{x,x}(\lambda)}$

E6, including statistical feature extractions, cross-correlation and coherence analysis. The frequency domain analysis is achieved by estimating power spectrum by Welch method, discussed in E3.

The periodogram of the signal x at the kth block with the length of M is calculated using E3 method, in which, DFT represents the discrete Fourier transform.

The cross-correlation ρ between two series x and y at the time lag of k is calculated using E5 method, in which γ is the cross-covariance. The coherence $|R$ between two series x and y at frequency λ is calculated using E5 method, in which f_x and f_y are Fourier Transform of x and y.

2.3.2.6 Electromyography

The surface electromyography (sEMG) technique is a non-invasive measure of muscle electrical responses during movement. The surface electromyography sensor is an amplifier that measures and records the micro-electrical impulses generated by muscle fibres when they contract, as shown in Figure 2.15. When the muscle cells are electrically or neurologically activated, a small electrical potential is generated at the surface of skin to be captured. This technique is used to measure subtle muscle activities and expressions that are not visible to the observer's eyes; participants are not even aware of them.

Figure 2.15: EMG Sensor

The sEMG sensor is applied to the zygomatic part and corrugator part of the subject's face in our experiment. Zygomatic EMG (ZEMG), which measures the muscle activity at the corners of mouth, often correlates with the positive emotional activity. Corrugator EMG (CEMG), which measures muscle activity between the eyebrows, usually works as an indicator of negative emotional activity. The sensors are attached to skin by a especially designed sticky pad. Skin preparation is recommended using an alcohol pad and the skin prepping gel [9]. Conductive paste can be used to achieve better skin-electrode contact.

The output of the sEMG sensor is an analogue root mean square (RMS) of the amplified electromyography (EMG) signal, which results in low changing rate of the signal [9]. The results are usually measured in microvolts, at the maximum of 1600 microvolts RMS.

The sEMG sensor captures the electrical signal caused by muscle contraction, and its amplitude and spectrum [9].

The ZEMG signal emerges when the subject is both in pleasant or unpleasant extremes, but is stronger in pleasant extremes. It attenuates in neutral states. The CEMG emerges when showing unpleasant emotions, and attenuates gradually when pleasant emotions emerge [42].

The most important feature about sEMG is the power of its raw signal, which shows the extent of contract at zygomatic part and corrugator part. The power of sEMG is calculated using the same method for EEG, which is to estimate the power spectrum density using the Welch method and to integrate the power within all frequency bands, as shown in Figure 2.16 and Table 2.3.2.6.

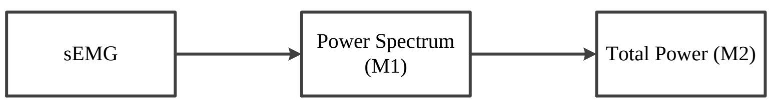


Figure 2.16: EMG Signal Processing

The power spectrum and power of EMG signals are calculated using M1 and M2 methods, as shown in Table 2.3.2.6 and Figure 2.16. The power spectrum is also

Table 2.6: EMG Signal Processing

M1	Power spectrum estimation by Welch method	$\hat{R}_x(k) = \frac{1}{M}\sum_{m=0}^{M-1}\lvert DFT_k(x_m)\rvert^2 \triangleq \{\lvert X_m(\omega_k)^2\rvert\}_m$
M2	Power	$x_{pwr}(n) = \lvert x(n)\rvert^2$

calculated using the Welch method discussed in the previous section. The power of EMG x_{pwr} is the squared amplitude $x(n)$, as shown in the M2 method.

2.4 Conclusion

In this chapter, the two main subjects involved in game play interaction — games and human players — were analysed. Game play models proposed from the game designers' perspectives were presented in Section 2.1.3, which showed that positive game experiences (or even optimal experiences) could be designed, but should be designed on the basis of understanding human players in real time during game play. Human information processing, which covers the feelings and thinkings during game play, was reviewed in Section 2.3.1. Objective measurements, which are used in this thesis to reflect game experience, were discussed in Section 2.3.2. The analysis of human players indicated the potential for using psycho-physiological signals to assess real time game experiences from player's perspectives as an information processing system, which is specifically proposed in the next chapter.

Chapter 3

Game Experience Model

Information's pretty thin stuff unless mixed with experience.

Clarence Day

As discussed in Chapter 2, a game is 'a system governed by rules involving problem solving and is designed to be fun'. This definition led to further discussions in Section 2.1.2 and Section 2.1.3 that games are a designed experience meaningful to players, intended as fun. For game designers, the ultimate goal is to achieve an optimal fun experience for players, and the longer it lasts the better. However, real game play is not accomplished by designers, but by players. Thus, both the game player interaction as game play and the game experience should be analysed from players' perspectives, which differs from the game play models discussed in Section 2.1.

However, similar to the definition of 'game', currently there is no widely recognised agreement on definitions and models of game play and game experience for human players. In this chapter, games, game play and game experience are defined, analysed and modelled from a human player's perspective. Specifically, definitions are presented in Section 3.1. The relevant research is discussed in Section 3.2. The game play interaction and game experience models as information processing systems are illustrated in Section 3.3. The evaluation of the models from the subjective and objective indicators derived before, after and during game play are addressed in Section 3.4. Designed game environments for testing the models are discussed in Section 3.5, with the final Section 3.6 concluding this chapter.

3.1 Definition of Games, Game Play and Game Experience

For game players, the journey of game playing is to find optimal solutions in the game problem field while maintaining an enjoyable attitude. Accordingly, games can be interesting problem spaces; good tools for problem solving, true engagement, instant feedback, and a win state represent successful problem solving.

From this view, game play is an exploration and exploitation interaction, between a human player as problem solver and the game as an interesting problem space. Unless the player chooses to drop out of the game play process, game play is a flow of interaction cycle between human players and games as a result of information processes: the game imposes problems upon the player, the player recognises the problems and responds game actions, attempting to solve the problem.

The game experience is correspondingly defined as all aspects of the human player experience when involved in game play: interaction with games are both enjoyable interfaces and environments. During game play interaction, the game experience of the human player is not constant. The game experience could be considered as the cognitive and affective processes, instead of the results, during game play. From a cognitive perspective, the player could be either more 'into' (engaged in) the problem solving, or more 'dropped out' from the process. From an affective perspective, the player's emotional state during game play is considered. Unless some particular negative emotions are expected, due to the objectives of the game design, in general, a cheerful excited emotion would contribute to improve game feelings. All these processes could influence the cycle of game play, as game actions and performance are the results of game experience.

Before proposing designed game play and game experience models, relevant research in game design, HCI and cognitive science on the analysis of game design and game experience is reviewed in the following section.

3.2 Related Research

3.2.1 Heuristic Game Design and Game Evaluation

Though there is no consensus in the existing definitions of game play and game experience, in academic game research and the game industry, heuristic game design principles and evaluation methods for the success of games have been studied and discussed. Within the realm of computer games, among various game design architectures and principles formulated by game designers [111, 113, 201], two main methods are used in the design and evaluation of games: prototyping and usability analysis.

3.2.1.1 Prototyping and Playtesting

Prototyping and playtesting are methods used in iterative computer game design, which is a cyclic process consisting of prototyping, playtesting, evaluating and refining. A prototype of a designed game is usually made from early questions and game ideas, is used to be played, evaluated, adjusted and played again, as an intermediate product to facilitate decisions in successive game design [248]. This idea originated from software prototyping, which creates simulations of some aspects of the final product to gain feedback from users in the early stage of software design.

As most computer game designers, especially in the twentieth century, have been or are computer programmers, it is natural that software prototyping methods were inherited by game design. Prototypes are important tools in most design areas. However, current game prototyping and playtesting lacks consistency and formal methodologies in facilitating prototype designs and also in evaluation and data analysis of the testing results. According to this situation, a heuristic usability test, which is usually used in HCI, is presented in the context of enjoyable interface design [158, 264].

3.2.1.2 Heuristic Usability Analysis

The usability evaluation of game success has been studied using HCI theories and methods to identify and analyse game usability issues. These heuristic methods are generally used at the game prototyping stage to improve the game design process and in the game evaluation stage to inspect the design.

However, usability analysis and user experience analysis of games are two different concepts. Usability is about the 'effectiveness, efficiency and satisfaction with which specified users achieve specified goals in particular environments', and user experience is about 'all aspects of the user's experience when interacting with the product, service, environment or facility', according to the international standards established by ISO [277]. In short, usability is about the ease of use, and the user experience is about the overall 'feelings' the product provides. Within the context of games, which intentionally impose problems on the players, the 'easy to use' standards for usability tests are not appropriate, or at least not sufficient, of analysing game experience.

3.2.2 Game Flow and Psychological Models

Bio-psychologists and social-psychologists have been doing relevant research in flow, presence, immersion, involvement, engagement, absorption, and dissociation. However, none of these concepts could be binarily selected to represent game experience in general (e.g., flow and out-of-flow). To justify this statement, each of these concepts has been reviewed in the following paragraphs.

Flow, as discussed in Section 2.1.2.2, is defined by Mihaly Csikszentmihalyi as psychological state that involves complete immersion with enjoyment [74, 76]. The flow state is identified with nine elements: 1) clear goal and immediate feedback; 2) balances between challenges and skills; 3) high level concentration on limited field;

4) the feeling of control; 5) the loss of self-consciousness; 6) altered perception of time; 7) the merging of action and awareness; 8) effortless; 9) the autotelic activity [74, 75]. These elements align well with game design principles: adapting flow to games, a GameFlow model was built to evaluate the player's enjoyment in games [284]. However, the first two and the last elements are design principles for the task. The middle five elements describe the optimal feelings to be achieved, but which rarely occur in real game playing. In other words, the feeling of flow may be the 'apex' of game experience. However, 'out-of-flow' does not mean the player is not enjoying the game.

Presence, as the feeling of 'being there', has been divided into three categories: telepresence, copresence and social presence [225]. Telepresence is defined as 'being present' in a virtual or mediated environment [143, 211]. Copresence means psychological connections to and with another person [119, 225]. Social presence reflects the ability of the medium to deliver the salience of another person [133, 265]. Among these three, only telepresence and social presence are applicable in the game domain; social presence is only applicable to online games and face to face games but not console games. The feeling of telepresence is affected by two main factors: interactivity, which shows the level and type of the feedback provided; and vividness, which is the breadth and depth of the feedback message [88, 275]. Interactivity is also correlated with the flow state in its form of constant feedback [147]. However, the feeling of telepresence, and presence in general, is only applicable to certain individuals as players, and in certain game genres. Interactivity and vividness, which affect telepresence in prominent ways, only relate to the feedback from the virtual environment. Presence is even narrower concept to define the game experience.

Immersion and involvement are both defined as necessary psychological states for experiencing presence [270], or direct functions to presence [260]. Though there are different definitions about these two concepts, involvement is generally recognised as a psychological state that is a consequence of focused attention on a set of stimuli; immersion is said to be the perceived psychological state of being enveloped by, included in and interacting with the virtual environment [270]. Immersion could also be described with three stages from low to high: that is engagement, engrossment and total immersion (presence) [48]. The terms immersion and involvement are usually used to describe game experience. As such, it is challenging to differentiate between immersion and non-immersion (or involvement and non-involvement) states using the broad definitions discussed above, even to define the game experience generally.

Absorption [289] and dissociation [35] both represent altered states of consciousness, but psychological absorption is non-pathological form of dissociation, which could also describe the video game playing experience. Absorption represents total engagement in one's representational resources [289]. The psychological absorption has more in common with flow, although there are differences in the type of affect involved and the motivation. Psychological absorption could involve negative emotions such as anxiety, and absorption does not require the task to be 'autotelic' [47]. From this definition, the notion of absorption is broader than flow, but an altered state of consciousness does not always happen during game play, and this altered state does not necessarily leads to enjoyment of game.

3.2.3 Limitations of Current Game Experience Models

The reviews of game design methods in Section 3.2.1 show that current studies of game experience in the game industry adopt their methodologies from software design and interface usability tests. However, games have their own particular attributes that make them different from traditional software and human–computer interfaces. First, engagement and enjoyment needs to be discussed in game play; second, games are not designed to maximise performance, so that user errors that are undesirable for most other user interfaces are probably desirable for games; third, although user errors might be desirable, games are designed to maximise experience so that unpleasant frustrations caused by an ill-designed framework need to be avoided; finally, games are multi-dimensional media that involve many artistic issues beyond technical issues in software design and the human–computer interface. Thus, the heuristic game design and evaluation methods are not sufficient for game experience analysis. Game experience models from player's perspectives, instead of heuristic playtesting and usability, need to be addressed.

The reviews of existing psychological models in Section 3.2.2 show that game experience must be a multi-dimensional concept, which has not been covered in any current established psychological concept.

In this case, general models of game play interaction and game experience in the context of games are proposed, and are specifically explained in Section 3.3.

3.3 Game Play and Game Experience Model

3.3.1 Game Play Model

The game play model is designed from a cognitive psychological approach, which is linked to the spread of computers as systems from the 1960s. From this approach, the game experience (both cognitive and affective) could be viewed as an information processing system that takes input — the games — and produces output — the playing actions. This process leaves 'traces' that can be reported, observed, or detected as indicators to infer the structure of the multi-dimensional game experience model. These indicators could be derived from subjective self-reports, objective physiological signals collected by sensors and devices, and the objective playing actions as outputs to the game system.

If computer programs could be designed to mimic the cognition process of humans to solve well-defined constraint problems, then computer information processing would also be a good model for cognition in the mind itself.

In this sense, game play interaction could be considered as the interaction of two information systems: the game system and the human system, which is shown in Figure 3.1. It could also be simply illustrated as the 'Ins' — the human consciousness that perceives and processes information as an entity, and the 'Outs' — the game that sends out energy to players as an entity. The human player information processing system discussed here adopts ideas from the human processor model [51], which consists of three processors. The perceptual processor reads sensory information from game environment and exchange information with the cognitive processor. Working memory receives activated chunks from long-term memory and stores information in long-term memory. Motor processor produces game actions by receiving commands from working memory. The human player information processing system includes the entire cognitive and affective processes of problem solving and decision making during game playing, which shares the same notion as the mental model discussed in Section 2.1.3.1.

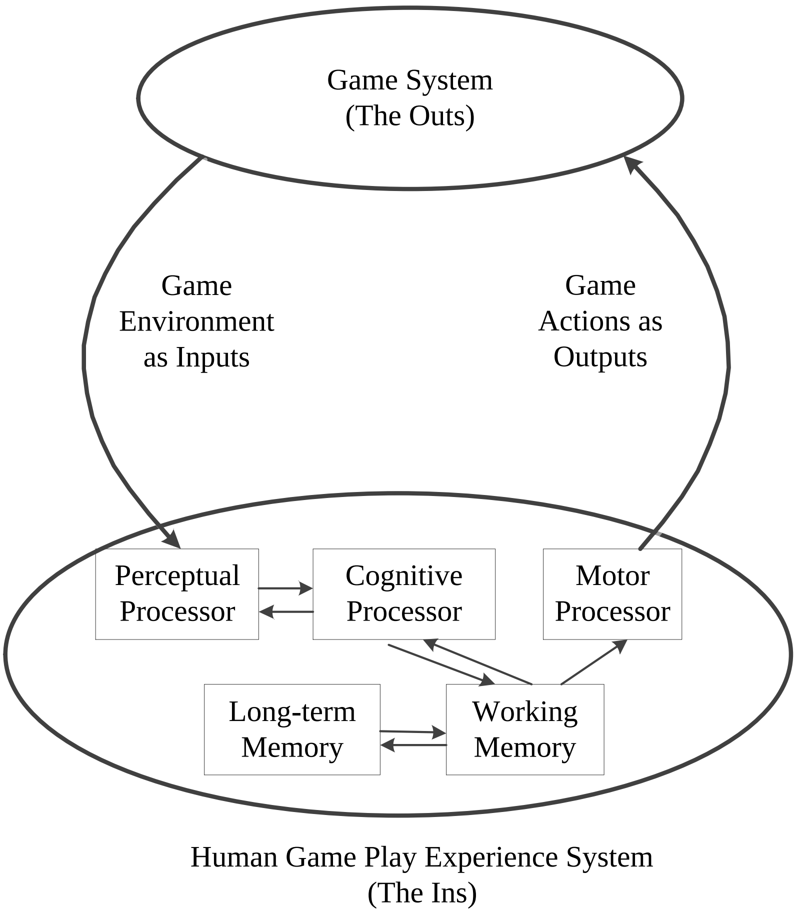


Figure 3.1: The Game Play Interaction Model of Game and Human as Two Information Processing Systems

3.3.2 Game Experience Model

A general game experience model is proposed by considering only the human information processing system involved in game play model 3.1, which could be built as in Figure 3.2. The model starts with the game environment and the world from the left side. The game environment sends out physical energy that has been received and transduced into neural signals by sensory apparatuses including eyes, ears, nose, mouth and touch. This process is called 'transduction' [104] — transducing physical energy into neural signals that can be processed within human neural networks. This step leads to sensation and perception of this information to pick up raw information and to recognize it. The sensation and perception usually work together to form a loop, so that the information from sensation and perception inform each other to produce recognition of the outside game world. This recognition feeds into our central processors to identify the problem, select information, search for alternatives, make decisions and evaluate consequences. Meanwhile, affection (emotion) as a conscious experience is produced alongside the cognitive processing. The cognition and affection work reciprocally to produce a decision, which drives the motor cortex to produce game actions and languages as outputs to the outside game environment.

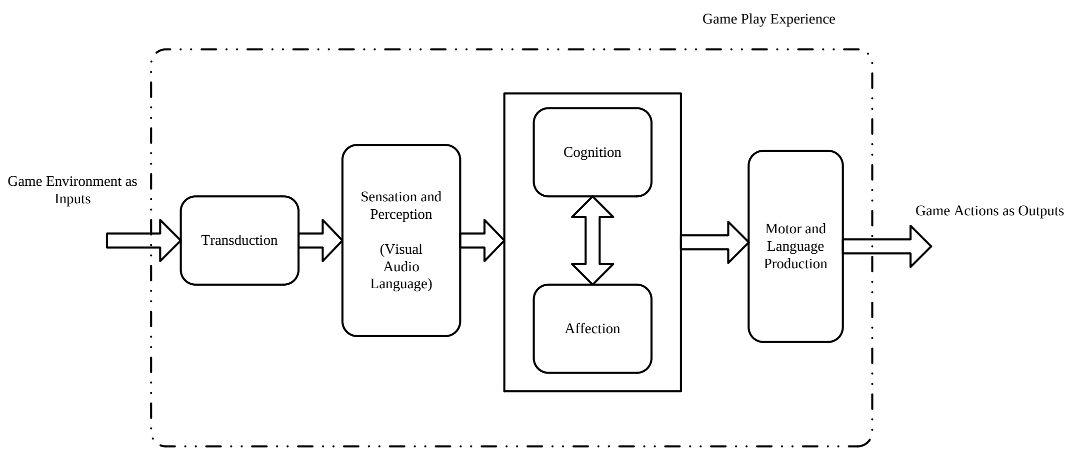


Figure 3.2: The Game Experience Model

Human information processing is not linear as represented in Figure 3.2. Practically, the processing of the latter components could influence the former components as a feedback loop. For example, cognitive decisions influence the sensation and perception of the inputs, as maintained by scientists in Gestalt psychology [171], 'What you want to see influences what you really see'.

The model presented in Figure 3.2 is also the smallest information processing unit in game play, with a chunk of environmental information as inputs and a single game action as output. The experience of game play in general is determined by the interaction of both the human system and the game system as a closed-loop architecture, in which humans and the game systems work together interactively, adaptively and reciprocally. This approach aligns with the ecological approach in cognitive psychology which focuses heavily on the modelling of environmental disturbance and the integrated interactions between human operators and the environment [103, 118, 137]. The human operator aims to meet the goals of a particular task by adapting to the environment, so that information processing is viewed as a closed-loop representation, but not an open-loop one [250].

This game experience as a human problem solving process is not static like a computer information processing system — generally, the same inputs would go through similar processing components and yield similar outcomes. Compared to computer systems, the human system is a 'fuzzy' one that is highly tolerant to noise, and yet highly variant. This is due to the neural structures in our 1.5 kg brain. The neuron's connections are enforced by synapses, following Hebbian plasticity [142]. When neuron A repeatedly fires neuron B, the synapse from A to B is strengthened. The neurons fire together, they wire together. This theory forms the biological foundation of learning and memory. Thus, the individual differences of memory and past experience would change the neural connections in the human central nervous system, so would change in perception, cognition, affection and action (e.g., human perception of an object is based on memory and past experience as a prototype. The new object is compared with the prototype within a range of variance [85]).

As discussed in Chapter 2, this process could be traced by measures including human languages and self-reports, game actions/game environment, and psycho-physiological observation techniques to collect electrical responses from the brain and the peripheral nervous system. These measurements could be used to extract two kinds of indicators: subjective indicators (self-reports) and objective indicators (game actions/environment and psycho-physiological data). These indicators are specifically explained in the following Section 3.4.

3.4 Evaluation of Game Experience Model

Human memory is not singular. It consists of both working memory and long-term memory: the latter has a great influence on the information processing of human players in designed models as the smallest experienced unit in game play. The evaluation of the model should consider player and game information before, after and during the game play, since all this information closely dependent upon each other.

To get this information, subjective and objective indicators are derived from human players in the form of self-reports, psycho-physiological data and game input/output files. Due to the characteristics of these observation methods, the self-reports are more appropriate for collecting human information before/after playing; the psycho-physiological data is perfect for collecting human information during playing with minimum intrusion; and the game input/output files are used to collect game information before, after and during playing. These indicators are specifically explained in the following subsections.

3.4.1 Subjective Indicators of Game Experience

The subjective game experience can be reported through human language by sending out questionnaires or usability tests (retrospective report, think-aloud report, etc.) before or after game playing, as all the variations in human players, resulting from their genes and experiences, contribute to players having different game experiences during game play.

The 'before playing' information is used to profile the player, including his/her background, game skill, game preference, motivations and emotional states.

The 'after playing' information is used to profile the player's preference for a particular game, including the final outcomes, self-rated performances, emotional states and evaluation of the game.

The subjective self-reports need to be designed according to the particular game in play to get the most accurate and useful information. Analysis of the information could be designed according to Figure 3.3.

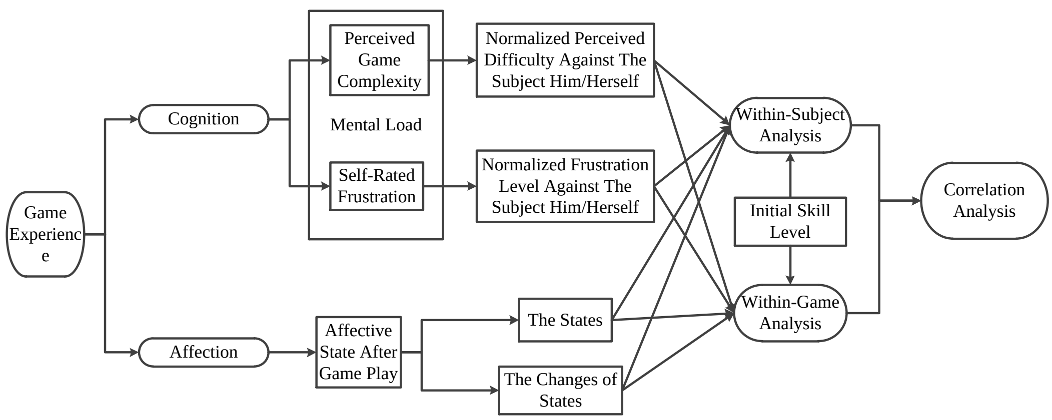


Figure 3.3: The Subjective Indicators, Features and Analysis Methods

3.4.2 Objective Indicators of Game Experience

3.4.2.1 Psycho-physiological Data as Indicators

As reviewed in Chapter 2, psycho-physiological data could be collected from human players during tasks using multiple sensors to estimate activities in both central and peripheral human neural networks. Among these signals, the EEG data is of most importance as it collects electrical responses from human brains.

The psycho-physiological signals derived could be used to indicate human information processing during game play, especially the cognitive and affective processes.

From the perspective of the cognitive process, brain functions have long been identified by brain surgeons as being divided into five main functional regions: 1) the frontal lobe adjusts and controls high level cognitive activities, including planning, decision making and target setting; 2) the parietal lobe is responsible for the sensory system of the human body; 3) the occipital lobe is the visual cortex; 4) the temporal lobe has a deep relationship with listening; and 5) the insular lobe is related to taste. The increasing frequency of information transmissions between neurons is an electro-physiological indicator of excitement and activation of the cerebral functional area. In contrast, decreasing frequency is an index of attenuation and inhibition of the cerebral functional area. The corresponding relationship between functional brain regions with cognitive specialities is listed in Table 3.1. The locations of the brain lobes are shown in Figure 3.4.

Table 3.1: The Psycho-physiological Indicators of Cognitive Process

Indicators	**Brain Functional Region**
Attention	Pre-frontal Cortex
Planning	Frontal Cortex
Situation Awareness	Parietal Lobe
Language	Wernicke's Area
Emotion	Limbic System
Visual	Occipital Lobe
Motor	Motor Cortex
Flexibility	Precentral Gyrus, Central Sulcus and Postcentral Gyrus

From the perspective of the affective process, human emotions are intricately linked to attention, perception, memory, decision making and learning [95]. There are at least two approaches to analysing emotions. One is to identify emotions as discrete categories [94]; another is to describe emotions using continuous scales or dimensions [244]. In the dimensional approach, emotion is represented as a set of points in a 2D emotion space characterised by the dimensions of arousal (intensity

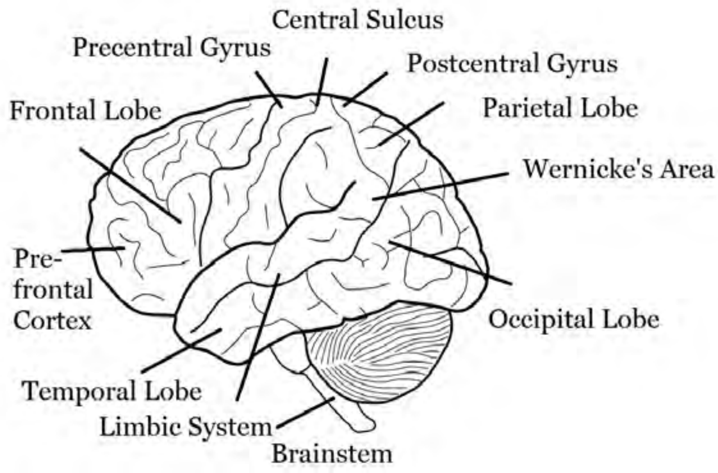


Figure 3.4: The Brain Lobes

of affect) and valence (type of affect). Arousal describes the intensity of affect from excitedness to drowsiness. Valence is characterised as a continuous range of affective states from pleasant to unpleasant [138]. The circumplex model proposed by Russell in 1980 is shown in as Figure 3.5.

According to the reviews in Chapter 2, psycho-physiological data could indicate human emotional states. By integrating the 2D dimensional emotion model in Figure 3.5, with the psycho-physiological indicators, the relationship between psycho-physiological signals and human emotions can be illustrated as shown in Figure 3.6.

Figure 3.6 shows that the change of psycho-physiological signals, besides EEG, could also indicate the emotional states of human players, according to the literature summary. For example, an increase of the SC level and heart rate of players may indicate a rise of arousal level, and vice versa. An increase in SC level and heart rate may also indicate a move of emotional states from negative to positive. ST, in contrast, decreases while the arousal level increases and vice versa. When the power of both EMG signals collected from zygomatic and corrugator muscle group

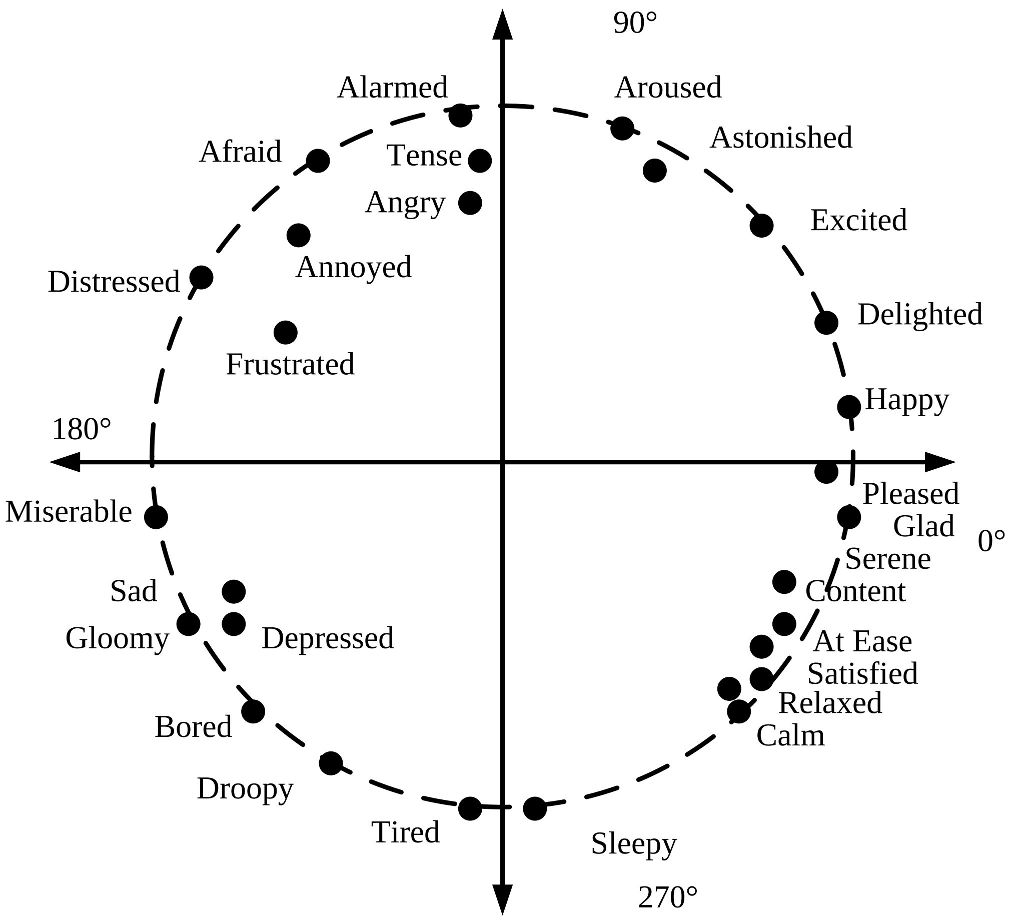


Figure 3.5: A Circumplex Model of Affect [244]

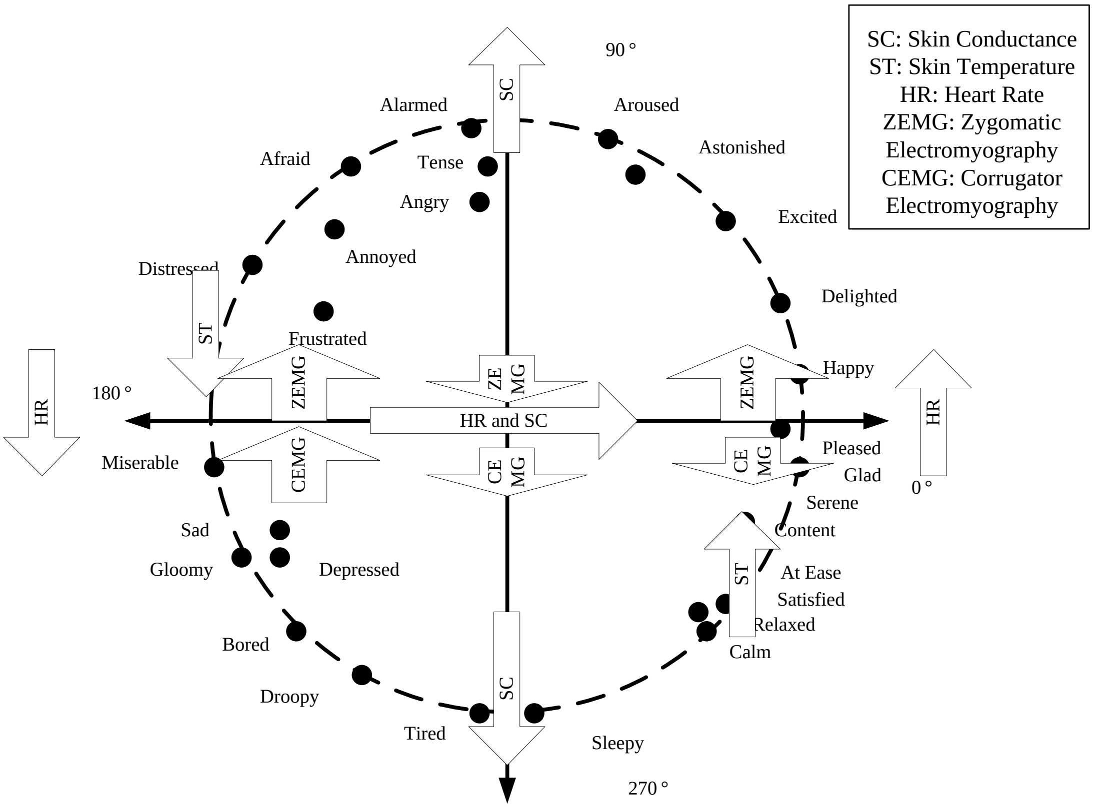


Figure 3.6: The Psycho-physiological Indicators of Affective Process

increases, negative emotions might be expected. Neutral valence emotion might happen when both EMG signals decrease. When the increase of EMG power from zygomatic position exists simultaneously with the decrease of EMG power from the corrugator position, this may indicate positive emotions.

3.4.2.2 Game Inputs and Outputs as Indicators

Finally, the game input/output files are documented to derive objective indicators for analysing game problems, game actions, game feedbacks and game performance. This information focuses on the game environment as inputs, and the game actions produced by players as outputs within the game play interaction.

The games as inputs could be analysed from three levels: 1) the fundamental level is the problem space that represents the abstract computational model of the game; 2) the medium level is the game interface that includes the graphics, the symbols, the layouts, the representations, the audio and so on; and 3) the upper level is the social context of the games that illustrates the social and cultural meanings of the game.

The game actions as outputs are decisions made by the player after problem solving processes. They have a close causal relationship with the player profile and the game experience during game play.

3.5 Game Experience in Game Design

Two game scenarios as 'Sandboxs' were designed to evaluate the general game play and game experience models due to the richness of games as contexts, with each sandbox targeting some controlled variables to evaluate the proposed models. This is also a game-based learning design principle proposed by James Paul Gee [113].

These two sandboxes are designed to address different aspects of the models. The first used a game with a relatively simple problem space requiring rapid mental and motor responses, which could be defined as a casual 'action' game. The second game requires high cognitive capacity to solve the problems, which could be defined as a 'strategy' game. These two games are used as experiment platforms and are specifically discussed in Chapters 4 and 5.

3.6 Conclusion

In this chapter, games, game play and the game experience are defined and analysed from a human player's perspective. The game play interaction and game experience model are proposed and presented. Evaluation of the proposed models could be achieved by deriving subjective and objective indicators from self-reports, psycho-physiological data and game input/output files. To evaluate the proposed model, experiments based on real game playing should be conducted, and they will be illustrated in the following chapters.

Chapter 4

The 'Snake' Game Experiment

The worst thing a kid can say about homework is that it is too hard. The worst thing a kid can say about a game is it's too easy.

Henry Jenkins

The first sandbox to start the game experience analysis is an experiment designed on a classic game concept known as 'Snake'. 'Snake' is not a single game with a definitive version. It originates from the arcade game 'Blockade' developed and produced by Gremlin in 1976 [83]. The concept of the game is to control a constantly moving forward dot, a line or an object to navigate on a bounded 2D game board. The controlled object leaves a trail on the board that has either increasing or fixed units of length. The player loses when the controlled object runs into the screen border, the object's own trail or other obstacles on the game board. As introduced in Section 2.1.2, the game became popular throughout the world from 1998, when Nokia provided it preloaded on most of their cell phones. The simplicity of the game concept makes it adaptable to different size of screen. Its popularity makes it familiar to most gamers born after 1970.

As illustrated, the 'Snake' game is a casual game that usually takes just minutes to complete a round of playing. The problem space to solve is relatively simple — finding the shortest paths towards goals while avoiding obstacles, but rapid mental and motor responses are required to solve the problems. In this thesis, the 'Snake' experiment was designed to reflect game play and game experience in the context of a highly demanding game task in rapid mental/motor responses.

This chapter reports on an experiment based on the game of 'Snake'. The experiment was designed using some of the notions in the game design process [248]. It starts with the pre-visualisation of the experiment (the experiment objective and game concept), followed by the experimental design and the game prototype. A proper controlled experimental procedure is then presented to conduct our experiments. Human subjects as players are involved in the evaluation of the prototype, and the results are discussed in the discussion and conclusion sections.

4.1 Research Question

The objective of this game scenario was to build a simplified game scheme to derive subjective and objective indicators, discussed in Chapter 3 for evaluating game play and game experience models, and to answer the following research question.

Snake Game Experiment Research Question:

RQ2: 'How do game play and game experience under the context of Snake game respond to proposed game play and experience models?'

Psycho-physiological signals collected from human players during game play were the focus of this experiment. The feasibility of real-time psycho-physiological signal collection was also tested during game play, especially for the 'Snake' game which requires rapid motor responses from players.

4.2 Game Concept Design

According to the proposed research question, in this experiment, a game that is designed to be simple (with well-defined problems and measurable computational complexity, and with simple clear rules and boundaries) but still requires a rapid response (both mentally and physically) from the players during playing, is desired.

For this purpose, a 'Snake' game was designed for this experiment based on the 'Snake' concept. The game is a casual action game that requires a few minutes to complete for each round of play. The basic idea is to control the moving directions of a dot with an initially fixed but increasing length of trace to navigate on a bounded game board. The dot will automatically move forward at a given pace. The task for the player is to both increase the score and increase the length of the trace by controlling the dot to get to positive rewards (labelled as food) on the game board. The lose condition is set as the contact of the controlled dot with any of: the edges of board, the trace of the dot or other obstacles. The dot has three degrees of freedom: forward, left and right. It can be controlled to turn around by turning left or right twice, but this action could not be achieved by a single game command. To use metaphors, the controlled dot is described as the 'head of snake'. The trace is the 'body of the snake. The positive rewards are 'food'. The negative reinforcement are 'walls, body of snake and poisoned food'. The layout of the game is shown in Figure 4.1. The white part is the game board for navigation. The red brick patterns are 'walls'. The black line is the controlled 'Snake' with its 'head, body and tail'. The red dots with green leaves are 'food' to eat, and the red crosses are 'poisoned food' to avoid.

The designed 'Snake' game has characteristics that correspond to the objective of this experiment, and should also be considered in the experimental design.

First, the game is familiar to a large audience. Some of the participants involved in the experiments will have past experience playing this game. The 'Snake' game concept was particularly popular around the world from 1998 to 2007 as a pre-installed games on Nokia cellphones. As the expected experiment participants would mostly be young adults ranging from age 20 to 35, they may have experience playing this game previously if they are gamers.

Second, the game is simple with well-defined problems, and has simple clear rules and boundaries. Considering games as well-defined problem spaces with bounded

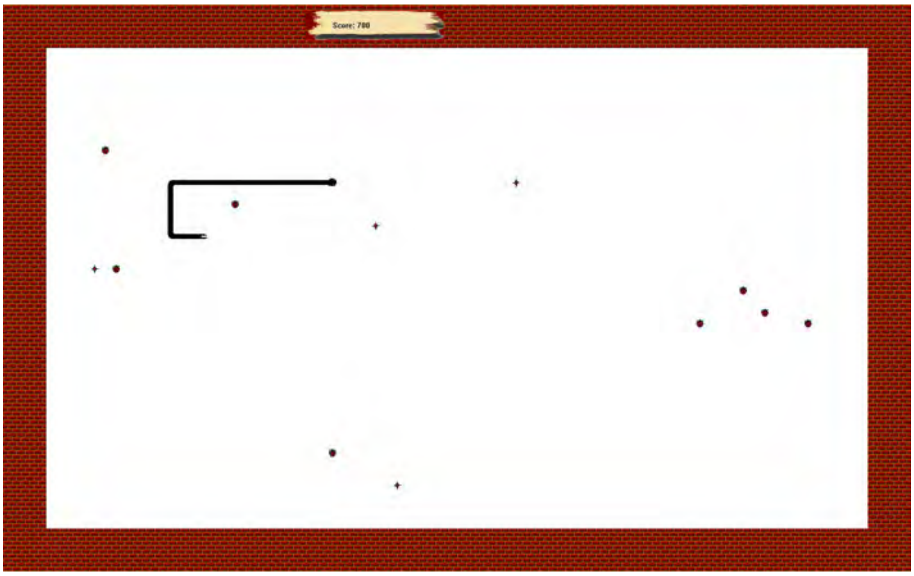


Figure 4.1: The Layout of the Designed Game *Snake*

rules and clear results, and game playing as a problem solving process to find the optimal solution with the given operands, the playing of 'Snake' could be considered a simple problem solving process to find the shortest paths towards goals in a bounded domain, while avoiding obstacles. The operands are the three degrees of freedom of the given controlled object. The rules are simple and clear even to players with no previous experience in this game concept.

Third, the outcome of the game is clear and unambiguous. There is no predetermined endpoint but the scores indicating the outcome of the game are clearly defined. The performance of the game is determined by two factors: the scores obtained and the duration of the game.

Fourth, the game requires rapid response from the players during playing. The player has no control of the speed of the snake. It moves automatically forward at a given pace. The game could be designed at a relatively high moving pace, which would require rapid responses to find optimal paths and to take control actions.

Fifth, the computational complexity of the game is well-defined and measurable. For a given position of the 'head of the snake', there are determined distances between the head and goals, and between the head and the obstacles, which represent the computational complexity of the game at a particular game state. Every possible game state, move, how the person traverses the problem space, and whether or not a solution is obtained can be mapped out.

Further, the game in this experiment is simple in the sense of its visual and audio interface and control method, without a social context to add another level of complexity. The game does not require complex visual and audio representations. Interfaces and tools that will change the players' information processing methods as sensory or computational devices involved in problem solving have been simplified. All experiments in this chapter were conducted on the same size of computer screen. The control of the snake is simply achieved by pressing four arrow keys on the keyboard (all participants have experience using computers and keyboards). Language is not involved in the play. The game concept is neutral to participants from different cultural backgrounds.

Last, the feelings during game play from the players' subjective perspectives are distinguishable upon variations, and could be described in natural language. The body length of the snake will grow when the scores are higher, which adds to the complexity of the game. As time elapses, the games becomes more difficult to play. This becomes one representation of the distinguishable game experience during game playing. This experience could be described using terms as 'frustration' or emotional feelings in accordance with the process (e.g, excitement, anxiety, relaxation, boredom).

4.3 Experimental Design and Prototyping

After the game concept is proposed and the characteristics of the concept are discussed, the prototype of the experiment is designed and presented in this section. The experimental design and discussion of the 'Snake' game experiment are summarised in Figure 4.2. Three kinds of indicators are derived for analysis according to the 'Snake' game experimental research question and hypothesis. The results are discussed from three approaches, as presented in the following sections of the chapter.

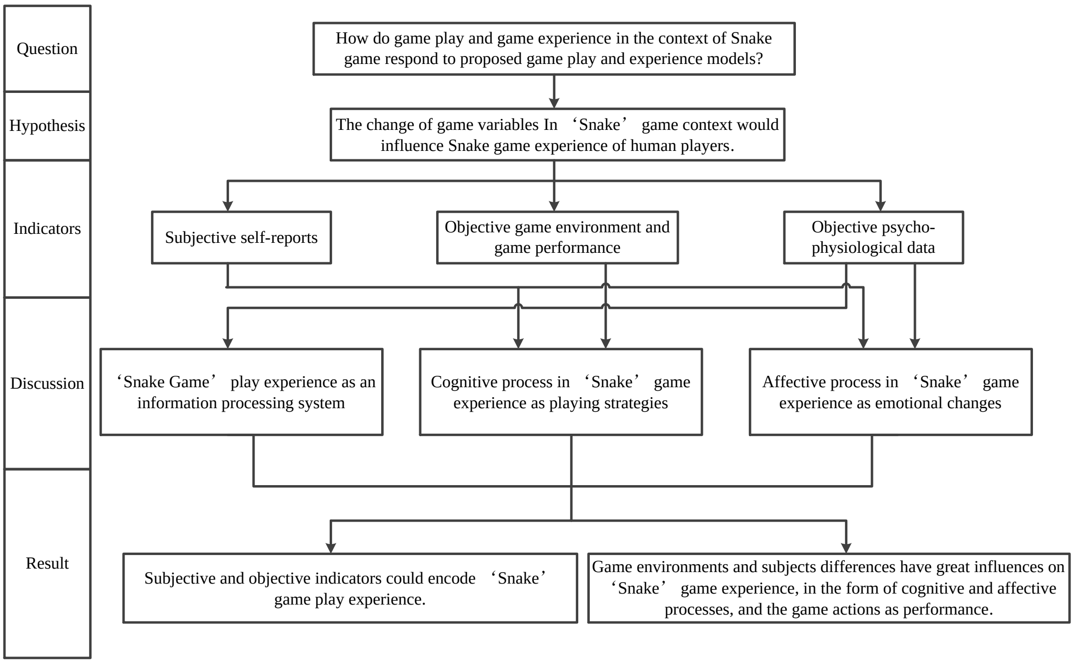


Figure 4.2: The Snake Game Experimental Design and Discussion

4.3.1 Identify Variables

As discussed in Chapter 3 and Section 3.3, the game play interaction and game experience can be reflected by subjective and objective indicators extracted from: 1) well-designed self-reports, 2) game inputs/outputs, and 3) psycho-physiological measures of players during game play; to evaluate the constructed models, the effects and changes of the extracted subjective and objective indicators are observed under controlled game environments.

From the 'Snake' game research question proposed, the independent variable of the experiment is identified as the 'controlled Snake game environment', and the dependent variables as 'subjective and objective indicators'. The experiment is designed by controlling game variables in the 'Snake' game scenario, and observing corresponding changes in subjective and objective indicators to reflect game play and game experience models proposed in Chapter 3.

4.3.2 Experiment Hypothesis

According to the proposed game play and game experience model in Section 3.3, the experiment hypothesis is presented based on the research question being asked.

Snake Game Hypothesis:

H2: The change of game variables in the 'Snake' game context will influence the 'Snake' game experience of human players, reflected by the subjective self-reports, objective 'Snake' game performance, and psycho-physiological metrics.

Two aspects need to be investigated to verify the hypothesis. First, the subjective and objective indicators derived from self-reports, game inputs/outputs and psycho-physiological measures are dependent upon each other in reflecting the game play and game experience models. Second, the variation of the 'Snake' game variables affects the self-report, game performance and psycho-physiological measures in the form of questionnaires, game durations/scores and cognitive/affective indicators derived from central and peripheral nervous signals.

4.3.3 Experimental Design

The independent variables to be controlled are determined as four game variables in the designed Snake game. They are: moving speed of the controlled snake, increased length of the snake after capturing food, frequency of adding extra food, and frequency of adding poisoned food as obstacles. Each game variable has two levels: low and high. The levels of game variables for each game are decided before the start of a particular round of game play without any changes within the playing duration. The four changing variables are chosen to make changes in game environment in the representations of game complexity and game variability.

Specifically, the four game variables are designed as in Table 4.1.

The dependent variables to be observed are collected from self-report question-

Table 4.1: The Four Game Variables as Independent Variables

Variables	Levels	Values
Moving Speed	Low	100ms/move
	High	70ms/move
Increased Length	Low	1 unit
	High	3 unit
Frequency of Adding Extra Food	Low	0
	High	7000ms
Frequency of Adding Poisoned Food	Low	0
	High	7000ms

naires, game scores, game actions and game environments recorded by the game applications, and EEG signals, as well as BVP, SC, ST, respiration, and EMG signals recorded during game play.

The experimental design method is determined as within-participants design (also named 'repeated measures design') due to: 1) the experiment is a human factor experiment in which the inter-participant variance is expected to be high; 2) due to the hardware constraint, the experiment should be conducted one subject at a time from beginning till end; and 3) the psycho-physiological signal collection devices need half an hour to prepare and mount, and requires 10 to 15 minutes to unmount and clean up, which makes the study unable to involve large numbers of participants. The experimental design methodology is explained in the following Figure 4.3.

To encode each variable as '0' (low level) and '1' (high level), each combination of variables could be represented as a hexadecimal ranging from 0x00 (0000) to 0x0F (1111). The overall number of combinations is 16. Each participant is expected to play through all 16 combinations of games, as shown in Figure 4.3.

As each participant have to go through all designed combinations of variables, to counterbalance the memories, fatigue, and learning effect through out the entire experiment, a Latin square design is adopted. Latin square allows the simultaneous control of two sources of nuisance variability. In this case, the two sources of variability to be eliminated are inter-participant variance (rows in Table 4.2) and the sequence

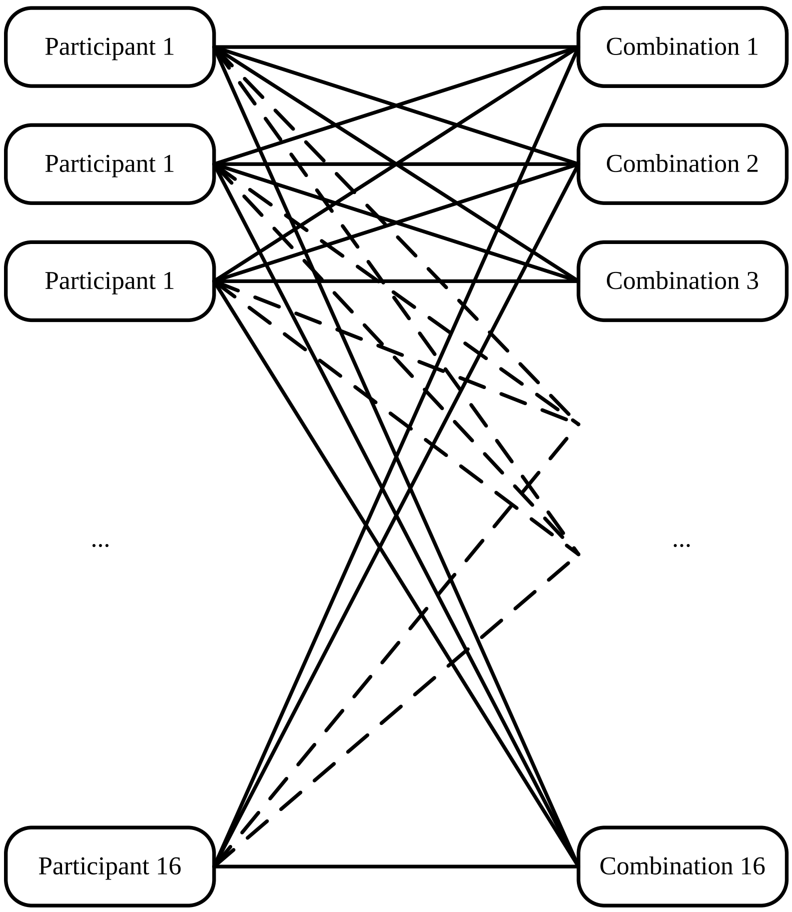


Figure 4.3: The Snake Game Experimental Design Methodology

of games to be played with different combinations of game variables (columns in Table 4.2).

Table 4.2: The Latin Square Design

	Sequences															
P1	0	1	F	2	E	3	D	4	C	5	B	6	A	7	9	8
P2	1	2	0	3	F	4	E	5	D	6	C	7	B	8	A	9
P3	2	3	1	4	0	5	F	6	E	7	D	8	C	9	B	A
P4	3	4	2	5	1	6	0	7	F	8	E	9	D	A	C	B
P5	4	5	3	6	2	7	1	8	0	9	F	A	E	B	D	C
P6	5	6	4	7	3	8	2	9	1	A	0	B	F	C	E	D
P7	6	7	5	8	4	9	3	A	2	B	1	C	0	D	F	E
P8	7	8	6	9	5	A	4	B	3	C	2	D	1	E	0	F
P9	8	9	7	A	6	B	5	C	4	D	3	E	2	F	1	0
P10	9	A	8	B	7	C	6	D	5	E	4	F	3	0	2	1
P11	A	B	9	C	8	D	7	E	6	F	5	0	4	1	3	2
P12	B	C	A	D	9	E	8	F	7	0	6	1	5	2	4	3
P13	C	D	B	E	A	F	9	0	8	1	7	2	6	3	5	4
P14	D	E	C	F	B	0	A	1	9	2	8	3	7	4	6	5
P15	E	F	D	0	C	1	B	2	A	3	9	4	8	5	7	6
P16	F	0	E	1	D	2	C	3	B	4	A	5	9	6	8	7

Participants as players are randomly assigned to the sequences of combinations according to the Latin square shown in Table 4.2. The optimal population size is 16 subjects to go through every sequence of combinations.

4.3.4 Prototype

The prototype of the 'Snake' game experiment was designed according to proposed research question 4.1, hypothesis 4.3.2 and experimental design 4.3.3, which are presented in this section. Due to the research ethics in Australia, this research involving human participants needs to be ethically approved by Human Research Ethics Advisory Panels.

4.3.4.1 Subject — The Who

The game play and game experience of healthy subjects is reflected in recorded measurements. Thus, the subjects involved in the experiment should be mentally and physically healthy. The participants were selected on a voluntary basis. No particular background knowledge or pre-requisites were needed. They might have had access to one or more computer games before. Some may have had experience playing games similar to 'Snake' before participating in this experiment.

4.3.4.2 Environment — The Where

All experimental sessions were conducted in a closed, bright, and quiet laboratory environment in the Cognitive Engineering Lab at the University of New South Wales, Canberra. Participants were required to sit on a comfortable chair during the entire experimental session. They were not expected to take breaks outside the laboratory before the completion of the experiment.

The laboratory environment and the experiment scene are shown in Figure 4.4.

4.3.4.3 Measurements — The What

Both subjective and objective measurements for this experiment were recorded. The subjective measurements were three type of questionnaires, which participants were required to complete before the experimental session, after each game in the session was completed, and after the entire session was completed: named as initial questionnaire 4.5, inter-game questionnaire 4.6 and final questionnaire 4.7.

The objective measurements were game inputs/outputs and psycho-physiological signals. The interested inputs and outputs from games are shown in Table 4.3.

Psycho-physiological signals were collected from both the central nervous system and peripheral nervous system, including EEG, EMG, Heart Rate /BVP (HR/BVP), SC, ST, and respiration signals. These were involved in this experiment. As reviewed in Chapter 2, these signals could be used to extract indicators for human information

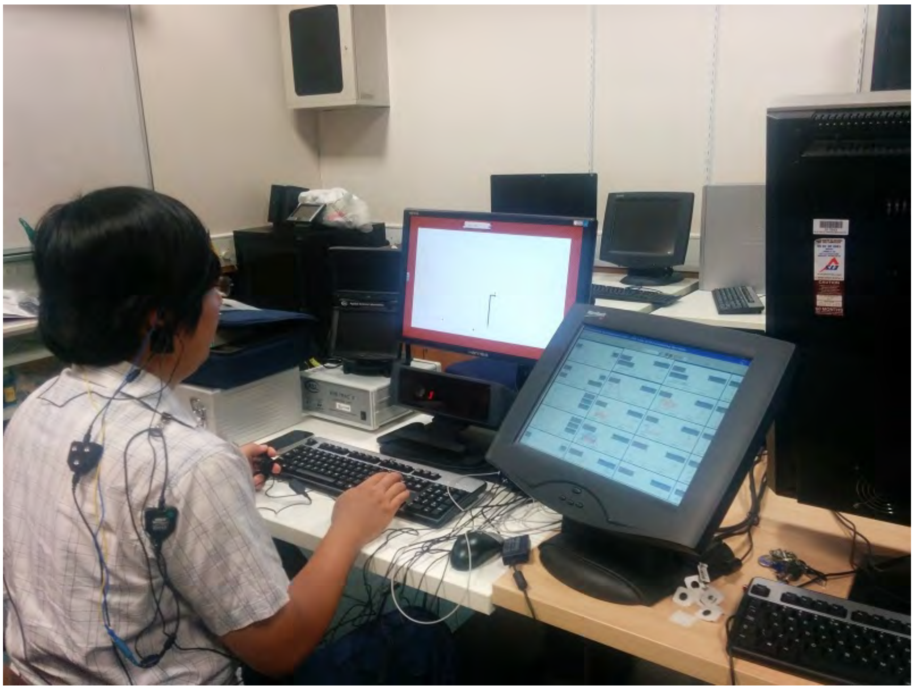


Figure 4.4: The Laboratory Environment and the Scene of the Experiment

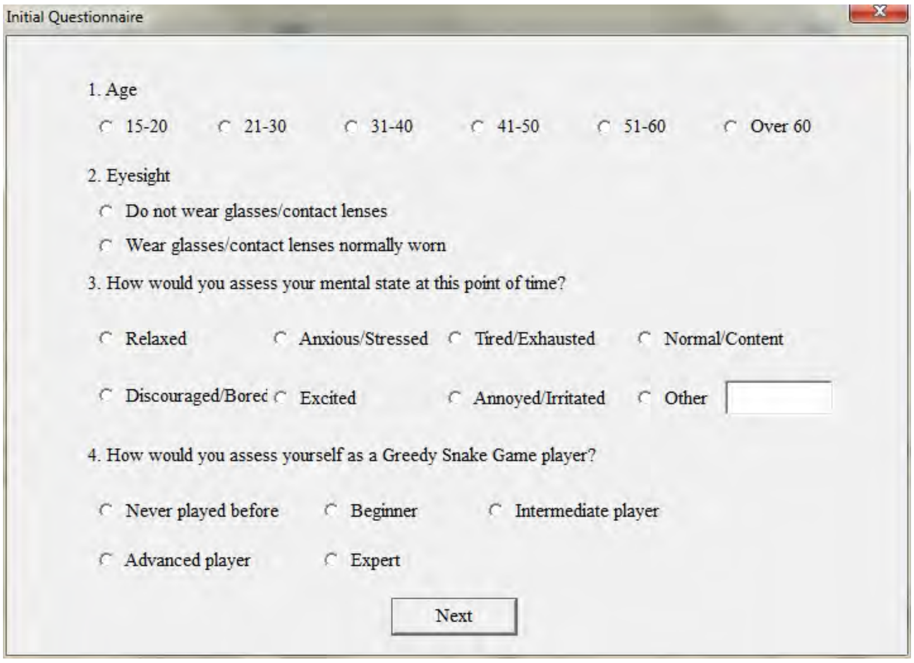


Figure 4.5: The 'Snake' Game Initial Questionnaire

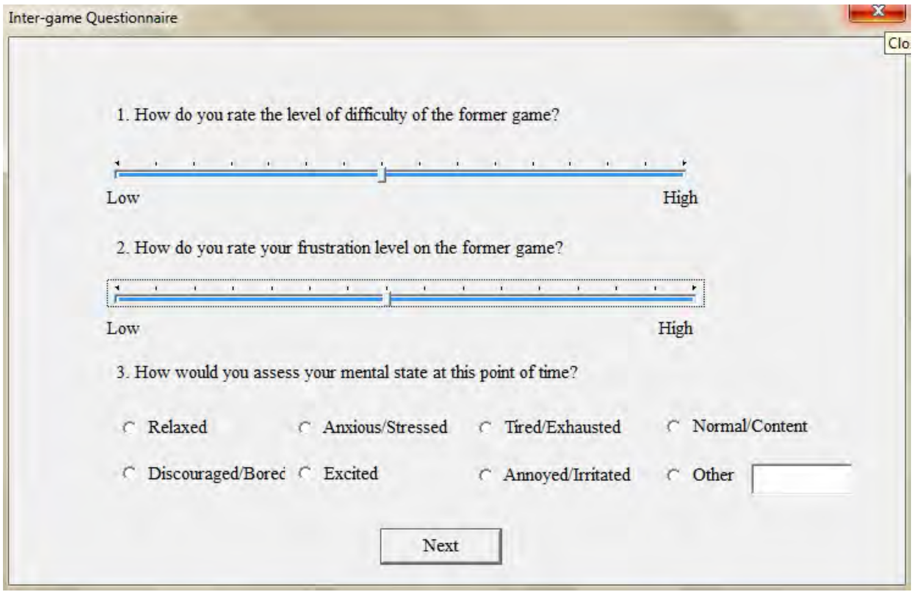
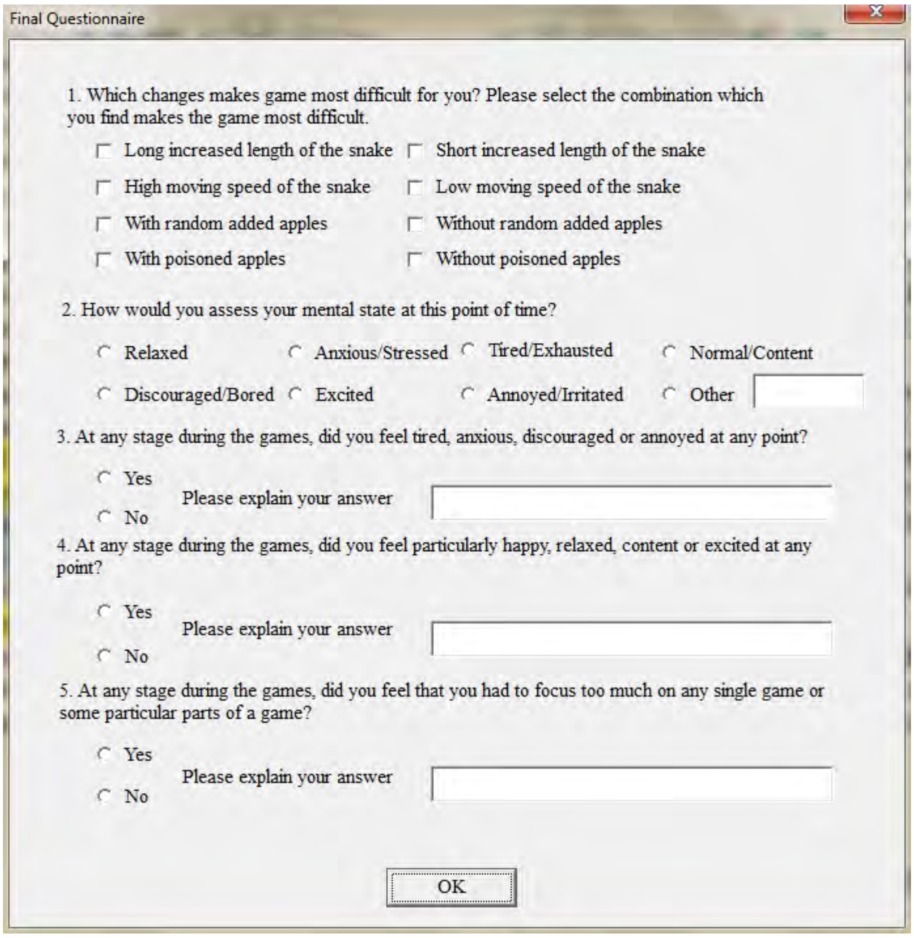


Figure 4.6: The 'Snake' Game Inter-game Questionnaire

Table 4.3: The Interested Game Input/Output Information

•	Game Inputs	Game Outputs
Measures	The objects' positions on game board at each time unit; input game actions	The duration of playing; the game scores


Final Questionnaire

1. Which changes makes game most difficult for you? Please select the combination which you find makes the game most difficult.

- Long increased length of the snake
- Short increased length of the snake
- High moving speed of the snake
- Low moving speed of the snake
- With random added apples
- Without random added apples
- With poisoned apples
- Without poisoned apples

2. How would you assess your mental state at this point of time?

- Relaxed
- Anxious/Stressed
- Tired/Exhausted
- Normal/Content
- Discouraged/Bored
- Excited
- Annoyed/Irritated
- Other

3. At any stage during the games, did you feel tired, anxious, discouraged or annoyed at any point?

- Yes
- No

Please explain your answer

4. At any stage during the games, did you feel particularly happy, relaxed, content or excited at any point?

- Yes
- No

Please explain your answer

5. At any stage during the games, did you feel that you had to focus too much on any single game or some particular parts of a game?

- Yes
- No

Please explain your answer

OK

Figure 4.7: The 'Snake' Game Final Questionnaire

processing.

The EEG suite provided by Thought Technology included all sensors used in this experiment to collect the target signals. These sensors were connected to an eight channel multi-modality encoder named ProComp Infiniti, as shown in Figures 4.8 and 4.9.

Figure 4.8: The PC used for ‘Snake’ Game Playing and the ProComp Infiniti 8 Channel Encoder for Data Collection

Figure 4.9: Psycho-Physiological Sensors Used in This Experiment

EEG sensors were attached to sites F3 and F4, as shown in Figure 4.10 according to the principal of international 10 to 20 electrodes placement system [156] on the participants' scalp, with a clip on both earlobes to as references. F3 and F4 are associated with executive control functions and working memory [115]. They were also selected as signals from these two sites maintain most of the information on the premise of reducing EEG channels to two sites [24, 180]. EMG sensors were attached on the participant's forehead and left side of the cheek to measure electrical responses of facial muscle activities by measuring small electrical impulses when facial muscle fibre contract, with the active range of frequency of the raw signal between 20 and 500Hz. The EMG sensors have three electrodes which are: positive, negative and ground. During the experiment, the positive and negative electrodes were attached to the facial muscles and the ground electrode was placed at neural sites (cheekbones and brow ridge). SC, ST, and HR/BVP sensors were attached to one hand (non-dominant hand) of the participant using elastic finger straps. The respiration sensor was placed around the abdomen and above clothes. It uses an easy fitting high durability latex rubber band fixed with a self-adhering belt for placement.

All the psycho-physiological signals were sampled at 256Hz in this experiment.

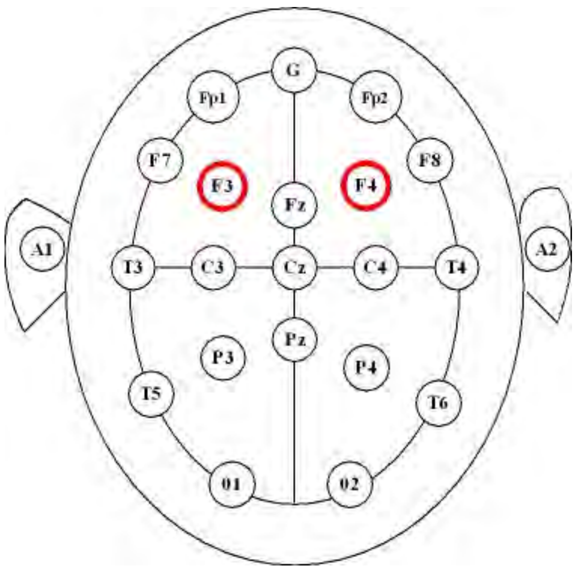


Figure 4.10: The Selected EEG Sites For 'Snake' Game Experiment

4.3.4.4 Process — The How

The designed experimental session consisted of 34 game sessions played consecutively by the participant. The first game (No. 1) and the last game (No. 34) were baseline games using basic game settings — all changing variables were low level and the encoded game configuration was 0x0000. The remaining 32 games (from No. 2 to No. 33) for each participant were configured following the sequence of the Latin square design by repeating each variable configuration twice. That was, take the first stream of sequences in Table 4.2 for example: the variable configuration for each game session in this particular experimental session was shown in Figure 4.4.

Table 4.4: The Game Variable Configuration of a Particular experimental session

Game1	0x0000	Game10	0x1110	Game19	0x1100	Game28	0x0111
Game2	0x0000	Game11	0x1110	Game20	0x0101	Game29	0x0111
Game3	0x0000	Game12	0x0011	Game21	0x0101	Game30	0x1001
Game4	0x0001	Game13	0x0011	Game22	0x1011	Game31	0x1001
Game5	0x0001	Game14	0x1101	Game23	0x1011	Game32	0x1000
Game6	0x1111	Game15	0x1101	Game24	0x0110	Game33	0x1000
Game7	0x1111	Game16	0x0100	Game25	0x0110	Game34	0x0000
Game8	0x0010	Game17	0x0100	Game26	0x1010	•	•
Game9	0x0010	Game18	0x1100	Game27	0x1010	•	•

The constants that did not change in the entire experimental session are summarised in Table 4.5.

Table 4.5: The Constants

Board Size	$56 \times 43(unit^2)$
Initial Snake Head	(28,21)
Initial Direction	Right
Initial Length	3(unit)
Initial Number of Food	4

The 'Snake' rules of the game, defined constantly through the entire experimental session were: 1) the game ends once the head of snake touches the wall, the tail and the poisoned food; 2) the player gains a score of 100 once the head of a snake touches any given food on the board; 3) both the food and the poisoned food are randomly assigned on the board; and 4) once a food is captured by the head of the snake, the food disappears and a new one randomly appears on the board.

4.3.4.5 Duration — The When

The experimental session has no fixed duration as the playing time of each game session was determined by the performance of players. However, the game was designed to be completed in minutes. Thus, the playing time was approximately 20 to 75 minutes. The duration of the entire experiment (which includes subject briefing, sensor setup and questionnaire completion) was approximately half an hour to a maximum of two hours.

4.4 Experimental Procedure

The 'Snake' experiment was processed following a strict experimental procedure based on the experimental design. Each experimental session was conducted one at a time, involving one participant only, with the thesis author controlling the procedure and monitoring the entire process.

The procedure is specifically explained in Figure 4.11.

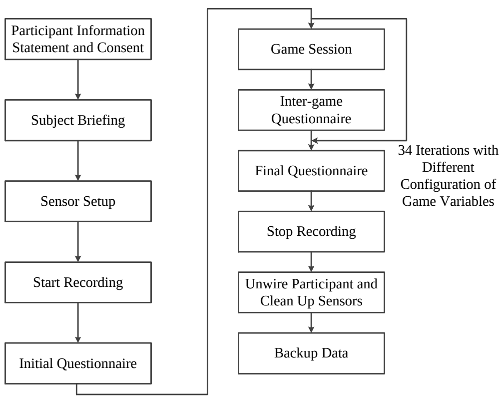


Figure 4.11: The 'Snake' Game Experimental Procedure

Prior to the experiment, the participants were advised not to drink alcohol in the 24 hours before the experiments to avoid extra noise with the psycho-physiological signals. They were also advised to have an adequate amount of sleep the night before the experiments.

The first step was to inform the participants of the objective and the description of the experiment, and ask for consent to join in.

Then, the participant was briefed on the experimental procedure, the sensors used to collect data, the game interface and the basic control functions. Once participants had no doubts and concerns about the experiment, the psycho-physiological sensors described in Section 4.3.4 were set up for the participant, according to the technical standards.

The quality of signals was tested by reviewing half a minute recording after the sensor set up was done. When the signal quality was satisfactory, the recording of the psycho-physiological data from sensors began.

The experimental sessions were processed according to the designed prototype 4.3.4. After the Initial Questionnaire was completed, there were 34 game sessions with different configurations of game variables, followed by an Inter-game Questionnaire after the completion of each game session. The Final Questionnaire automatically popped out at the end, after all game sessions were played.

After the final questionnaire was completed, the psycho-physiological recording was stopped and the sensors were unmounted from the participant. After acknowledging the participant, the sensors were cleaned and the data was backed up at the end to close the entire experimental procedure.

4.5 Data Collection

A trial experiment, plus 16 actual experiments, were conducted by strictly applying the experimental protocol and procedure. The experiments were conducted under the Ethic Approval No. A-11-58, issued by the University of New South Wales, Canberra Campus.

16 participants, including seven males and nine females, voluntarily participated as players in this 'Snake' game experiment. All were right-handed. Among them, three participants labelled themselves as 'Never Played This Kind of Game Before', seven as 'Beginner' and six as 'Intermediate Player'. The ages of the participants ranged from 21 to 40. Nine wore glasses or contact lenses, but all participants could visually capture the instructions and game contents showing on the screen. The participants had different nationalities and cultural backgrounds, but all were proficient in English reading, listening, speaking, and writing to communicate with the researchers and to convey their self-reports using English. All participants were healthy during the experiment, and two of the female participants were pregnant. The background information of the players is summarised in Figure 4.12.

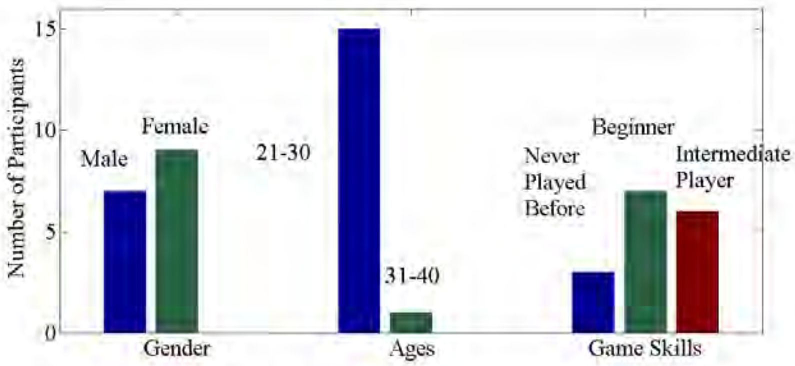


Figure 4.12: Background Information of 'Snake' Game Players

The valid data records collected from each participant include questionnaires, game input/output files, BVP, SC, ST, Resp, EEG at Channel F3 and F4, EMG at the corrugator and the zygomaticus muscle groups. Among the collected data, Resp data of a beginner player and an intermediate player were missing, and the BVP data of a first-time player was missing. The missing data was due to the loss of sensory contact or the requirements of the participants.

4.6 Signal Processing and Feature Extraction

The collected information of the 'Snake' game experiment were processed and discussed under proposed game play and experience models in Chapter 3. In this section, the subjective and objective indicators involved in this experiment are extracted under the 'Snake' game context according to the psycho-physiological signal processing in Chapter 2 and the subjective/objective feature extraction in Sections 3.4.1 and 3.4.2, Chapter 3. In the following section, these indicators are discussed based on the proposed 'Snake' game research question and experiment hypothesis.

4.6.1 'Snake' Game Self-reports as Subjective Indicators

Subjective indicators would be extracted from the three types of questionnaires: initial questionnaires, inter-game questionnaires after the completion of each game, and final questionnaires, as presented in Section 4.3.4. Specifically, the subjects' self-evaluation of the games, self-rated skills, performances and emotional states, are the main foci. These indicators are used to profile the players before, during and after game sessions. The extracted subjective indicators are listed in Table 4.6.

Due to the fact that the popping out of the Inter-Game Questionnaires would influence the game experience, the number of questions were limited to three, as shown in Section 4.3.4 to minimise interruptions to the playing experience.

4.6.2 Performance and Task Complexity as Objective Indicators

Two main objective indicators — game performance and task complexity — are to be extracted from game input/output files in this section. The game input/output file includes the game environment, the changing game variables, the game actions produced by players and the game feedback produced by the scenario. Specifically,

Table 4.6: 'Snake' Game Subjective Indicators

Indicators	**Description in 'Snake' Game Context**	**Features**
Skill Evaluation	The previous 'Snake' kind of game experience and skill development during playing	Former experience; self-rated game difficulty
Performance Evaluation	The self-rated performance against goals and objectives	Self-rated frustration
Game Evaluation	The self preferences and evaluation of game sessions	Self-rated frustration; most difficult variable combination; particular time when feel negative emotion, positive emotion and extra attention
Affective States	The emotional feelings during game play	Emotional states before sessions, after sessions and after each game

the game performance is described by scores, playing durations and efficiency as features. Task complexity is represented by the changing game variables and the movement capacity. The extracted performance and task complexity indicators are listed in Table 4.7.

Table 4.7: The Extracted 'Snake' Game Performance and Complexity Indicators

Indicators	**Description in 'Snake' Game Context**	**Features**
Game Performance	The performance in 'Snake' game playing	Final scores; playing duration; efficiency
Task Complexity	The computational complexity of game sessions	Initial speed; increased length; frequency of adding extra food; frequency of adding poisoned food; movement capacity

Efficiency as a game performance feature is calculated by Equation 4.1, which represents score/time ratio during game playing. The 'E', '$Score$' and 't' using in Equation 4.1 represent the efficiency of game as feature, the final score that the player has obtained for one game session, and the time duration of the game session in seconds.

$$E = \frac{Score}{t} \tag{4.1}$$

The movement capacity is the maximum units of movement in the current direction if no new game action is input into the game system to change direction. For example, in Figure 4.13, the movement capacity in this game state is the number of units in between the snake head and the poisoned food.

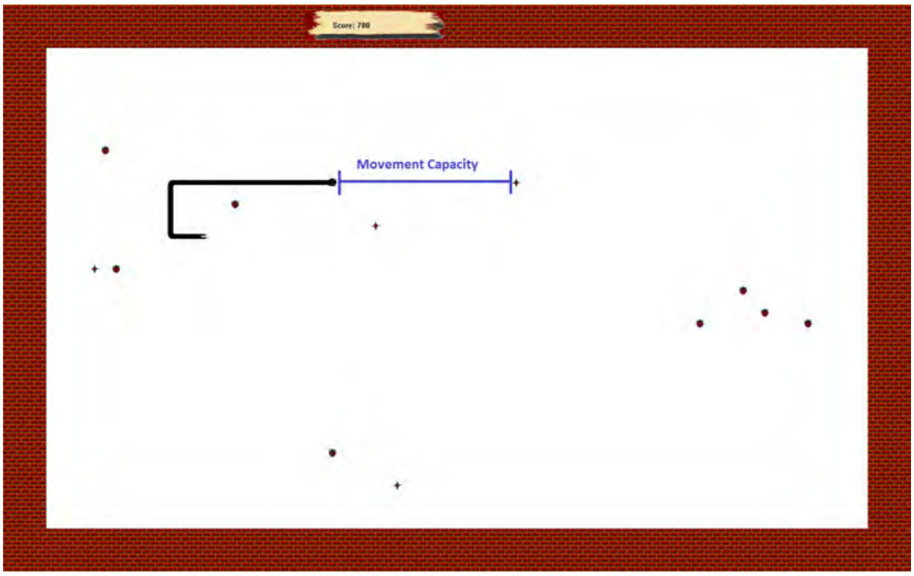


Figure 4.13: The Movement Capacity in Game Context

4.6.3 The Psycho-physiological Metrics as Objective Indicators

The psycho-physiological indicators in this 'Snake' game experiment are extracted according to signal processing methodologies described in Sections 2.3.2 and 3.4.2. In this experiment, BVP, SC, ST, Resp, EEG collected from the pre-frontal cortex, and surface EMG collected corrugator and zygomaticus facial muscle groups are emphasised. Besides the signal processing methods of these signals discussed in Section 2.3.2, cross correlation between indicators are also calculated to facilitate analysis.

4.7 Discussion

In this discussion section, the extracted subjective and objective indicators from the former section are discussed in the context of 'Snake' game playing, according to the proposed main research question in Section 4.1 and the experiment hypothesis in Section 4.3.2. The discussion is illustrated in three aspects in the following subsections: first, objective indicators are used in evaluating game play and game experience models in general; then, the cognitive process in the game experience model is discussed, mainly using subjective indicators and game actions/performance indicators; last, the affective process in the game experience model is discussed using both subjective indicators and psycho-physiological measures. The results verify the 'Snake' game experiment hypothesis that 1) the game play and game experience of Snake game could be represented as an information processing system as proposed in the models, by evaluation of the extracted subjective and objective indicators, which are also dependent upon each other; 2) the variation of game variables, as changes of game environments would influence subjective and objective indicators, which could reflect the change of game experience during 'Snake' game play.

4.7.1 'Snake' Game Experience as an Information Processing System

The first aspect to be discussed is the game play and game experience in the 'Snake' game context complying with the proposed models in Chapter 3 as an information processing system.

As discussed in Section 3.3, game play could be modelled as an interaction of two information systems: the game system as the 'Outs', and the human system as the 'Ins'. Correspondingly, the game experience, as shown in Figure 3.2, could be modelled as a human information system, which takes game environment as inputs, processes with the collaboration of 10^{11} neurons as a massively parallel, adaptive and distributed computational network, and drives muscles to produce game actions as outputs. This human information processing has not been discussed under game contexts, but has already been recognised in cognitive psychology, as discussed in Section 2.3.1.

According to the resource theory discussed in Chapter 2 — an analogue to digital information processing system — if the game experience is an information processing system, it will have finite processing resources. The human information processing capabilities will have an upper limit. If two processes use the same resources concurrently, the two processes interfere with each other. This interference is a two-way development, where each process interferes with the other process. These several active cognitive and physical processes competing for limited processing resources cause the performance of a human on a given task to diminish [224]. The primary resource — 'time' was originally conceived as non-shareable among tasks [70]. The theory has since evolved into a limited but shareable capacity-limited processor [216, 302]. Different resource models have been studied and proposed, ranging from a single channel bottle neck theory [302] to multiple resource models [309] in the last 50 years.

Psycho-physiological signals collected in real-time during game playing are considered potential indicators of human information processing and processing resources. As discussed in Section 2.3.2, the galvanic skin responses, ST, heart rate, and Resp are mostly autonomic dependent variables that are largely controlled involuntarily by the autonomous nervous system. Thus, though at times those signals could be controlled by the somatic nervous system, the processes that generate those signals are generally not considered to consume cognitive resources. In this case, EEG and EMG signals which are generated and determined by the central nervous system, are the main focus. Specifically, the EEG signals collected from F3 and F4 channels are used to observe inter-hemisphere neuron activities on the frontal cortex. The surface EMG signals collected from forehead and cheek position are used to observe facial muscle activities — the corrugator supercilii muscle group associated with negative emotions and the zygomaticus muscle group associated with positive emotions. Relationships between pre-frontal neuron activities and facial muscle activities, as well as features extracted from different EEG sites and different EMG sites, are investigated, to study if there is functional collaboration and resource competition happened during 'Snake' game play, which characterises the game play and game experience as a human information processing system.

Specifically, three aspects are investigated in this section. First, is there synchronisation between neuron activities collected from EEG channels F3 and F4 on the frontal cortex during 'Snake' game playing (RQ2.1)? Then, is there a relationship between facial EMG signals collected from the corrugator supercilii muscle group and zygomaticus muscle group during 'Snake' game playing (RQ2.2)? Finally, is there resource competition during tasks that require rapid decision making and motor responses, like 'Snake' game playing (RQ2.3)?

The synchronisation between EEG channels is measured to assess the functional connectivities between different brain regions; and to show the degrees of functional cooperation between underlying neuron substrates during tasks as massive parallel processing [64, 301]. Former clinical studies have also shown that compromises in brain functions would lead to the decrease of synchrony, thus the increase of asynchrony [136, 170, 194, 299]. Therefore, inter-hemisphere correlation values could also show the degree of cooperation of both hemispheres required in given tasks. The facial EMG are used to measure emotional positive valence (smiling) and negative valence (frowning) in former studies under game context [140]. The corrugator muscles are also reported to have a relationship with mental efforts during interactions [300], and the perception of goal obstacles [230].

The neural synchrony is a multi-scale phenomenon that represents the information encoding of neurons from a local scale (spatial scale of less than 2mm and temporal delay of typically 4 to 6ms) to a large scale (spatial scale larger than 1cm, and transmission delays larger than 8 to 10ms) [295] in neuroscience. In most studies of computational neural science, the models of neural encoding and decoding are generally studied for a small time window (hundreds of milliseconds) to analyse the relationship between stimulus and electrical responses. However, in this study, the large-scaled generalised neural features from both spatial and Temporal perspectives are preferred, instead of the firing a particular neuron or small amount of neurons towards a stimulus, to discuss general cognitive and physiological responses towards tasks as objective indicators of game experience.

The statistical method cross-correlation is the most common method to estimate large-scaled synchronisation between different EEG recording sites. The correlation between two different signal sequences is computed according to the convolution theorem, with a one second window within each game. The correlation sequence is a function of time 't' and 'τ' which is known as 'time lag'. The correlation between 'g' and 'h' is shown as Equation 4.2. The $Corr(g, h)$ represents the correlation coefficient.

$$Corr(g, h) = \int_{-\infty}^{+\infty} g(t + \tau)h(t)d\tau \tag{4.2}$$

To compute the correlation between discrete sequences, the function is shown as Equation 4.3

$$Corr_{xy}(m) = \begin{cases} \sum_{n=0}^{N-m-1} x_{n+m}y_n^* & m > 0 \\ Corr_{yx}^*(-m)) & m < 0 \end{cases} \tag{4.3}$$

Here, 'x' and 'y' are two discrete time series with the length 'N', and 'm' is the displacement in time between 'x' and 'y'.

The collected data was processed for each participant separately according to the signal processing methods presented in Chapter 2. The collected time domain EEG and EMG signals were divided into 34 different parts according to the time stamps of each game been played. The correlation between the two EEG signals collected from F3 and F4, and the two stream of facial EMG signals collected from the corrugator and zygomaticus muscle activities were then computed using a one second window. The cross-correlation are computed based on Equation 4.3, upon each game as a unit.

The cross correlation results are normalised so that the autocorrelations of the sequences themselves at time lag '0' are identical and equal to 1.0. The corresponding means and standard deviation are computed at the level of all 34 games played by each player. The average value reported is the mean of the correlation coefficient sequences in all games being played. The results are shown in Table 4.8. The subjects are grouped according to their reported 'Snake' game skill levels before experiments, so that the first three participants (subjects 1 to 3) in Table 4.8 had no experience in 'Snake' kinds of game; the next seven (subjects 4 to 10) were beginner players, and the last 6 (subjects 11 to 16) were intermediate players.

Table 4.8: The Correlations of 'Snake' Game Psycho-physiological Signals Collected from Different EEG and EMG Channels

Subject	Correlation between EEG F3 and F4	Correlation between Corrugator and Zygomaticus EMG
1	0.44 ± 0.12	-0.96 ± 0.04
2	0.59 ± 0.14	-0.86 ± 0.17
3	0.39 ± 0.20	-0.93 ± 0.08
4	0.87 ± 0.11	-0.79 ± 0.09
5	0.51 ± 0.08	-0.84 ± 0.06
6	0.74 ± 0.09	-0.97 ± 0.03
7	0.55 ± 0.16	-0.94 ± 0.08
8	0.52 ± 0.07	-0.93 ± 0.11
9	0.50 ± 0.08	-0.95 ± 0.10
10	0.83 ± 0.11	-0.91 ± 0.11
11	0.50 ± 0.08	-0.86 ± 0.06
12	0.67 ± 0.23	-0.92 ± 0.06
13	0.49 ± 0.08	-0.93 ± 0.08
14	0.88 ± 0.10	-0.93 ± 0.09
15	0.79 ± 0.10	-0.92 ± 0.11
16	0.41 ± 0.06	-0.93 ± 0.07

As shown in Table 4.8, during 'Snake' game play, there is medium to high cross correlation between EEG time-domain signals collected from left and right hemisphere at the pre-frontal cortex, and a strong negative correlation between EMG signals collected from corrugator and zygomaticus facial muscle groups. Though there is always high negative correlation between EMG signals among groups, the positive correlation between EEG F3 and F4 of the first time player group is on average lower than that of the beginner and intermediate player groups. The results verify that there may be collaboration between inter-hemisphere pre-frontal brain regions during 'Snake' game play, and muscle activities of corrugator and zygomaticus facial muscle groups may indicate facial expressions of opposite emotions.

The positive correlation between hemispheres at the pre-frontal cortex may indicate the collaboration of both hemispheres working together as a massive parallel distributed system during 'Snake' game play. Specifically, the perception and processing of the 'Snake' game as sensory input, and game actions as motor output requiring functional connections, information communication [97] and the binding of different features into a single perception or decision [271] between left and right hemispheres at the pre-frontal cortex, according to former research. The pre-frontal cortex is known to be functionally responsible for central executive control of human information processing systems. Thus, the higher the cross-correlation between hemispheres, the stronger the interaction in human executive control centres would possibly be during game tasks. Combined with the players' performance results discussed in Section 4.7.2, the high EEG cross-correlation generally correlates with the higher game performance in Table 4.9. Thus, the synchronisation of left and right hemisphere at pre-frontal cortex could be considered an indicator for mental efforts and engagement in 'Snake' game playing.

The strong negative cross-correlation between EMG corrugator and zygomaticus facial muscle groups reflects that the emotional responses, which triggered muscle activities at these two sites, are generally opposite. The result is in accordance with former studies: that the sEMG activities detected from the corrugator muscle group reflect negative valence emotions and the signals from the zygomaticus muscle group reflect positive valence emotions [140].

The correlation between EMG corrugator and zygomaticus facial muscle signals show almost the opposite trend, compared to the EEG. That is, this is an inverse correlation. By further analysing this trend, each game for each player is examined and plotted with the correlation sequences. Figures 4.14 and 4.15 show the correlation coefficient sequences within the first game played by one player. During the game, while the difficulty increases due to the increasing length of the snake and decreasing freedom to navigate on the 2D game board, the correlation between EEG F3 and F4 increases, while the correlation between the EMG corrugator and zygomaticus facial muscle signals decreases. This trend is shown in almost all other games. There appears to be an anti-correlation between these two processes. This can be interpreted as a resource shift from facial activities to brain functions across the duration of the game: a prioritising of resources to planning and decision making as the difficulty of game increases. This trend shows resource competition during demanding tasks requires rapid decision making and motor responses like 'Snake' game playing, as the difficulty increases. This may reinforce the hypothesis that 'Snake' game experience could be considered as a human information processing system, as proposed in Chapter 3.

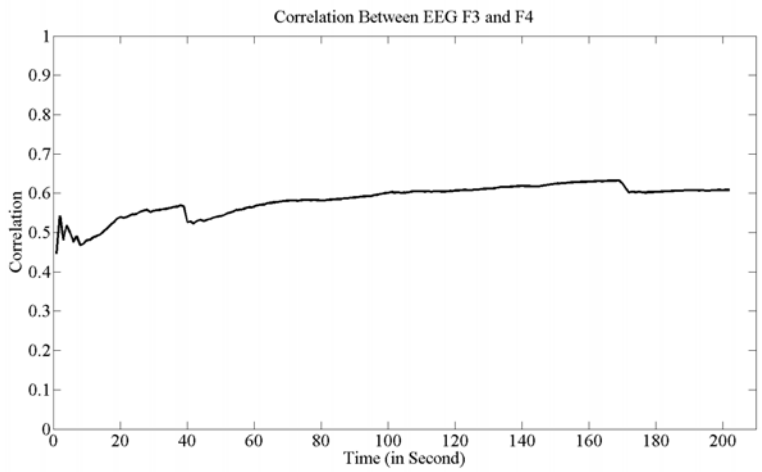


Figure 4.14: The Correlation Between EEG F3 and F4 of a Game Session

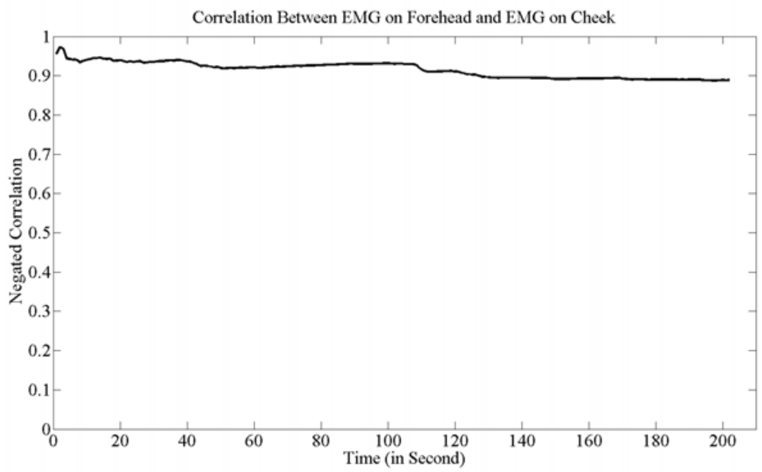


Figure 4.15: The Correlation between Corrugator EMG and Zygomaticus EMG of a Game Session

4.7.2 Cognitive Process in 'Snake' Game Experience

In the former section, the game experience model as information processing system was discussed under the 'Snake' game context by evaluation EEG and EMG signals collected during game play. In this part, the cognitive process that characterises the problem-solving, decision making and playing strategies during 'Snake' game play is focussed on by evaluating subjective self-reports, objective game environment, game actions and performance information collected before, after and during game play. Specifically, the playing goals, the playing strategies, and the outcoming game performance are discussed in 'Snake' game play to evaluate: 1) how subject differences change the cognitive processes of game experiences, and; 2) how game environments change the cognitive process of game experience.

4.7.2.1 Subject Differences in Influencing 'Snake' Game Experience

Besides internal resource allocation in human minds, other factors, including goal setting, self-efficacy, ability, strategies, engagement and attention will also have a great influence on the game experience and performance as outcome. The effect of goal settings on the enhancement of task performance as a motivation mechanism has long been established [193]. Self-efficacy captures the human ability to estimate his or her own ability to select and execute a course of action within a given context. It is normally associated with a number of factors, including one's past experience, experience gained in watching others doing similar tasks, ability to persuade others and self, arousal and other mental activities [29]. Goal commitment, including goal commitment to task performance, is strongly affected by self-efficacy as a major predictor of future performances [192]. Attention has multiple components that can positively influence the ability of a human to achieve a task, including strategies selected, self-regulation and efforts put in the task [128].

The playing goal (motivation component in engagement and progression loop illustrated in Figures 2.2 and 2.3) of player for each game action, especially in the 'Snake' game which requires a rapid response, is hard to measure by direct self-reports.

However, from the designers' perspective, game play is a designed experience catering for a wide range of playing goals. In this designed 'Snake' game, the game play goals could be analysed as a hierarchy architecture, as shown in Figure 4.16.

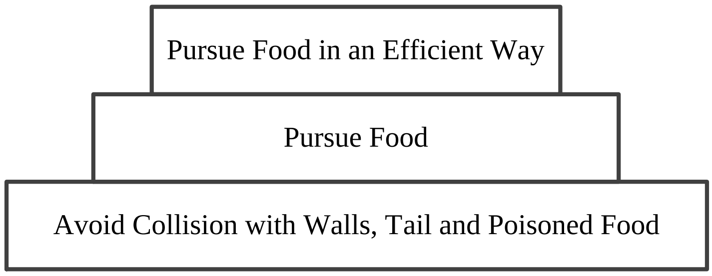


Figure 4.16: The Designed Goals of 'Snake' Game

The bottom-up architecture shows the significance of the goals from high to low in 'Snake' game playing. The goal of highest priority is to avoid collision, which results in the termination of the current game and the obtained score as final. The second layer is to capture food to get a higher score. The third (highest) layer is to capture food in a shorter amount of time.

Accordingly, the playing strategies towards different levels of goals in the 'Snake' game would be different, and would yield different game actions as outcomes. A player targeting a bottom level goal would try to achieve longer playing duration; at the third level would obtain higher scores, and at the highest level would achieve higher efficiency.

The goals and corresponding strategies could be traced by the extracted objective indicators from game input/output files as playing duration, game score and efficiency. These indicators are expected to have dependencies upon the different background of players, which could be reflected by subjective indicators, including previous skills, self-rated performance, and game evaluation.

The playing durations that indicate the 'Snake' game goal at the bottom level of all 16 participants are first analysed, as shown in Figure 4.17. The diagram shows the entire playing period after the completion of the initial questionnaire to the start of the final questionnaire. As none of the players labelled themselves as advanced players or experts, the players are categorised into three groups: First-time Player (red), Beginner (green) and Intermediate Player (blue), as seen in Figure 4.17.

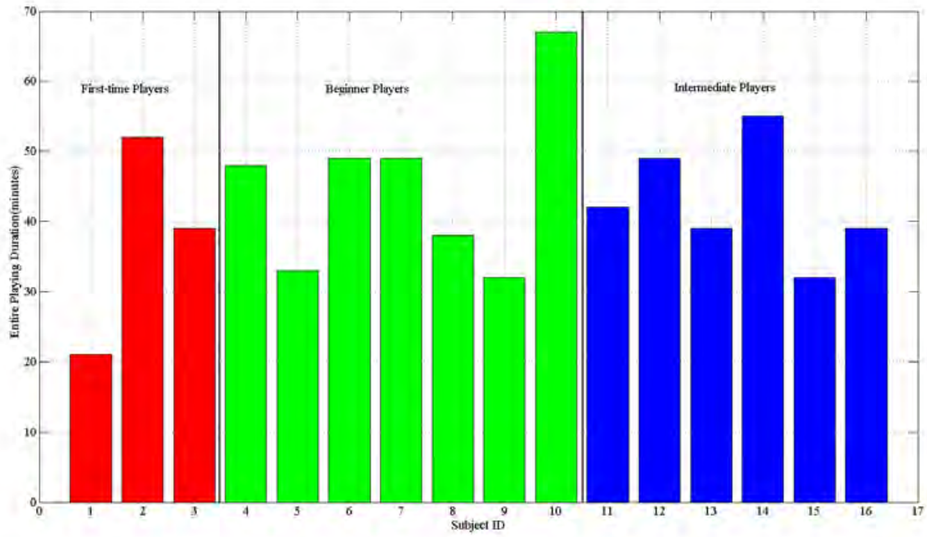


Figure 4.17: The Duration of the Entire Snake Game Session

As shown in Figure 4.17, the duration of the game sessions range from 21 minutes to 67 minutes. The shortest duration is achieved by a first-time player with average score 1038 ± 932. In contrast, the longest duration is achieved by a beginner player with average score 3300 ± 3070, which is significantly higher than the first-time player with shortest duration.

To further analyse the game duration, scores and efficiency as objective indicators and the corresponding subjective indicators, the average playing duration per game, the average scores obtained, the efficiency of playing calculated upon each player and self-rated complexity and frustration level, are presented in Table 4.9. The results are calculated by excluding the time spent on the inter-game questionnaires and the two baseline games at the first beginning and at the end of the experimental sessions. As all participants played same sets of games (with different sequences), the objective task complexities of game sessions for all participants were the same, but due to the players' skills and the sequence of games, the self-rated average complexity and frustration were expected to be varied according to the game experience.

The range of options for complexity and frustration selection in our designed questionnaires is from 1 to 15. To eliminate subject bias, the self-rated complexity and frustration measurements are normalised against the players' themselves among $[0, 1]$ using 0-1 normalisation method, as in Equation 4.4 and 4.5.

$$C_{Normalised} = \frac{C - C_{min}}{C_{max} - C_{min}} \tag{4.4}$$

$$F_{Normalised} = \frac{F - F_{min}}{F_{max} - F_{min}} \tag{4.5}$$

Here, 'C' represents the self-rated complexity measure, '$C_{Normalised}$' is the normalized result, 'C_{min}' and 'C_{max}' are the maximum and minimum value the player has rated in playing all 34 games. 'F' represents the self-rated frustration accordingly.

The skill level, average playing durations, average scores, efficiency calculated by Equation 4.1, self-rated complexity and frustration have been shown for each participant in Figure 4.9. As shown in Table 4.9, according to the designed game goals 4.16, participant No.10 as a self-rated beginner player obtained both the longest average playing duration and highest average score. However, when considering the efficiency of food pursuing at the highest level of game goal architecture, participant No.10 is only in fourth place. The other three players who have higher average efficiencies than No.10 are all intermediate players (Players No.13, 14 and 15). The four well-performed players reported subjective game complexity and frustration lower than average, except player No.10. Among them, participant No.15 had below average playing duration: this may show the playing strategy of No.15 was to challenge him/herself to obtain higher score in an efficient way.

Linear correlations are calculated among features shown in Table 4.9, which are

Table 4.9: The Indicators of Cognitive Processes in Snake Game Play

ID	**Skills**	**Average Playing Duration (seconds)**	**Average Score**	**Efficiency**	**Self-rated Complexity**	**Self-rated Frustration**
1	First-time Player	32 ± 27	1038 ± 932	30.8 ± 8.7	0.00 ± 0.00	0.06 ± 0.25
2	First-time Player	72 ± 68	991 ± 1142	12.4 ± 6.7	0.00 ± 0.00	0.00 ± 0.00
3	First-time Player	52 ± 83	476 ± 755	8.4 ± 8.2	0.34 ± 0.24	0.42 ± 0.35
4	Beginner	76 ± 47	2159 ± 1511	29.7 ± 8.8	0.59 ± 0.30	0.52 ± 0.23
5	Beginner	42 ± 33	953 ± 775	21.5 ± 7.1	0.58 ± 0.22	0.59 ± 0.22
6	Beginner	77 ± 78	2541 ± 2191	25.3 ± 8.2	0.72 ± 0.28	0.71 ± 0.21
7	Beginner	78 ± 70	1812 ± 1767	23.4 ± 10.8	0.66 ± 0.28	0.56 ± 0.42
8	Beginner	56 ± 37	918 ± 747	15.5 ± 6.7	0.31 ± 0.28	0.35 ± 0.26
9	Beginner	48 ± 39	1418 ± 1063	29.4 ± 7.8	1.00 ± 0.00	0.61 ± 0.48
10	Beginner	100 ± 77	3300 ± 3070	31.3 ± 7.8	0.47 ± 0.28	0.73 ± 0.24
11	Intermediate Player	75 ± 67	1270 ± 1104	15.1 ± 8.9	0.23 ± 0.32	0.00 ± 0.00
12	Intermediate Player	43 ± 59	1979 ± 1230	28.4 ± 7.4	0.30 ± 0.27	0.37 ± 0.27
13	Intermediate Player	59 ± 46	1982 ± 1652	34.2 ± 8.1	0.00 ± 0.00	0.09 ± 0.30
14	Intermediate Player	77 ± 60	3091 ± 2960	38.6 ± 11.3	0.35 ± 0.22	0.23 ± 0.22
15	Intermediate Player	45 ± 39	1438 ± 1250	31.4 ± 6.2	0.44 ± 0.31	0.40 ± 0.26
16	Intermediate Player	61 ± 60	1385 ± 1396	21.2 ± 8.7	0.39 ± 0.25	0.48 ± 0.20

presented in Figure 4.18.

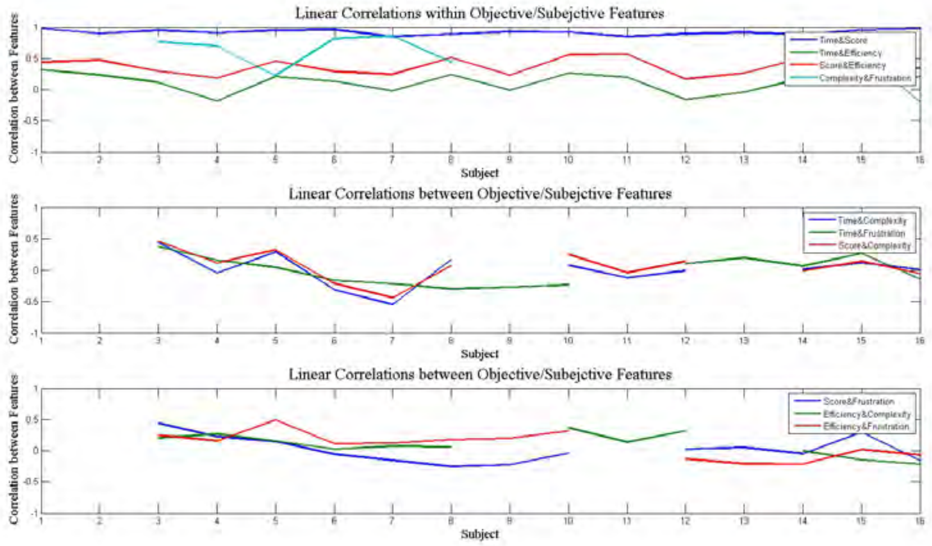


Figure 4.18: The Linear Correlation between 'Snake' Game Features

As shown in Figure 4.18, there is a strong correlation between playing duration and final score obtained by the players. The longer the play, the higher the scores. The correlation between scores and efficiency is medium, and the correlation between playing duration and efficiency is weak or even negative. This indicates that high scores and long play duration do not guarantee high efficiency in pursuing the food. The self-rated complexity is generally parallel with self-rated frustration, but this trend is subject-dependent, and some players chose the same level of complexity/frustration among all game sessions, which makes this correlation result between subjective reports less informative.

The correlations between subjective and objective features are generally weak and subject-dependent. This implies that the self-reported complexity of game and frustration during game collected after the game session does not correlate with game performance, without considering the subject differences among players.

The features in Table 4.9 were then studied according to the self-rated 'Snake' game skill levels collected before the experimental session, and the results are shown in Figures 4.19 and 4.20. In these figures, the first-time players are labelled as red, beginner players as green and intermediate players as blue.

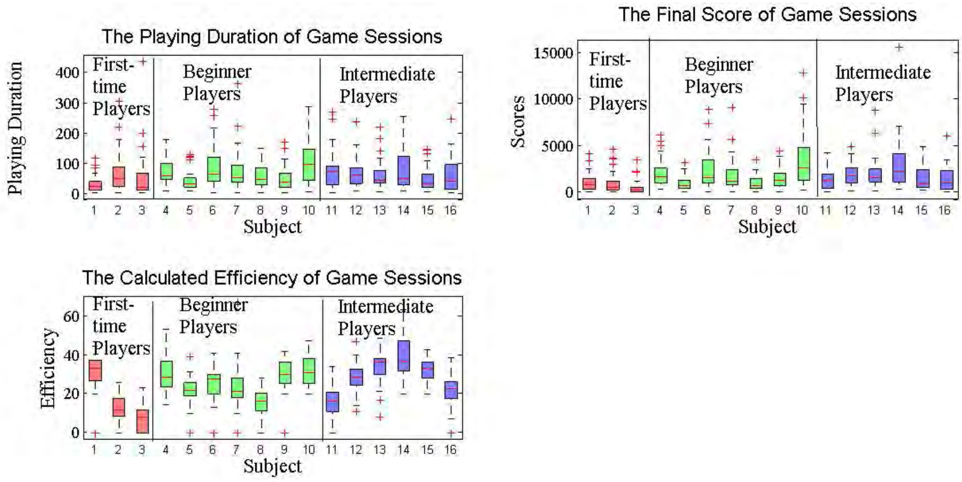


Figure 4.19: The Game Performance Boxplots of the Entire 'Snake' Game Session

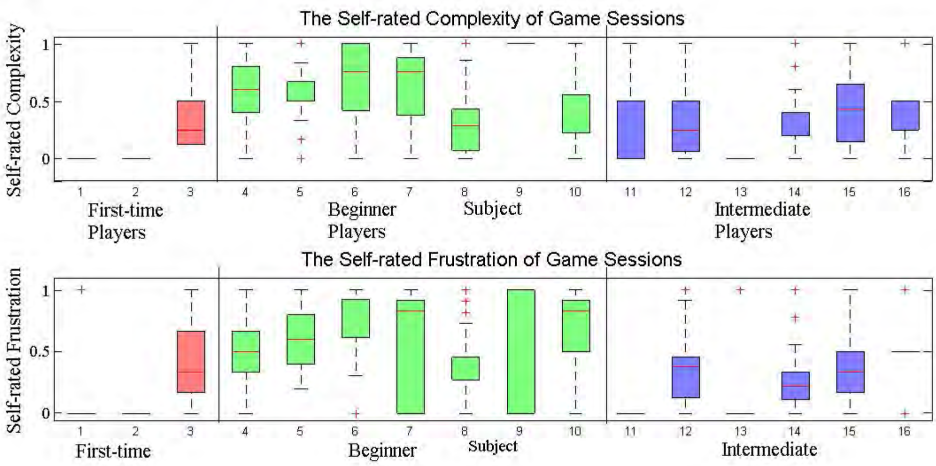


Figure 4.20: The Self-rated Complexity (top) and Frustration (bottom) Boxplots of the Entire Game Session

As shown in Figure 4.19, when players have more experience in this kind of game and have higher levels of self-recognition of their skills, they tend to play longer, achieve higher scores and form better strategies to pursue food in a more efficient way. This is shown as the increasing tendency of average playing time, score and efficiency from red to green to blue group in Figure 4.19. Since the 'Snake' game concept is designed to be very accessible (simple concept, rules and control methods), although there is a remarkable difference in performance between experienced players (green and blue group) and non-experienced players (red group), the difference between advanced players (blue group) and beginner players (green group) is not significant, especially regarding playing duration and scores. This result is expected because: 1) 'Snake' is a casual game with easy to learn skills; 2) 'Snake' is generally designed as a single-player game, which makes it difficult for players to assess their skills; 3) 'Snake' was widely popular about 5 to 10 years ago, advanced players also did not have access to this kind of game for long. However, the advanced players generally show higher efficiency in playing the games, as in Figure 4.19, compared to first time players and beginner players. This may indicate that as players develop their skills, their playing goals tend to shift from lower level (avoid collision) to higher level (pursuing food in efficient ways) in playing goal hierarchy 4.16. The change of goals may also change the levels of complexity in the 'Snake' game problem space: to avoid collision is easy, but to avoid collision while pursuing food in an efficient way makes the problem more difficult. As playing goals shift from lower levels to higher levels, the players intuitively and autonomously add complexity to the problem space to fit their developed skills. The result is in accordance with Csikszentmihalyi's flow theory discussed in Section 2.1.2.2 and Sweetser's game flow [284], as shown in Figure 4.21. However, the pleasant game experience shown in Figure 4.21 does not share the same definition with flow or game flow. It does not require the loss of self-consciousness or altered perception of time.

The results are also in accordance with the former research that self-efficacy, which is defined as the self-recognition of competence in achieving goals, has significant positive correlation with task-related performance [273]. As the 'Snake' kind of game is usually designed as a single-player game (players are just competing with the system but not another player or another group of players), players who have experience in playing this game do not have a general metric to define their skills. Their self-recognition as beginner players or intermediate players mostly reflects their self-efficacy on the performance of this game. The objective performance data is positive related with their self-efficacy.

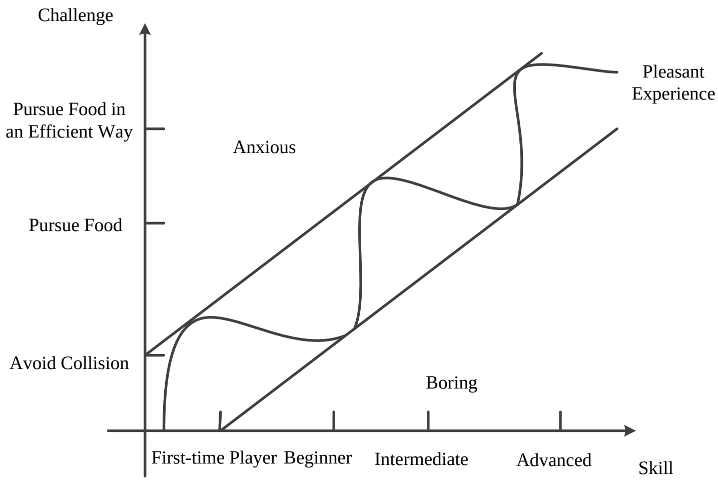


Figure 4.21: The Contribution of Skill Level and Challenges to a Pleasant Game Experience

As the skill level develops in games, players tend to shift their playing goals from lower levels to higher levels to add complexity to the game problem space. However, if shifting goals to the highest level still does not meet their requirements for new challenges and variations, the players tend to feel bored and drop the game. The game evaluations in the final questionnaires support this statement. In the final evaluation of the entire game sessions, four among six intermediate players stated that 'the game is too simple and play it for long is discouraging' in their own languages. Only two among seven beginner players thought the game was simple and boring, and no first-time players reported this. In this game environment, players were required to complete all game sessions (their participation in the experiment was voluntarily but they were not allowed to quit in the middle), so they do not have the choice of dropping the game. This condition of not being able to drop the game resulted in a deteriorating game experience for these skilled players. Four of six intermediate players revealed their final emotional states after experiment as negative emotions: 'Anxious/Stressed', 'Tired/Exhausted' and 'Annoyed/Irritated'. one revealed positive emotions as 'Excited', but explained that as 'feeling excited to finally stop playing'. Only one intermediate player revealed a 'Normal/Content' emotional state at the end. Compared to non-experienced and beginner groups, only two among seven beginner players showed negative emotions at the end, and none of the first-time players showed negative emotions. One of the intermediate players (shown as No.16 in Figure 4.19 and 4.20) indicates in the final questionnaire that the game was too boring so he/she intentionally played to trap his/her snake in a dead-end position — to 'bite its own tail', to add variation. This playing strategy violates the fundamental goal of avoiding collision and also deteriorated his/her game performance. This represents that when the players has explored everything the games can offer, they tend to break the rules to challenge themselves.

Within each group, players also show different strategies among subjects toward different main goals in 'Snake' game playing. Generally, the higher the skill level, the more goals they could handle at the same time. In first-time player group, the first player (No.1) tends to achieve higher efficiency in playing, but his/her playing duration and scores are relative low; the No.2 player and No.3 player seem to focus on the fundamental playing goal to avoid collision, which have longer average playing duration but lower scores and efficiency. The No.3 player achieves the highest single game session playing duration among all players. In the beginners' group, they generally could focus on more than one goal to achieve higher duration, scores and efficiency at the same time; only No.5 and No.8 players had lower scores and efficiency compared to the group. In intermediate players' group, most revealed their abilities to handle more than one goal, but they tend to show variations in choosing their own preferred goals: No.13 showed his/her preference in chasing efficiency, No.14 achieved the highest single game score and highest average efficiency among all players, the No.16 player (as mentioned in the previous paragraph) chose to break the rules to add challenges to the game playing.

As shown in Figure 4.20, the higher the self-rated skill level, the lower self-rated average game complexity. The intermediate group generally show lower normalised average self-rated complexity than the beginners group. However, as some of the players chose the same complexity measures and frustration measures in all game sessions, the result is not prominent.

In summary, the subject difference in choosing game strategies leads to different game actions and performances in the 'Snake' game context. The game strategies are chosen to reach their playing goals, which are influenced by the backgrounds of the players, including previous game experience with skills and self-efficacy, and are reflected as game actions and game performance. Game strategies and decision making are considered cognitive processes in 'Snake' game experience.

For a simple casual game like 'Snake', there are still different layers of playing goals structured as a hierarchy architecture. The hierarchy architecture of game goals in 'Snake' has an influence on game complexities perceived by players. The higher the goal sits in the hierarchy, the more difficulties the players choose to impose on themselves. Previous experience in same kind of games and self-efficacy of players' skill levels have a positive influence on game performances. More skilled players or self-recognised skilled players tend to choose more goals or shift to higher layer goals in the hierarchy autonomously, to obtain better game experience. If shifting goals to the highest layer still could not meet their requirements, their game experience would deteriorate. Last, pleasant game experience requires balance in players' skill level and difficulty of challenges.

Previous experience in the same kind of games and self-efficacy of players' skill levels has remarkable influence on the cognitive processes of 'Snake' game play, including goal settings and game strategies. However, to identify the individual game experience in 'Snake' game play, more individual factors need to be considered, other than the previous experience.

4.7.2.2 Game Environments in Influencing 'Snake' Game Experience

In this section, the game variables, which were configured to change game environments, are investigated for their influences on the cognitive processes of human players in 'Snake' game playing. The configurations of game variables are controlled by the experimental design, and the cognitive processes, including game strategies and decision making; these are again reflected by objective game performance indicators.

The game environment is configured according to Table 4.1 in the proposed experimental design. From high-order digit to low-order digit in this binary encoding of game configurations, the corresponding game variables are: 1) moving speed; 2) increased length; 3) frequency of adding extra food; 4) frequency of adding poisoned food. For example, the configuration 0x1010 means the game is configured with high moving speed, short increased length, adding extra food at a given frequency, and no poisoned food.

The variation of game environments are designed to: 1) change the complexity of games at the gamer's level and; 2) add new variables to the games, so that to observe the players' game experience under the changed environments. Specifically, considering the low level of game variables as defaults, the change of the four game variables from low to high are designed to influence the objective game performance features, as shown in Figure 4.22.

As shown in Figure 4.22, changing game variables from low to high will have negative effects on all three game performance features. However, some may have positive effects on performance features. The high moving speed may increase game scores and efficiency as it increases the speed of food capturing; adding extra food may also contribute to game scores and efficiency as it makes the food capturing process easily by spreading more food on game board.

From a design perspective, the significance of variables could be rated from high to low following the sequence: 1) moving speed; 2) poisoned food; 3) extra food; 4) increased length. The reasons are explained as follows. The increase of moving speed changes complexity from the start of the game alongside every game state. The adding of poisoned food adds 'pitfalls' on the board that do not exist in other game settings. The extra food added on the board would have both positive and negative effects on the game play process, but it only influences the number of food without adding new variables. The increased length would only add complexity to the games when considerable amounts of food are captured at the later stage of game playing.

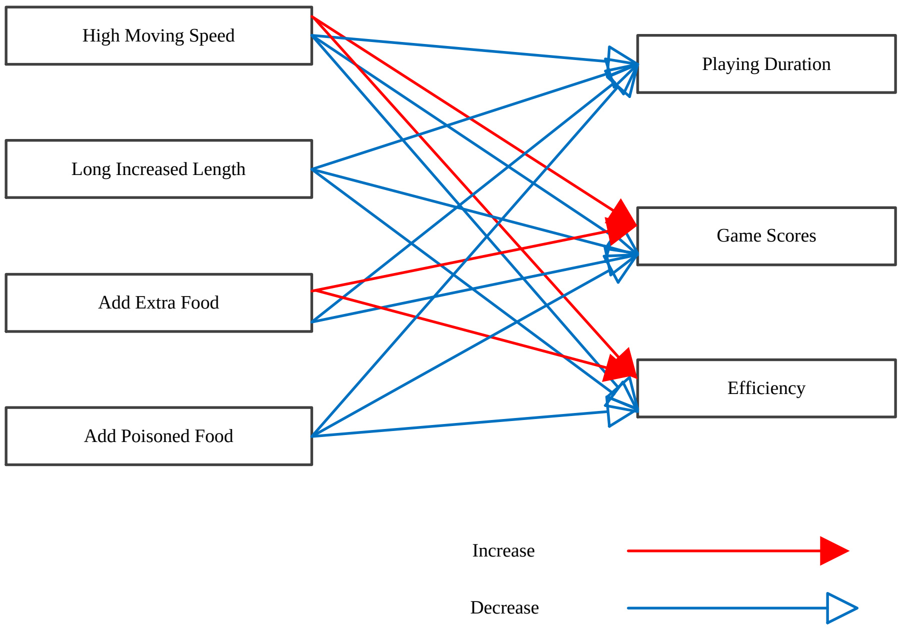


Figure 4.22: The Influence of Designed 'Snake' Game Variables on Game Performance Features from Design Perspective

The game performance features and subjective features are averaged upon all players playing game sessions with same variable configurations. The results are shown in Table 4.10.

Table 4.10: The Game Performances against Different Game Settings

Configuration	**Average Playing Duration (seconds)**	**Average Score**	**Efficiency**	**Self-rated Complexity**	**Self-rated Frustration**
0x0000	93 ± 76	1959 ± 1386	22.8 ± 9.7	0.26 ± 0.38	0.38 ± 0.30
0x0001	66 ± 64	1509 ± 1378	22.2 ± 10.4	0.34 ± 0.32	0.42 ± 0.41
0x0010	89 ± 78	2978 ± 3569	29.2 ± 12.5	0.33 ± 0.32	0.34 ± 0.29
0x0011	62 ± 50	1863 ± 2091	26.7 ± 13.2	0.34 ± 0.25	0.34 ± 0.29
0x0100	99 ± 93	1891 ± 1372	23.2 ± 9.3	0.33 ± 0.40	0.29 ± 0.23
0x0101	70 ± 56	1375 ± 1093	21.1 ± 8.0	0.33 ± 0.33	0.40 ± 0.35
0x0110	78 ± 66	2394 ± 2479	26.0 ± 11.4	0.40 ± 0.44	0.41 ± 0.47
0x0111	69 ± 47	2088 ± 1984	27.1 ± 11.2	0.46 ± 0.21	0.44 ± 0.53
0x1000	60 ± 40	1416 ± 920	24.9 ± 11.4	0.45 ± 0.07	0.35 ± 0.41
0x1001	52 ± 38	1236 ± 1036	23.7 ± 11.6	0.42 ± 0.04	0.34 ± 0.41
0x1010	59 ± 60	1843 ± 2229	27.7 ± 13.2	0.44 ± 0.06	0.37 ± 0.28
0x1011	38 ± 30	1150 ± 1204	26.7 ± 14.1	0.47 ± 0.07	0.40 ± 0.28
0x1100	47 ± 41	1019 ± 902	21.0 ± 12.0	0.49 ± 0.25	0.40 ± 0.41
0x1101	61 ± 55	1244 ± 1033	23.1 ± 12.7	0.43 ± 0.44	0.35 ± 0.46
0x1110	51 ± 45	1556 ± 1575	28.2 ± 12.0	0.42 ± 0.34	0.49 ± 0.41
0x1111	42 ± 35	1231 ± 1352	25.8 ± 11.9	0.47 ± 0.50	0.40 ± 0.23

As shown in Table 4.10, the longest average playing duration is achieved by players playing games with the configuration 0x0100 (low moving speed, long increased length, without extra added food, and without poisoned food). This result is different from the expectation that the increased length would only contribute to the decrease of playing duration, as it adds complexity after each food capturing, compared to the default state 0x0000. However, including two baseline game sessions, each player would be expected to play default game sessions 0x0000 four times. The repetitions of the simplest game may contribute to a loss of concentration and may discourage players. A slight change of variable may stimulate players to play longer.

The highest average score and highest efficiency is achieved by playing games 0x0010 (low moving speed, short increased length, with extra added food, without poisoned food). This is expected, as the more food available for capturing, the easier it is for players to form efficient game strategies.

In contrast, the shortest average playing duration is achieved by playing games

0x1011 (high moving speed, short increased length, with extra added food, with poisoned food). The shortest playing duration is expected to be achieved by game 0x1111. However, the increased length is the least significant variable in our design. The game session 0x1111 has the second least playing duration.

The lowest average score and efficiency is correspondingly achieved by playing games 0x1100 (high moving speed, long increased length, without extra food, without poisoned food), due to the increased game complexity and the lack of extra food.

The means of game performance features and subjective reported features, as shown in Table 4.10, have also been analysed through multivariate analysis of variance (MANOVA) among groups of game variables. The results show that there are differences between the effects of game variables on subjective self-reported features and objective game performance. There are significant differences ($p < 0.05$) in the means of players' self-reported complexity and frustration levels between high-speed and low-speed games. However, there are no significant differences among different players in the other three game variables (long/short increased length, with/without poisoned food, with/without extra added food). For the objective performance features, there are significant differences ($p < 0.05$) towards the means of players' playing duration, scores and efficiency between high-speed and low-speed games, as well as between with and without poisoned food games. However, no significant differences have been shown among different players towards the rest two game variables (increase length and extra added food). The results of the MANOVA test supports the designs of game variables: that the moving speed and the poisoned food are expected to be the top two game variables with significant effects on game performance and self-perceived game experience.

The moving speed was designed to be the most significant game variable among independent variables to change game performance in the former discussion. The results in Table 4.10 support the design. Significant decreases of average playing duration and average scores when moving speed changes from low to high (the first-order digit changes from 0 to 1 in configuration) is shown, but the efficiency stays in the same range (which also support that the increase of moving speed also have positive effects on efficiency of food capturing).

Meanwhile, the highest self- rated complexity occurred after the game session 0x1100, which also has the lowest average score and efficiency. However, the self-rated frustration of this game session is about average. The highest self-rated frustration occurred after game session 0x1110. This high level of frustration may be due to the difficulty of controlling the snake in high speed mode, so that the more food is available on board, the more frustrated the players would be if they fail to obtain them, according to the game evaluations in the final questionnaires. Players also explained their reasons when feeling particularly discouraged in the final questionnaire. Besides those players stating that the game sessions were too simple and boring, others explained there were 'too many things on the screen, that they 'pressed the wrong buttons and failed' and that their 'eyes become tired'. None of them related game difficulty with negative feelings in game playing. This indicates that there is no significant positive relationship between objective/subjective task complexity and negative feelings (frustration and discouraged) in game playing. The main source of frustration may occur at the time when players have the ability to achieve the task, but they failed due to objective reasons (too many things on board confuse the players' eyes) or subjective reasons (accidentally pressed the wrong buttons).

In the final questionnaires, each participant was also asked to choose one variable combination that made the game most difficult for them. Nine among 16 players found the most difficult combination as 0x1111, while another four chose 0x1101; one for 0x1011; one for 0x1001 and one for 0x1000. Players explained their reasons for choosing 0x1111 as 'too many things on board makes the game stressful' and it was 'hard to distinguish between poisoned and non-poisoned food'.

The performance results generally accord with the design on how independent 'Snake' game variables would change game performance as a result of cognitive processes, as shown in Figure 4.22.

In summary, in this section, controlled 'Snake' game environments are discussed for their influence on the cognitive processes of 'Snake' game play, which are shown as objective game performance and subjective self-rated complexity and frustration. The objective and subjective indicators are discussed by grouping them together among all players under the same game configurations. The results reinforce the game design that the change of game environments would affect the game experience in 'Snake' game playing.

Specifically, the change of game variables would result in the change of objective and subjective task complexity, according to Figure 4.22 and Table 4.10. The increase of task complexity would result in a negative impact on game performance, but no significant impact on players' frustration in game playing. Finally, the main source of frustration in 'Snake' game playing occurs when the players have the competence to achieve the goals, but eventually fail due to both subjective and objective reasons.

The results show that cognitive processes in game experience needs to be discussed under the analysis of game environments and game variables as context.

4.7.3 Affective Process in 'Snake' Game Experience

As the cognitive process of the 'Snake' game experience have been discussed, the third aspect of this discussion section is to evaluate how affective processes during 'Snake' game playing is reflected by extracted subjective and objective indicators.

First, the changes of affective states before and after the experimental session are reflected by comparing subjective indicators derived from self-reports before/after experiment, as shown in Figure 4.23, and averaged EMG signals, which may indicate facial expressions. In the figure, the bars on the left represent self-reported emotional states before game play and the right bars represent emotional states after completion of all 34 game sessions.

As shown in Figure 4.23, the majority of players assessed themselves as 'Relaxed' or 'Normal/Content' before the experimental session, which is expressed as neutral/negative arousal and neutral/positive valence in the 2D emotional model. However, after the experimental sessions, the players reported more negative affective states, including 'Tired/exhausted' (negative arousal and neutral/negative

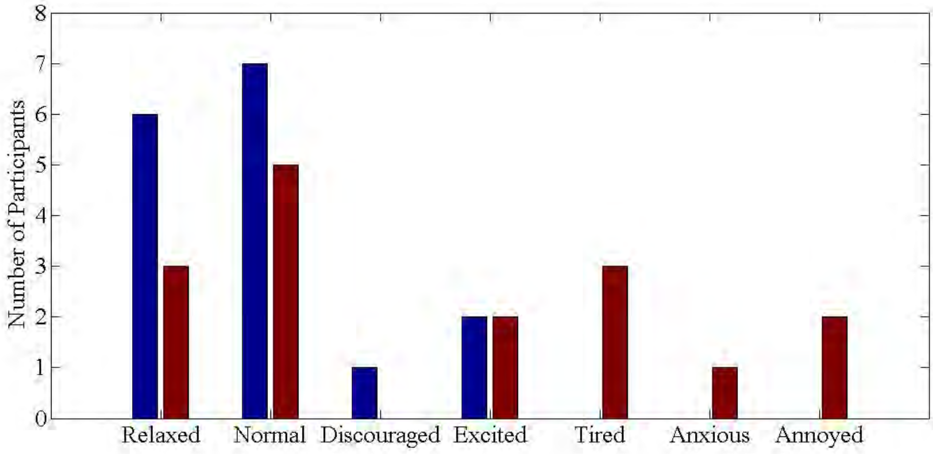


Figure 4.23: The Comparison of the Initial Affective States Before Experimental Session (left) and the Final Affective States After Experimental Session (right)

valence), 'Discouraged/bored' (negative arousal and negative valence), or even 'Annoyed/irritated' (positive arousal and negative valence). This shows that the designed game sessions have influenced the players' affective states in game experience, but possibly in negative ways.

EMG corrugator and zygomaticus responses are used as objective indicators for negative and positive valence emotional states to facilitate the analysis of affective processes. According to the initial/final valence of the players' self-reported affective states, the players are grouped into three different groups: positive-positive valence group, positive-negative valence group, and negative-negative valence group, as summarised in Table 4.11. The normal/content and relax affective states are considered as positive valence instead of neutral. No players participating in experiment showing positive valence change after playing the game sessions.

The collected EMG signals are first pre-processed to eliminate outliers and noise signals irrelevant to 'Snake' game playing, and then processed according to signal processing methods presented in Chapter 2. The mean and standard deviation of these electrical signals were calculated among each group of players, as shown in Table 4.11.

Table 4.11: Before and After Game Affective States

	P-P	**P-N**	**N-N**
Subject ID	4, 5, 6, 7, 8, 11, 12, 13, 14, 15	1, 3, 9, 10, 16	2
EMG Corrugator	5.23 ± 5.32	6.69 ± 9.20	1.12 ± 0.64
EMG Zygomaticus	6.38 ± 9.01	5.56 ± 6.74	1.83 ± 1.32

As summarised in Table 4.11, among 16 players, ten players stayed in positive valence states before and after the experiment. Five players reported the change of emotional states from positive to negative valence, and one player stayed in negative valence states before and after the experimental session.

Compared among these groups, the P-P group show higher averaged ZEMG electrical activities and higher standard deviation within groups during the game playing collected compared with P-N group. Meanwhile, the P-P group also show lower CEMG averaged muscle activities and lower standard deviation within groups with P-N group. Combined with the former study that the muscle activities from zygomaticus muscle group reflected positive valence emotional state and those from corrugator muscle group reflected negative valence state [140], the objective physiological indicators are in accordance with the subject reported emotional states that the P-P group experienced more positive valence emotional states during 'Snake' game playing. The standard deviation indicates the degree of muscle activities. Therefore, the higher the standard deviation, the higher degree the players' facial expressions would possibly be during 'Snake' game playing. The N-N group show low level facial muscle activities in both corrugator and zygomaticus regions.

Second, EEG signals collected from pre-frontal cortex are used to extract features that may indicate real-time affective states during 'Snake' game play.

As reviewed in Chapter 2, the asymmetric EEG activities at the frontal cortex would reflect the positive/negative valence of emotional states. Generally, if the EEG responses collected from subjects are left-lateral, the subjects are supposed to experience positive valence emotion [19, 67, 120, 290]. In contrast, if the EEG responses collected from subjects are right-lateral, the subjects are supposed to experience negative valence emotion [155, 257, 282].

The frequency of EEG signals also shows the arousal level of the player, as reviewed in Chapter 2.

To process and to visualise the players' affective states in real-time during game playing, a real-time emotional states estimation system was designed and implemented based on the above features of EEG signals collected from the players. The EEG signals are processed to extract frequency features in analysing affective arousal and valence according to signal processing methods in Chapter 2.

The implemented system is called 'Traffic Light', as shown in Figure 4.24, which shows the real-time processing of EEG data stream captured from one of the players. The implementation of traffic lights interface is used in demonstrating the current arousal and valence level of participant during tasks. The emotional states of the subject were shown by different colours of lights in this 8×8 table. Each emotion within these 16 categories is identified as one of four levels: weak, moderate, moderate strong, strong. The corresponding colours of lights are shown as green, olivine, orange and red. Every time there are 16 traffic lights lighting up. One colour of light lights up for each emotional state. It is quite unlikely that two red lights show up in two extreme dimensions, as a person can hardly be tense and calm at the same time.

The 'Traffic Light' system is used in the 'Snake' game context to monitor the affective states during game play. The emotional coordinates calculated for a beginner player and an intermediate player averaged at the time frame of each game session are shown in the following Table 4.12, as an example to analyse the emotional states; these changed during game play. The Anxious /Stressed, Normal /Content, Tired /Exhausted, Discouraged /Bored, and Annoyed /Irritated emotional states have been abbreviated to Anxious, Normal, Tired, Discouraged, and Annoyed in the table.

The centroids of the calculated affective coordinates of each affective state are visualised in Figure 4.25, based on the cognitive move diagrams to visualise the dynamics of affective states during information processing and decision making [154]. As shown in figure, the beginner player generally changed his/her self-reported

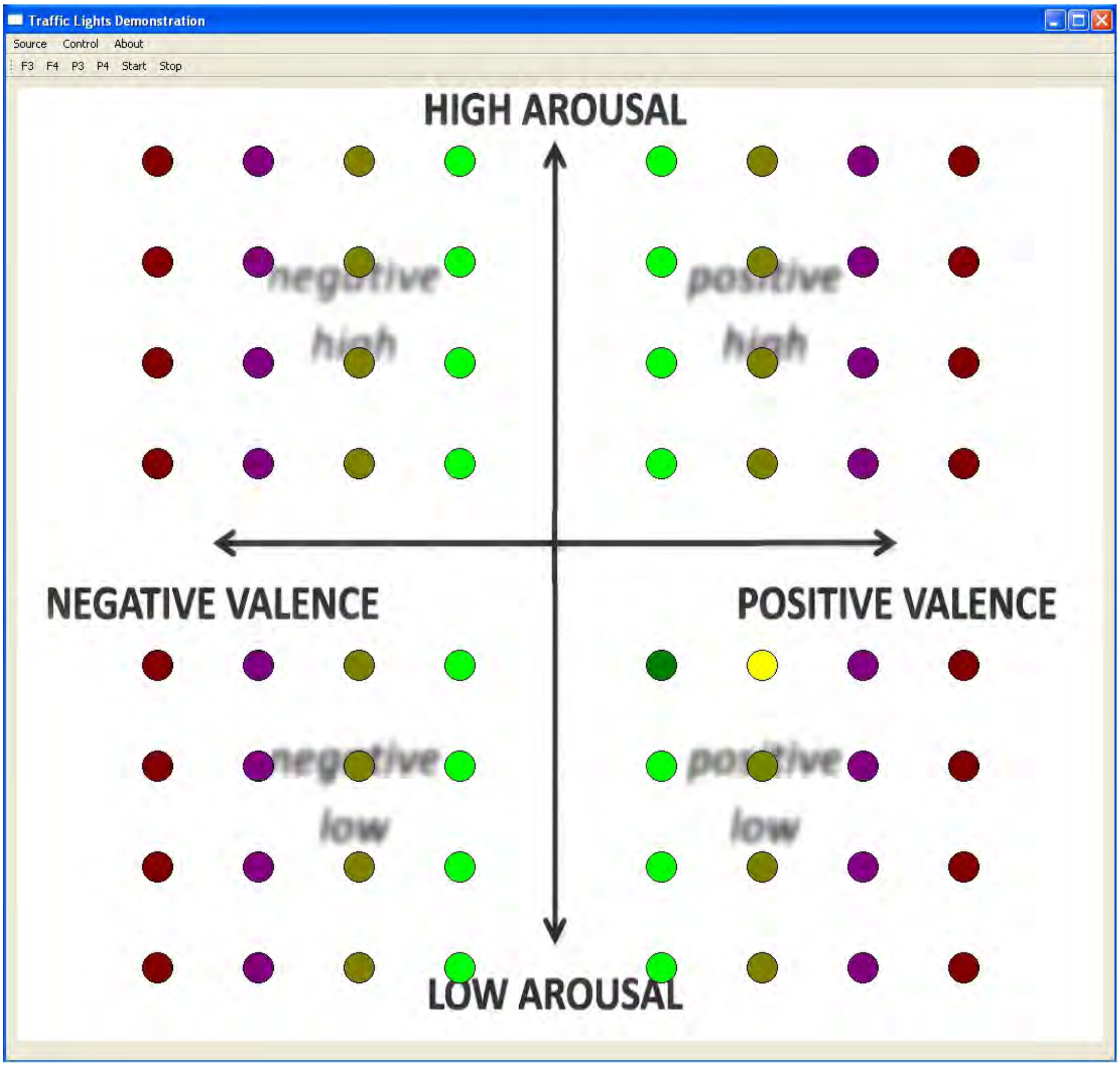


Figure 4.24: The 'Traffic Light' Real-time Affective States Processing and Visualisation System based on EEG signals

Table 4.12: The Affective States During 'Snake' Game Playing

	Beginner	**X axis**	**Y axis**	**Intermediate**	**X axis**	**Y axis**
Overall Emotion	Relaxed to Annoyed	−0.1160	0.0101	Discouraged to Anxious	0.3950	0.1007
Game 1	Anxious	0.23	0.10	Normal	0.72	0.19
Game 2	Anxious	0.23	−0.01	Normal	0.73	0.24
Game 3	Anxious	0.18	0.03	Normal	0.66	0.15
Game 4	Anxious	0.12	0.06	Normal	0.63	0.18
Game 5	Anxious	0.21	0.00	Normal	0.61	0.10
Game 6	Anxious	0.11	0.02	Normal	0.62	0.09
Game 7	Anxious	0.02	0.07	Normal	0.54	0.07
Game 8	Anxious	0.04	0.06	Normal	0.49	0.20
Game 9	Anxious	0.04	0.04	Normal	0.45	0.12
Game 10	Anxious	0.03	0.03	Normal	0.48	0.07
Game 11	Tired	0.04	0.05	Normal	0.51	0.05
Game 12	Discouraged	−0.01	−0.01	Normal	0.44	0.06
Game 13	Discouraged	−0.22	0.01	Normal	0.45	0.07
Game 14	Discouraged	−0.19	0.02	Discouraged	0.32	0.14
Game 15	Discouraged	−0.21	0.00	Normal	0.36	0.16
Game 16	Discouraged	−0.17	0.03	Normal	0.37	0.10
Game 17	Discouraged	−0.18	−0.02	Discouraged	0.33	0.06
Game 18	Discouraged	−0.19	−0.02	Discouraged	0.32	0.03
Game 19	Excited	−0.18	−0.03	Discouraged	0.32	0.16
Game 20	Normal	−0.20	−0.06	Discouraged	0.35	0.05
Game 21	Annoyed	−0.21	−0.01	Normal	0.35	0.05
Game 22	Annoyed	−0.21	0.04	Normal	0.39	0.13
Game 23	Excited	−0.24	0.02	Normal	0.38	0.08
Game 24	Annoyed	−0.30	0.00	Normal	0.24	0.07
Game 25	Annoyed	−0.28	−0.02	Discouraged	0.22	0.10
Game 26	Annoyed	−0.35	−0.0	Discouraged	0.20	0.13
Game 27	Annoyed	−0.33	−0.02	Discouraged	0.21	0.11
Game 28	Annoyed	−0.34	−0.02	Normal	0.23	0.07
Game 29	Annoyed	−0.25	−0.01	Normal	0.22	0.04
Game 30	Annoyed	−0.15	0.001	Normal	0.24	0.10
Game 31	Annoyed	−0.27	0.01	Normal	0.20	0.11
Game 32	Annoyed	−0.22	−0.02	Normal	0.19	0.11
Game 33	Annoyed	−0.17	0.01	Normal	0.27	0.06
Game 34	Annoyed	−0.14	−0.02	Normal	0.23	−0.01

affective states from anxious (dark blue, colour index 1), to tired (blue, colour index 2), to discouraged (light blue, colour index 3), to excited (yellow, colour index 4), back to normal (red, colour index 5) and finally to annoyed (dark red, colour index 6). The intermediate player changes from normal (red, colour index 5) to discouraged (light blue, colour index 3) and back to normal again. As shown in Figure 4.25, both the affective arousal and valence levels of the beginner player move negatively during the experimental session; except during the last few games the arousal level moved positively due to the annoyed/irritated emotional states. The emotional states of the intermediate player during game play move in a small range from normal/content (higher arousal and valence) to discouraged/bored (lower arousal and valence) and back to normal/content again. The calculated affective coordinates have captured the self-reported emotional states and emotional changes during 'Snake' game play in a more quantitative way.

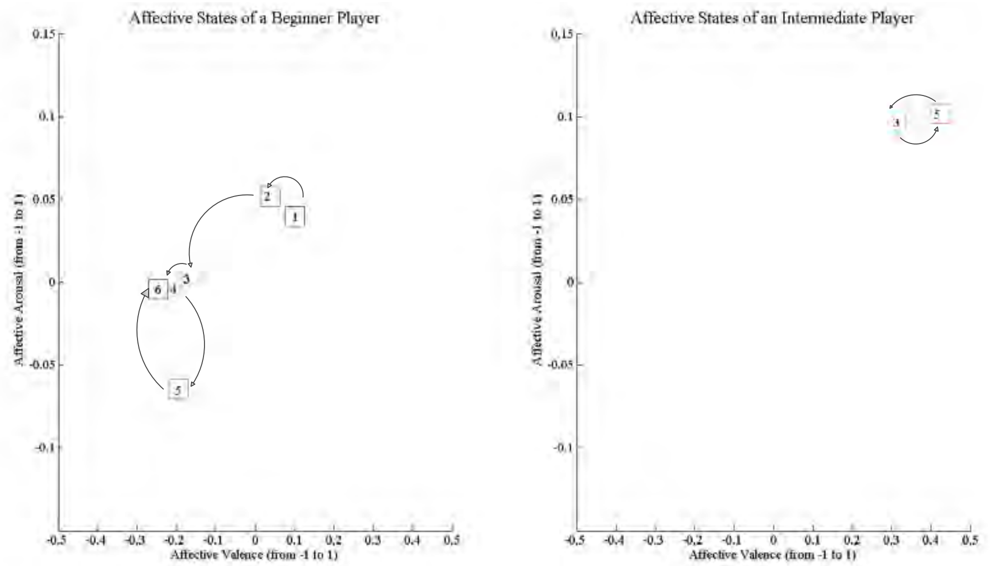


Figure 4.25: The Affective States Visualisation during 'Snake' Game Playing

Compared with the affective state before/after experiment, though the intermediate player reported negative valence emotions before and after game sessions, he/she generally report more calm and cheerful emotional states when playing games. The beginner, in contrast, reported a relaxed state before the experiment, but during the experiment, he/she reported more negative valence emotions including feeling anxious, tired, discouraged and annoyed. From objective measure generally, the intermediate player who reported calm and cheerful emotional states has higher valence and arousal levels calculated from EEG signals compared with the beginner player.

However, during the entire experiment, both of the two players showed decreasing trends of valence during the entire experimental session. They had shown stable high valence states in the first six games. After playing seven games, they showed a decreasing trend of their valence level from the calculated affective coordinates, and the decrease continues towards the end of the 34 game sessions. After the first time the player reported feeling discouraged/bored, there was a rapid decrease of valence. This indicates the deteriorating game experience caused by the repetition in playing the same kinds of games. From the perspective of affective arousal, more stable neutral arousal levels were shown for both players during the entire experimental session. However, the arousal levels of both players also decreased alongside the game play. This may indicate a loss of attention and interest after playing the same kinds of games for too long.

According to the 2D emotional model presented in Figure 3.5 in Chapter 3, affective coordinates are proposed to each reported affective state in natural language, discussed in this experiment from -1 to +1 for both arousal and valence levels. For example, the arousal level of anxious/stressed has been proposed as -0.2, and valence as 0.8. Correspondingly, tired/exhausted are [-0.2,-0.5], discouraged/bored are [-0.5, 0.5], normal/content are [0.2,-0.2], annoyed/irritated are [-0.5,0.3] and relaxed are [0,0].

Linear correlation analysis has been performed between the proposed self-reported affective coordinates after each game play and the estimated affective coordinates from EEG signals during each game play among all 16 players (those who reported varied affective states among different game sessions). The results show a moderate correlation of 0.32 ($p < 0.05$) as average correlation coefficient. The correlation results show that the estimated affective states using EEG signals are in accordance with self-reports after game play.

In summary, objective measures including EEG and EMG could be used together with subjective self-reports in analysing players' affective processes during 'Snake' game playing. However, subjects' differences have shown the absolute values of objective affective measures when the same emotion was reported after game session. The changes of objective measures may better indicate affective changes during game play than absolute values.

4.8 Evaluation of the Prototype

The 'Snake' game prototype designed in this experiment as the first 'sandbox' to assess game play and game experience model is appropriate as its design helps to answer the main research question

'Snake' Game Experiment Research Question:

RQ2: How do game play and game experience in the context of 'Snake' game respond to proposed game play and experience models?

The main research question has been discussed from three aspects: the general information processing system, the cognitive process and the affective process. The results verify that game play and game experience are information processing systems by evaluations of both subjective and objective indicators derived from self-reports, game environment/game actions, and psycho-physiological data. These dependent multi-factor indicators, especially psycho-physiological signals, could be analysed to track 'Snake' game experience during game play. However, individual differences should be considered in analysis of cognitive and affective processes during game play, under the Snake game context.

The 'Snake' game context is designed in this experiment to target casual action games, which are easily accessible with simple problem spaces, but require rapid mental/motor responses in solving the problems. Small amounts of game variables are involved and controlled in this design; thus, the playing goals, game complexities and game strategies could be estimated.

However, in this design, the skill assessment of 'Snake' is difficult and subjective due to the 'Snake' game being a single-player game. EEG data has shown its potential in both cognitive and affective process analysis in this experiment, but the limited number of EEG capturing sites restrict the further analysis of central nervous systems during game playing.

In order to assess the model under another game context, which involves high mental load and more variables, another experiment is designed based on the classical Asian board game 'Go', with four EEG capturing sites involved in experimental design. This experiment is specifically explained in Chapter 5.

4.9 Conclusion

The proposed game play and experience model 3.3 has first been evaluated under a designed 'Snake' game concept as a casual action game in this chapter, by analysis of both subjective and objective indicators derived from human and game information before, after and during game play. The game experience as an information processing system, cognitive process and affective process in game experience have been discussed. Generally, the 'Snake' game play could be considered as the interaction of game system and the human system. The human element is an information processing system with limited resources allocated for the high priority brain functions as the difficulty of the game increases. Psycho-physiological signals collected from players during 'Snake' game play could be used to derive indicators of the human information process, including cognitive and affective processes, to facilitate analysis of subjective self-reports. The subjective evaluation of the game experience under the 'Snake' game context is an off-line, interruptive, non-quantifiable, yet effective and reliable way to understand the players' perception of the games and the corresponding experience, especially when analysed together with objective measures. Game environments and subjects' differences have great influence on the 'Snake' game experience, in its form of cognitive and affective processes, and the resulting game actions as performance.

Chapter 5

The 'Go' Game Experiment

Everything in nature starts with one. The overall number of points on Go board is 361. The one is the evolving foundation for the others. To get hold of the one is to influence the other four directions. The 360 represents the number of days in a lunar year. The 4 quarters represent the number of 4 seasons. 90 points in each quarter represent 90 days in a season. 72 squares represent 72 solar terms in lunar calender. For the 360 points, black and white occupies half of them - represents the balance of Yin and Yang. The lines and points and squares consists of the game board. The board is static and squared. The stones are dynamic and round. From ancient time till now, there is no single Go game that is the same with others.

– Translated by the author from Qijing Shisan Pian (Go Manual in 13 Chapters, Song Dynasty, 10th –13th Century AD [317])

The Asian board game 'Weiqi', better known as 'Go', was said to be invented in the twentieth century BC by the sage-king emperor Yao in ancient China [22]; at the same time that Stonehenge was built in Britain, the Egyptians proposed their very first solar calender, and megalithic temples were built on the islands of Malta. The 'Go' game was considered as one of the four cultivated arts of the Chinese scholar gentlemen in history, and is still played now by hundreds of thousands of amateur and professional players around the world. In 2010, the International Go Federation had 74 membership countries around the world and four memberships cover multiple countries [4].

Along with the rapid growth of video games since the popularity of personal computers and game consoles, classical board games have never ceased to develop: they still appeal to players from different backgrounds in all age groups. Compared with video games, most of the classical board games, including 'Go', have charmingly simple rules and a vast number of variations in playing. They also provide tangible communications with other players, other players' strategies and game objects during play, which video games can hardly provide. Among the board games, the game of 'Go' is a zero-sum, perfect-information, partisan, deterministic strategy game which is currently one of the most complex games in the world. The complexity of 'Go' is proven to be PSPACE-hard [239] and the possible number of game permutations is 361! (ignoring the suicide moves).

The game play and game experience model proposed in Section 3.3 were discussed in Chapter 4 under experiments designed around the game concept of 'Snake'. As evaluated in Section 4.8, the game of 'Snake', as a problem space, is simple, easily accessible, and involves small amount of variations during play. In order to discuss the proposed model from a complex game perspective, a second 'Sandbox' experiment is designed based on the game of 'Go' in this chapter to further analyse the game experience under a complex, high-demanding game context. The potential further research of this 'Go' game experience analysis in this chapter could also be to: 1) understand the cognition of 'Go' game play; 2) neural feedback training of 'Go' players in obtaining optimal arousal to raise game performance; and 3) the design and development of computer 'Go' AI programs.

The chapter is structured as follows. The designed 'Go' game concept for this experiment is presented in Section 5.1. The relevant 'Go' game research is reviewed in Section 5.2. The experimental design and procedures are specifically explained in Section 5.3 and 5.4. The experiment data is collected and discussed in Section 5.5 and 5.7. Finally, 5.8 concludes this chapter.

5.1 The 'Go' Game Concept

5.1.1 The Introduction of 'Go'

The game of 'Go' is an oriental competitive board game originating China, with the name 'Weiqi', which means a board game aimed at surrounding its territories. Literally, the strategy of the 'Go' game play is to use stones as 'walls' — to surround larger territories, and as 'troops' — to surround the opponent's stones to 'kill' them. This game has the same kind of historical and current status in Asia as chess in the Western world, due to its war-like features.

The 'Go' game has its name transliterated from the Japanese pronunciation of 'Weiqi' as 'Igo' [293]. This game is a perfect information game where chance plays no part. The game is played by two players with each one holding either black or white stones. The two players consecutively put one of their stones on an empty intersection of a square grid of 19 × 19 lines on the game board [184]. The objective of the 'Go' game for each player is to surround larger areas than the opponent on the game board by using his/her stones. Once the stone is put on the board, it can never be moved. It can be removed if captured by the opponent.

Figure 5.1: 'Go' Game Board 'FloorGoban' by Goban1 — Own work. Licensed under Public domain via Wikimedia Commons

The term 'liberty' is used to describe the adjacent empty intersections (up, down, left, and right) or adjacent intersections where there are already the same colour stones. If a stone has no 'liberty', it is called 'dead' and can be captured by the opponent.

Both players have freedom to 'pass' (put no stone on board) any game step during the entire game session, but they can never put more than one stone on the board at each time.

The game is ended by one player announcing the intention to resign at any stage of the game, or by both players choosing to 'pass' consecutively. If one player resigns, his/her opponent will automatically win the game, no matter what the game board looks like. If the game ends by two consecutive 'passes', all the 'dead' stones are removed from the board, and the result of the game is computed by comparing the sum of the territories and available stones of both players on the board. There are differences in calculating the final scores under Chinese, Korean and Japanese rules. Rules used in a specific game must be agreed before the game begins.

The ordinary size of the game board for 'Go' competition is 19×19. Beginners also play on training boards with the board size 7×7, 9×9, 13×13 or 17×17. In formal competitions, the player who is holding black stones always puts the first stone on the board and starts the game. He or she also gets a first move advantage. The smaller the board size, the larger the advantage to the Black player over the White player. This advantage is usually compensated by 'Komi' in formal competition with equal ranks of players. 'Komi' is a pre-defined rule with extra points adding to the White player when counting the results of the game. The extra points range from five to seven under different rules [204].

5.1.2 The 'Go' Game Rankings

Currently, there is no universal ranking system in 'Go' game playing. However, in those countries/regions where 'Go' games are popular — China, Korea, Japan, Europe and America, nationally recognised 'Go' ranking systems are available. As there are several international 'Go' tournaments each year, the rankings of different systems can also be compared through their competition results. In general, the 'Go' game skills are ranked by kyu (gup in Korean and ji in Chinese) and dan (dan in Korean and duan in Chinese) scales to rank amateur and professional players, as listed in the following Table 5.1, according to the data presented in Sensei's library [6]. The European ranking system do not rank beginner players less than 20K.

Table 5.1: The 'Go' Game Ranking System

Description	**Rank**	**Skills**
Two-digit Kyu	30-20K	Beginner
Two-digit Kyu	19-10K	Casual Player
One-digit Kyu	9-1K	Intermediate Amateur
Amateur Dan	1-7D	Advanced Amateur
Professional Dan	1-9P	Professional Player

As illustrated in Table 5.1, the Kyu rank is awarded for learners and students. The lower the Kyu rank is, the higher the skill level is for the student. A student can be awarded amateur Dan once he or she achieves good results in tournaments and exams. Since then, the higher the Dan rank is, the higher the skill level of the player is. 7D is the highest rank for an amateur 'Go' player. If a higher rank is desired, he or she must choose to become a professional 'Go' player as a career through rigorous competition to acquire a professional diploma. Then, as a professional player, he/she would start with 1P and the rank could be improved by participating in competitions regularly held among professional 'Go' players. Once a rank is achieved, it cannot be lost. The 'Go' game ranking systems are slightly different from region to region, but generally, they are all using the same notions of Kyu and Dan as the scale of 'Go' playing skills illustrated in Table 5.1.

5.1.3 The 'Go' Game Concept for This Experiment

In Chapter 4, the proposed game play and game experience model have already been evaluated and discussed under a popular casual action game concept: 'Snake'. However, the 'Snake' game play and the experiment were conducted under a lab environment strictly controlled to involve small amount of variations. The premium objective of this 'Go' game experiment in this chapter is to discuss game play and game experience from a more realistic complex way, which involves complex problem solving by professional recognised players in real situations.

In general, the game designed in this chapter should be computationally complex with more variables to involve higher levels of mental efforts during game playing, but still be under control. The board game 'Go' is an appropriate choice for this situation due to the following characteristics.

First, the 'Go' game is one of the simplest yet one of the most complex game around the world now. It is simplest in its rules and concepts, but most complex in its possibilities and playing strategies. The game has a simple, clear and fair rule set that has been tested under thousands of years of playing and tens of international and local 'Go' tournament each year. The game is also constraint with a maximum amount of steps to the number of points (361 for a 19×19 game board) on a given game board, and generally there is a total or single step time limit for each player.

Second, the game outcome is unambiguous. There are clearly defined 'win and 'lose' states of the game once the rules are recognised for both players.

Third, the 'Go' game could be played outside lab in a more realistic playing environment, once the board and the stones are handy. The time, location, environment, the quality of the equipment and other external factors would not influence any game variables.

Fourth, due to the complexity of 'Go' game playing, it is not easily accessible for a first-time player, so players participating in this game and this experiment have recognised amateur or professional dan rankings.

Last, compared to 'Snake', the 'Go' game is more 'abstract' and the game experience is mainly influenced by the complexity of the game instead of the graphical interfaces or controlling methods.

However, for this experiment, the traditional two-player board game of 'Go' is not a perfect platform to assess human player experience during playing. The complexity of this two-player 'Go' game session is largely dependent on player's opponent, so that the complexity is not deterministic for a single game. For example, for any 'Go' player, playing against top 9P player would have a completely different complexity level compared to playing against an amateur player. Thus, to keep the complexity of the game under control, an AI-based computer 'Go' should be designed, and the solution is explained in Section 5.3.

5.2 Related Research

Compared to casual game 'Snake' discussed in Chapter 4 the 'Go' game has long been researched in game theory, AI, and cognitive science. The experiment in this chapter is designed to combine both computer 'Go' (from AI and game theory perspective) and human 'Go' (from cognitive science perspective). Thus, it is important to review the related research in both areas.

5.2.1 Computational 'Go'

Due to its game complexity, the game of 'Go' has long been studied as a challenging problem in mathematics and game theory. The combinatorial game theory, which focuses on perfect information sequential games, has been inspired by the study of the 'Go' game of John Horton Conway, which also leads to surreal numbers in game tree analysis [68, 169]. The 'Go Infinitesimals' is still analysed in combinatorial game theory as a good example.

The game complexity of 'Go' has also been analysed and discussed. The rules of the 'Go' game are relatively simple, but the strategies are much more complex. Due to the diversity of problems and strategies, the game of 'Go' is proven to be more complex than other two-player, complete information and zero-sum games. Among these games which are exponential time complete, as a function of the size of the board (like 'Checkers' [241] and 'Go' [240]), 'Go' is polynomial-space hard [189].

5.2.2 Computer 'Go'

Due to the rapid growth of AI and its applications in different domains, in most classical games, computer programs built upon AI methods can have better performances than human players. There are lots of famous computer AI programs that that eventually perform better than humans, such as Deep Blue program in chess game [150], Chinook program in checkers [251, 252], Logistello program in Othello [49], and Victoria program in Go-moku [21]. However, there is no mature model for 'Go' to overcome the complexity of the game compared with other games, like Othello, checkers and chess, which already have classical models and good solutions using those models [40]. Currently on a normal 19×19 Go game board, computer 'Go' is still easily beat by professional top 'Go' players.

Therefore, lots of AI methods being used in other games are useful but not sufficient to build up a strong computer 'Go' AI, so it becomes an attractive area for researchers to study.

The first computer 'Go' program that played against a human player was based on the influence model [318, 319]. The idea of this model is to segment the game board and determine the influence domain of the stones [318]. After that, the model of abstract representation of the board [238] and the adoption of patterns to recognise situations [38] were developed in computer 'Go' AI. Current research trends focus on combinatorial game theory [218], learning [57], abstraction, planning, and cognitive modelling [40].

Among these, the Monte-Carlo techniques for 'Go' is surprisingly effective and now dominates most of the computer 'Go' programs in almost all kinds of board size. There are many famous programs developed from Monte-Carlo techniques which have performed well in 'Go' competitions like Zen, Erica, and Fuego. The Monte-Carlo tree search has also been applied to games other than 'Go' and non-game domains now.

Currently, there are also several computer 'Go' competitions held on a regular time basis to test the strength of computer 'Go' programs, like Ing Cup Computer Go

Competition, FOST Cup, KGS tournament, TCGA, UEC Cup, Computer Olympiad, European Go Congress, and so on. The number of Human vs. Computer Go Competition is less due to the weakness of current programs in playing 19×19 'Go' games compared to human professional players.

5.2.3 Cognitive 'Go' Game Research

The development of invasive and non-invasive techniques has put forward cognitive analysis between human behaviour and brain activities, making this a new trend. Functional magnetic resonance imaging developed in 1992 and EEG has provided both temporal and spatial information, which makes it possible to monitor brain and ANS activities during real cognitive tasks.

To identify the neural basis of cognitive processing and problem solving, there is a widespread interest in using cognitive neural imaging techniques (e.g., positron emission tomography (PET) activation and functional magnetic resonance imaging (fMRI)) or EEG in conjunction with cognitive tasks to take place of the former studies from experience and indirect inferences [71].

The game of 'Go' could be a good cognitive task for this purpose. The complexity of 'Go' (equally hard for human player and for computer to play) and the visual nature of 'Go' (the choice of move requires recognition of certain patterns which are meaningful to the player, and the recognition and reproduction of these patterns could be different in professional 'Go' players and amateur 'Go' players) makes it a good example. Analysis can be meaningful to understand the cognitive basis of 'Go', training of players, computer 'Go' game developers and the development of other games to keep the players in flow.

Chess and the game of 'Go' can be viewed as good examples of cognitive tasks involving highly sophisticated problem solving skills. Chess has a long history and a wide population of players in Western world. It is also the focal point of application domain of AI research since the 1970s [221, 272]. Its neural basis is first investigated through an experience study that since more left-handed players are found in professional serious players, the playing skills may be specified in the right hemisphere of human brain [71]. Oxygen-15-Water Positron Emission Tomography technique was used later in identifying the activated neural networks in chess playing [223]. Four cognitive tasks involved in chess playing are isolated and identified, including: black/white discrimination, spatial discrimination, rule retrieval and checkmate judgement. During these processes, functionally distinct cerebral areas, including the prefrontal cortex, occipito-parietal junction, left temporal lobe, superior frontal lobe and some more areas are activated. To investigate the cortical process during real chess playing situation but not isolated tasks, another fMRI study is performed on six novice chess players while playing from middle of chess games, when the pieces are fixed in place and randomly placed [27]. The results show that bilateral activations are observed in the superior frontal lobes, the parietal lobes and the occipital lobes. The left hemisphere shows more activities than the right hemisphere. fMRI studies are later applied to professional chess players to identify the neural activations of perception [175]. EEG coherence measures are also used in comparison of chess experts and novice in solving chess problems [298].

'Go' involves similar cognitive processing styles as chess, but is rooted in Asian countries. The difference between 'Go' and chess is that in 'Go' the playing techniques are more focused on choosing the positions of stones instead of choosing the chess piece, because all stones have identical value. Since 'Go' has a larger board than chess, it is considered much more complex than chess in problem solving. 'Go' is also the last kind of game where 'Go' AI could be easily defeated by a professional human 'Go' player on a normal 19×19 game board. fMRI techniques are used in studying the amateur players playing 'Go' game from the middle game [61] and the comparison of activated patterns in professional players and amateur players when solving 'Go' problems [227]. Research found that 'Go' playing requires the participation of a network of cortical areas, including mid-dorsal, dorsal pre-frontal, parietal, posterior cingulate areas, occipital area and posterior temporal area. These areas are engaged in attention, spatial perception, imagery, manipulation and storage in working memory, retrieval in episodic memory and problem solving. Also, moderate stronger activation in right parietal area than in left was found in fMRI study. The comparison of activation patterns between chess playing and 'Go' playing has also been investigated [27, 61]. This type of right hemisphere lateralisation differs from left hemisphere lateralisation found in chess.

5.3 Experimental Design

The 'Go' game experimental design is explained in this section. Specifically, the main research question, independent and dependent variables, experimental hypotheses and a computer-based 'Go' experiment prototype are proposed and designed in the following sub-sections in order to assess the players' game experience during complex 'Go' game playing. The experimental design and discussion are summarised in Figure 5.2. Three kinds of indicators are derived for analysis according to proposed 'Go' game experimental research question and hypothesis, just as the analysis of the 'Snake' game experiment. The discussion is illustrated from three aspects, as presented in the following sections of the chapter.

5.3.1 Research Question

Similar to the research question proposed in the 'Snake' experiment, the main experiment research question to be asked in 'Go' is:

'Go' Game Experiment Research Question:

RQ3: How do game play and game experience under the context of complex 'Go' game respond to proposed game play and experience models?

Specifically, the effects of game environments and game skills on 'Go' game experience are analysed, as reflected in self-reports, game performance and psycho-physiological measures. The experiment is designed under a computer-based 'Go' game environment.

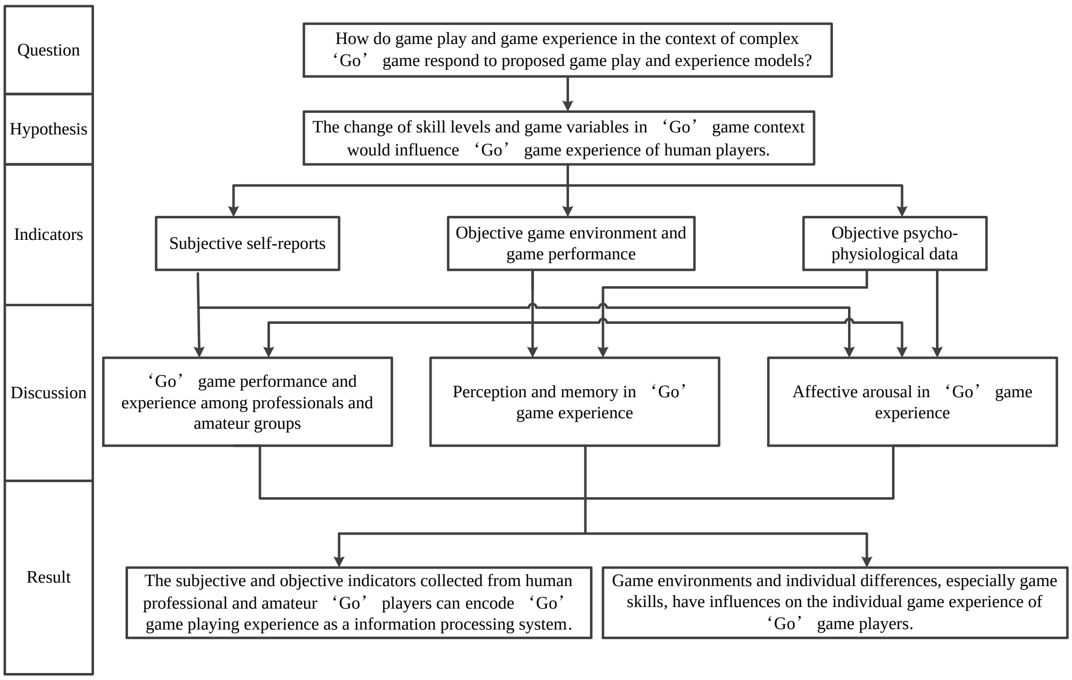


Figure 5.2: The ‘Go’ Game Experimental Design and Discussion

5.3.2 Identify Variables

As illustrated in the research question of the ‘Go’ game experiment, the independent variables can be identified as ‘game skills’ and ‘game variables under computer-based Go game environment’, the dependent variables should be again the ‘subjective and objective indicators’ derived from human and game information. The experiment is designed to control the game variables and game rules involved in the ‘Go’ game environment to change human game experience. Additionally, the skill level of players, which have been identified in the former ‘Snake’ experiment as an important factor contributing to the different cognitive processes of game play, have been controlled as another independent variable, as the skills of ‘Go’ game players could be evaluated by using widely recognised ranking and rating system.

The relationships among dependent variables and independent variable, as well as the relationships among dependent variables, are still the focal points of this experiment to evaluate game play and game experience during ‘Go’ game play.

5.3.3 Experimental Hypothesis

Similar to the experimental hypotheses proposed for the 'Snake' game, under the 'Go' game environment, the experimental hypotheses is proposed as:

'Go' Game Experiment Hypothesis:

H3: The change of skill levels and game variables in 'Go' game context will influence the 'Go' game experience of human players, reflected by the subjective self-reports, objective 'Go' game performance, and psycho-physiological metrics.

5.3.4 'Go' Game Experiment Design

According to proposed research question and hypothesis, the task for 'Go' game experimental design would be to design appropriate game variables based on computer 'Go' to influence game experience under complex 'Go' game play.

As discussed in Section 5.1.3, the game of 'Go' in general is an appropriate game platform to be incorporated in this experiment to answer the proposed research question, but the traditional two-player 'Go' game is not perfect as the complexity of the game is not under control. To target on this problem, AI-based computer 'Go' programs as opponents of human players would be essential parts involved in this experiment, as the skill level of the same computer 'Go' program will be constant through every play.

However, due to the complexity of the 'Go' game, as discussed in Section 5.2.1, the design of 'Go' game AI is by its own an important topic in AI community (as discussed in Section 5.2.2. To avoid deviations of the main research problem in this thesis, I chose to cooperate with a research team led by Prof. Chang-Shing Lee at the National University of Taiwan, who have their main research interests in computer 'Go' AI. They also have their leading computer 'Go' programs developed named 'MoGoTW'.

By inviting several professionals and amateur players to challenge the computer 'Go' programs introduced later in Section 5.3.5, a human versus computer 'Go' competition was held in June 2012, Brisbane, Australia under the support of Prof. Chang-Shing Lee's team, National Science Council of Taiwan, and Brisbane Marketing. As professional players have dozens of international and local tournaments each year, their schedules allowed less than three days for the competition. The human versus computer Go competition was planned to be held for two days in total. All the players were expected to play against a computer program at the same time from 9am to 5pm. Thus, different to the 'Snake' game experiment, the data collection for this experiment needed to be done simultaneously.

The Human versus Computer Go Competition is a kind of 'Go' competition among human 'Go' players and computer 'Go' programs. The special features about the 'Human versus Computer Go Competition @ IEEE WCCI 2012' are 1) three professional human players with different rankings are involved; 2) three amateur human players with same rankings are involved for comparison; 3) different computer 'Go' programs are tested against human players; 4) 'Go' games with different game variables (including board size, komi, rules, etc.) are played; and 5) games in particular setting, including playing blindfolded, or unnatural situations like 'Kill-All Go' are played in this competition.

Due to the fact that there were only two sets of psycho-physiological signal collection equipments available (4 EEG channels in total), and some participants (or the legal guardians of the participants) requested not to participate in the experiment or not to wear particular sensors, the experiment was designed under constraints to six subjects playing less than 20 games. Under these constraints, the 'Go' game experiment was designed to counter-balance the subject's skills and the game variables.

Specifically, the game variables as independent variables in this experiment are listed in the following Table 5.2. The corresponding rules such as 'Kill-all' and 'Blind' rules are specifically discussed in Section 5.3.6.

The computer 'Go' programs that were challenged as opponents in this experiment, besides MoGoTW, includes Many Faces of Go, Zen, Erica, Fuego, Pachi and

Table 5.2: The 'Go' Game Variables as Independent Variables

Variables	**Effect**
Board Size	Influence the complexity of the game, generally the computer 'Go' program performs better when the board size is small.
Komi	Influence the complexity of the game, the higher the Komi, the less advantage the Black player have on the White player.
Black/White	It will change the complexity of the game by working together with the Komi rule.
Kill-all/Non kill-all	Special rules apply for kill-all game, which has higher Komi advantage for the Black player. The Black could only win the game by capturing all the White stones, if not all White stones are captured, the White wins.
Blind/Non-blind	Influence the complexity of the game, generally the blind games are much harder compared to non-blind games.
Computer 'Go' Programs	Different 'Go' programs are built upon different designs. There is no standards on the skills of each program. However, the playing strategies and skills of different programs are considered to be different.

Coldmilk.

The 'Go' rankings of participants as another independent variable are listed in Table 5.3. One of the professional players has been rewarded the highest professional ranking 9P, and the other two players in the professional group have high rankings of 5P and 6P. In the amateur group, all participants have the same amateur ranking 6D, which shows their strong skills among amateur players. Due to the research ethics regulations, the identities of the participants will remain confidential unless given with the permission of the participants. Thus, the participants involved in the 'Go' game experiment are identified by their 'Go' rankings, and the three 6D players are labelled as 6D1, 6D2 and 6D3.

Table 5.3: The 'Go' Game Skills as Independent Variables

'Go' Players	**Ranking**	**Ranking**	**Ranking**
Professional Players	9P	6P	5P
Amateur Players	6D	6D	6D

Under the constraints of both schedule and equipment, to counter-balance between game variables and skills, the experiments are designed according to the following Table 5.4. The design is based on the combination of within-subject and between group design.

5.3.5 The 'Go' Game Prototype

The prototype of the 'Go' game experiment was designed according to proposed research questions hypothesis and experimental design, which is presented in this section. The 'Go' game experiment was conducted in combined with the Human versus Computer 'Go' Competition @ IEEE WCCI 2012 held in June 2012, Brisbane, Australia. The designed prototype is illustrated from five aspects as follows.

Table 5.4: The 'Go' Game Experimental Design

Board Size	**Skill**	**Other Variables**	**Board Size**	**Skill**	**Other Variables**
7×7	9P	Komi9.5, human play White	7×7	6P	Komi9.5, human play White
7×7	9P	Komi8.5, human play White	7×7	6D1	Komi8.5, human play White
7×7	9P	Komi8.5, human play Black	7×7	6D1	Komi8.5, human play Black
7×7	9P	Komi9.5, human play Black	7×7	6D1	Komi9.5, human play Black
19×19	5P	Human play White vs. Many faces of Go	19×19	5P	Human play White vs. Pachi
9×9	5P	Blind	9×9	5P	Non-blind
7×7	6D2	kill-all, human play White	7×7	6D2	kill-all, human play Black
13×13	6D2	kill-all, human play White	13×13	6D2	kill-all, human play Black

5.3.5.1 Subjects — The Who

The subjects were both mentally and physically healthy with the knowledge and experience of 'Go' game playing, and the participation of the experiment was on a voluntary basis. The subjects were able to convey their game experience in languages and expressions that were understood by the researchers with only general knowledge of 'Go' game.

Compared to the 'Snake' game experiment, the skill levels of the game have been taken into account in the research question as independent variables. Thus, the subjects of this experiment had recognised ranks in 'Go' game ranking systems.

This experiment as a human involved experiment, again, was approved by HREA panel due to the research ethics of Australia.

5.3.5.2 Environment — The Where

The experiment was conducted at Room M4, International Convention Centre of Brisbane, Australia, when the conference WCCI2012 was held. The room is an open environment for visitors to enter and leave freely at any time, as shown in Figure 5.3. However, the environment was generally very quiet during game play.

Figure 5.3: The Environment of 'Go' Game Experiment

The subjects were required to sit on a comfortable chair during game sessions against computer 'Go' programs displayed on a laptop PC in front of them. They were not allowed to take breaks within a single session of game play, but they were free to take breaks between sessions.

5.3.5.3 Measurements — The What

In this 'Go' game experiment, similar to the 'Snake' experiment, three kinds of measurements were taken from the game playing: the subjective self-reports, the objective game environment and game performance, and the objective psycho-physiological signals, in order to extract the three kinds of indicators of game experience.

The subjective self-reports were still classified into three categories: the initial questionnaire, the inter-game questionnaires and the final questionnaire, which were required to be completed by participants before all game play, after each game session and after all games. The self-reports were used to collect background information, go ranking, emotional states, game evaluation, self-performance evaluations and overall experience. As all the participants were from Taiwan, these questionnaires were originally written in English but were translated to Mandarin Chinese by a native Chinese speaker.

Specifically, the initial questionnaire focused on the players' background information and self-evaluation of their 'Go' skills. The inter-game questionnaire had only two questions for the participant to answer: that were, their self-rated game complexity and performance in the former game at a scale of 1 to 5. The final questionnaire summarised the entire experiment with a final evaluation of the experiment, the games and their own performance.

The objective game environments and game performance were recorded by professionals before and after each game session. The data included the game variable settings of each 'Go' game program, and the final results of the playing.

The objective psycho-physiological data was again collected by using the EEG suite provided by Thought Technology. In the 'Snake' experiment, two EEG channels at F3 and F4 positions in the international 10 to 20 system were focused on to analyse the electrical activities at the players' pre-frontal cortex during game play. However, in the 'Go' game context, besides the pre-frontal cortex as central executive centre of human brain, the electrical responses from parietal lobe as integration centre of sensory information were analysed to investigate the cognition and perception of human game experience. As the EMG sensors attached on face skin are disruptive in long-time game playing, and 'Go' game playing did not consist of and did not encourage many facial expressions, the EMG signals were not collected in this design.

Similar to the 'Snake' game design, psycho-physiological signals including BVP, SC, ST, Resp, EEG signals were collected from players. Due to the limited number of equipments and the requests of the participants, there were two sets of psycho-physiological data collection plans for the participants to choose from, as shown in the following Table 5.5. The EEG F3, F4, P3 and P4 represents the channel positions in the international 10-20 system, as shown in Figure 5.4. The F3 F4 channels are located on top of the left and right frontal cortex. The P3 P4 channels are located on top of the left and right parietal lobe. All the psycho-physiological signals were sampled at 256Hz during the data collection.

Table 5.5: The 'Go' Game Psycho-physiological Data Collection

Data Collection Plan	**Sensors**
Plan A	BVP, SC, ST, Resp, EEG F3, EEG F4, EEG P3, EEG P4
Plan B	BVP, SC, ST

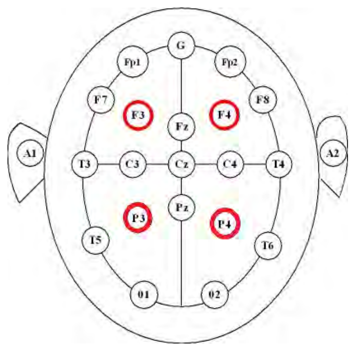


Figure 5.4: The EEG Channel Positions of the 'Go' Experiment

SC, ST, and HR/BVP sensors were attached to one hand using elastic finger straps. EEG sensors were attached to the scalp of human participants. A small quantity of $NuPrep^{TM}$ Skin Prepping gel on a cotton swab was applied on the vertex of scalp to remove contaminants to the EEG signal. The electrode of EEG sensor was filled with a very small amount of $Ten20^{TM}$ conductive paste to attach the EEG electrodes and record EEG signals. The same preparation and placement steps were repeated for reference voltage clips attached to the ear lobes. The respiration sensor was placed around the abdomen together with a latex rubber band and a self-adhering belt to fasten the band.

5.3.5.4 Process — The How

The experiment was planned to be conducted over two days consecutively according to the Table5.4. There was no fixed sequence for the games. However, all the game sessions in the design were required to be played by each particular player at least once. The rules of games, game settings, opponents, and special requirements (e.g., kill-all games or blind games) were made known to the participants before the start of each game session. During sessions, the players were free to ask questions about the games and the experiments.

5.3.5.5 Duration — The When

The experiment was planned to be conducted on 12 to 13 June 2012 in Brisbane, Australia. The schedule ran from 9am to 5am, with coffee breaks and lunch breaks each day.

The game session had no fixed duration as the playing time of each game session was determined by the game variables, the skill of players and the performance of players and the computer 'Go' programs. However, there was a total time limit for both human players and computer programs in each game based on the game settings and the board size. Both the player and the computer were not allowed to exceed their total time limits in planning their 'Go' steps. Specifically, the time limits for each game setting in design are listed in the following Table 5.6.

5.3.6 The 'Go' Game Rules in This Experiment

In this 'Go' game experiment, Chinese rules were adopted as basic rules. For each game setting, there was equal time allowance for each side (human and computer) to decide moves. The generally Komi rules for players with same ranks were -7.5 for

Table 5.6: The Time Limits of 'Go' Games in Design

Board Size	**Other Variables**	**Time Limits**
7×7	None	15min per side
7×7	kill-all	20min per side
9×9	None	30min per side
9×9	Blind	30min per side
13×13	kill-all	30min per side
19×19	None	45min per side

9×9 game and 0.5 for 19×19 game. During game play, the score was calculated by areas surrounded. Suicide was not allowed. Basic Ko and long cycle rule were allowed, but super Ko was not allowed [41].

At the end of each game, the result was calculated according to Chinese area scoring rules. That was, the territories were counted by the surrounded areas (the numbers of empty intersections being surrounded), and the number of stones being captured. The suicide move is a move that blocks one or several stones of the player him or herself without any liberty. This kind of move was not allowed. Ko is a condition when a stone is played to capture the stone that is used to capture another stone in the last move. The rules that prohibited Super Ko consider the whole game board, in which a repetition was not allowed, so that players could never repeat the same moves during the same game. The game adopted Long Cycle Rule which calculated the results and colour the game board as soon as the last move was made.

The other rules in Chinese rules included: 1) For 19×19 'Go', each side (both computer program and human player) must finish all their moves in 45 minutes. If one side had not completed 125 moves in 45 minutes, this side lost automatically. 2) For 9×9 'Go', the time limits for each side was 30 minutes.

During play, the player using the black stones started the game, no matter the player was human player or computer program. The human and the computer program moved alternately during the game. The player and the computer program could choose to put a stone on an empty intersection of the grids, one at a time, or choose to pass without putting any stone. Both sides could choose to resign at any time during the game, and the opponent wins the game. If two blocks of stones are adjacent and have the same colour then it is called connected. The empty intersections adjacent to the blocks are called liberties. A stone was captured when it had no liberty. The stone was removed from the board and the intersection under the removed stone was again coloured empty.

For 'Blind Go', the human player played the game by looking at a blank game board to facilitate his/her planning, without putting stones on this game board. The positions of the moves of the computer 'Go' was announced to the human player by an assistant. The assistant was responsible for making a move exactly as the human player had decided and spoke out to him or her. The human player must try to remember the position of both Black and White stones, so 'Blind Go' is much harder than an ordinary 'Go' game.

The game of 'Kill-All Go' was played as the same as the ordinary 'Go' game. As the rules for deciding the winner were all the same: only the rules of komi and handicap were modified. For example, in 19×19 Go, the black player can have a handicap of 17 stones, but the black player can only win the game by captured all the stones of the white player. In this condition, the Komi was 360.

5.4 Experimental Procedure

The 'Go' game experiment was conducted strictly following the experimental design proposed in Section 5.3, combined with the Human versus Computer Go Competition @ IEEE WCCI 2012 was held in June 2012, Brisbane, Australia, to test the strength of different computer 'Go' programs and to measure psycho-physiological responses of human players during the game play. Six 'Go' players (3 professional players and 3 amateur players) participated in the competition. Their rankings are 9P, 6P, 5P and three 6Ds. The experiment was conducted under the approval of Human Research Ethics Advisory Panel at the University of New South Wales with the reference number A-12-18.

Before the experiment started on 12 June, there was an trial experiment conducted on 11 June to inform the participants intuitively on how the experiment would be conducted and how the psycho-physiological data would be collected. The players were informed of the objectives and procedures of the experiment and asked for consent to take part in. All the participants who agreed to join were required to fill in a consent form and an initial questionnaire before the competition.

During the competition, all the 'Go' games were played on a laptop using a pre-designed game interface. On the game board, each intersection of the grid was coloured black if a black stone was put on top of it, in contract, it was coloured white, or empty if no stone was there. Initially, before the start of the game, the board was empty without any stones on it unless the game was handicapped.

If the game session played in competition was included in the experimental design, and the player was agreed to join in the experiment, the player was wired up with psycho-physiological sensors following Plan A or B in Table 5.5 of the player's choice, before each game session according to technical standards. After checking the quality of the signals by reviewing half a minute recordings, the psycho-physiological data collection was started. At first, the players were required to close their eyes to relax for one minute, and then open their eyes to relax for another minute. These two minutes psycho-physiological data were used as baseline information. Then, the 'Go' game session started at any time once the player was ready. The data collection was not interrupted and the sensors were not removed during play, unless the participants requested to remove one or more sensors. After the game ended, the recording was stopped and the sensors were removed from the players.

The players were asked to fill in an inter-game questionnaire after each game session on their perceived complexity of the played 'Go' game and the self-rated performance. The results and the game settings were recorded as game files.

After the two days of experiments, all the participants were asked to fill in a final questionnaire to review the entire experiment, including the user perceived task complexity of all kinds of 'Go' games, their mental states during playing, their overall rated performance and their understandings of the most important attributes as a 'Go' player. All the data collected in the experiment were backed up and kept confidential.

5.5 Data Collection

Six Go players (five males and one female) voluntarily participated in the experiment to play 16 game sessions, according to the design 5.3. The number of participants involved was determined by the availability of top professional Go players. Currently there are only few top professional Go players around the world, and Go game competitions in this experimental design take long time (from 15 minutes to 1.5 hours) to complete. The ages of participants ranged from 15 to 60. There are two amateur players in the age group 51 to 60, and one player each in his/her 10th, 20th, 30th and 40th. All the participants were from Taiwan, with Mandarin Chinese as the native language and English as the second language. All were reported in healthy physical and mental state during experiment.

The recorded psycho-physiological data is a continuous data stream with each physiological measure or each EEG position as a channel. The valid data records collected from each participant are summarised in Table 5.7.

5.6 Feature Extraction

In this section, under the 'Go' game context, subjective and objective indicators of the players' game experience are extracted from collected data during game play. Similar to the 'Snake' game experiment, the indicators are discussed from three aspects: the self-reports, game inputs and outputs, as well as the human psycho-physiological metrics, as illustrated in the following sub-sections.

Table 5.7: The Collected 'Go' Game Data

Board Size	**Skill**	**Other Variables**	**Game File**	**Question-naires**	**Physiological Signals**
7×7	9P	Komi9.5, human play White	√	√	Plan A
7×7	9P	Komi8.5, human play White	√	√	Plan A
7×7	9P	Komi8.5, human play Black	√	√	Plan A
7×7	9P	Komi9.5, human play Black	√	√	Plan A
7×7	6P	Komi9.5, human play White	√	√	Plan B
7×7	6D1	Komi8.5, human play White	√	√	Plan B
7×7	6D1	Komi8.5, human play Black	√	√	Plan B
7×7	6D1	Komi9.5, human play Black	√	√	Plan B
19×19	5P	Human play White vs. Many faces of Go	√	√	Plan A
19×19	5P	Human play White vs. Pachi	√	√	Plan A
9×9	5P	Blind	√	√	Plan A
9×9	5P	Non-blind	√	√	Plan A
7×7	6D2	kill-all, human play White	√	√	Plan A
7×7	6D2	kill-all, human play Black	√	√	Plan A
13×13	6D2	kill-all, human play White	√	√	Plan A
13×13	6D2	kill-all, human play Black	√	√	Plan A

5.6.1 'Go' Game Self-reports as Subjective Indicators

The subjective indicators of the 'Go' game experience are derived from initial, inter-game and final questionnaires filled in by all six players. These indicators are summarised in the following Table 5.8.

Table 5.8: The 'Go' Game Self-reports as Subjective Indicators

Indicators	**Description in 'Go' Game Context**	**Features**
'Go' Skills	The previous 'Go' game experience and 'Go' rankings	'Go' ranking; number of years of playing; number of competitions participated each year
Self-efficacy	The self-recognition of the player's competence in achieving his/her goals	The confidence in winning the competition
Affective States	The emotional feelings as experience before, after and during game playing	Emotional states before sessions, after sessions and after each game
Opponent Evaluation	The evaluation of the opponent's skill level in 'Go' game	The difficulty of game sessions
Self-performance Evaluation	The evaluation of the player's own performance in 'Go' game	The self-rated performance in all game sessions and in each game session
Game Variables Evaluation	The evaluation of other game variables besides the difference of programs as opponents	The difficulty of each game setting (if played that game settings during experiment); the most difficult setting

According to the answers in the initial questionnaires, the 'Go' game players, especially the professionals, do not consider 'complexity' and 'difficulty' of the 'Go' game sessions as equivalent notions. All three professional players describe 'complexity' as 'hard to find patterns in game' or 'hard to simplify the situations in a close game'. The 'difficulty' of a game session is described as 'in a disadvantage position of a game', or 'just mental states like timidity' (answered by the 9P professional player, which shows the self-confidence of the player in his/her skills). Because of this, the notion of 'difficulty' as a more accurate representation of game complexity is used in the inter-game questionnaires and final questionnaires to collect evaluations of opponents' skills and game settings.

Compared to the 'Snake' experiment, not all indicators derived from 'Go' game self-reports are 'subjective'. For example, the 'Go' rankings of all the players are recognized by official 'Go' communities, and the former 'Go' game experience is quantifiable by the number of years playing this game and the number of 'Go' competitions participated each year.

5.6.2 Game and Game Performance as Objective Indicators

The objective indicators derived from the perspective of games could again be categorized into two classes: the game difficulty and game performance. Specifically, the relationship between these two indicators and corresponding features is summarised in the following Table 5.9.

Table 5.9: The Game Difficulty and Performance Indicators

Indicators	**Description in 'Go' Game Context**	**Features**
Game Difficulty	The features influence game complexity in a single game session	Board size; time limit; Handicap; Komi; Black or White; computer 'Go' program
Game Performance	The game results	Win or loss; resign or not; number of points at the end

For the game performance, if one of the player resigns in the middle of the game, the opponent must show a strong advantage over the resigned player so that the player finds it impossible to win no matter how hard he/she tries. So, if sorting the game performance from high to low based on the objective game results, the sequence should be: Win+Resign (W+R), Win+Positive Points (W+No.), Loss+Negative Points (L+No.), Loss+Resign (L+R).

The corresponding game variables influencing game difficulties are analysed as shown in following Figure 5.5. The advantage of one player represents the difficulty of the opponent.

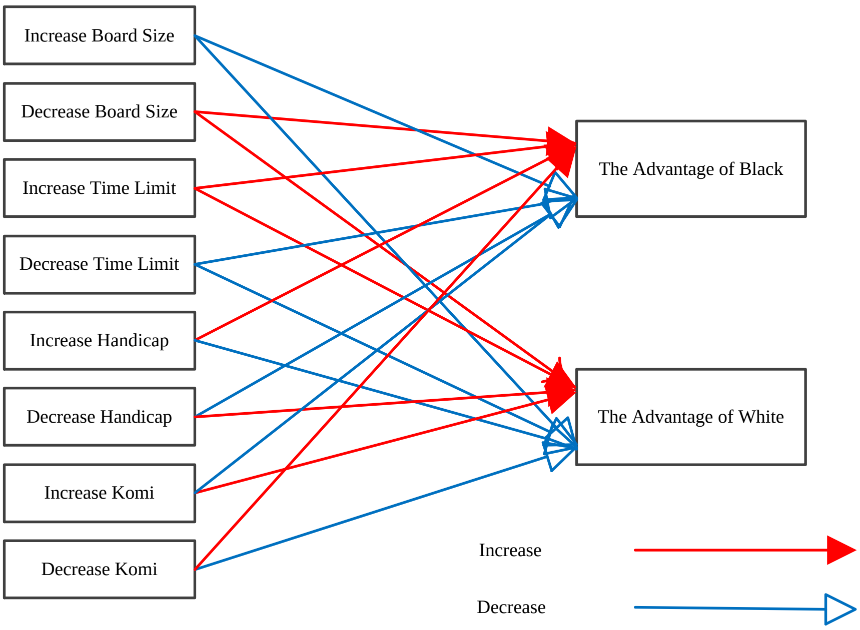


Figure 5.5: The Relationship between Game Complexity Features and Corresponding Advantage of Each Side

5.6.3 Psycho-physiological Metrics as Objective Indicators

All collected psycho-physiological signals are first pre-processed to remove artifacts. The outliers of galvanic skin response signal and ST signal could be simply removed by visual inspection. However, due to the variation of amplitude, the noise in BVP and Resp signal could lead to spurious identification of peak wave resulting in wrong calculations of HRV and inter-beat intervals, which can not be simply excluded from the raw signal to avoid artifacts. The data cleaning methods range from simple smoothing and median filtering to more sophisticated artifact detection methods [36, 62]. The outliers in inter-beat intervals extracted from BVP and Resp signal were cleaned by: 1) locate outliers that are 20 percent deviated from its predecessor, 2) spline interpolation to replace the outliers by using the normal IBI identified before and after the outliers.

The EEG signals were subject to filters before processing. They were first denoised by visual inspection, and then the frequency bands of the signal below 1Hz and higher than 40Hz are filtering out by bandpass filter to exclude most of the eye-blinking, movements, AC electricity noise at 50Hz, and high frequency artifacts.

Features are extracted from signals after preprocessing. Statistical time and frequency domain features are extracted from physiological signals, including time domain features like mean, variance, standard deviation of NN intervals derived from HRV, and frequency domain features, like spectrum.

The EEG data after preprocessing are also analysed according to both time and frequency domain. It is also filtered into five frequency bands for analysis.

All the signal processing are performed based on the methods presented in Chapter 2.

5.7 Discussion

In this section, the extracted subjective and objective features in the former section is discussed under the 'Go' game context towards the players' game play interaction and game experience, according to proposed research question and hypothesis. In particular, the discussion is divided into three subsections. First, the comparison of game experience between professional players and amateur players is discussed, mainly using the subjective self-reports and objective game environments and game performance as indicators. Then, perception and memory (both working memory and long-term memory) as perceptive and cognitive processes in game experience model are discussed under highly strategic 'Go' game playing in the second subsection, by using EEG features and game performance as objective indicators. Finally, the affective process in the 'Go' game experience is investigated by psycho-physiological indicators. The results show that game experience under a strategic 'Go' game context could still be considered as human information processing system which consists of different mental processes. These mental processes could be investigated by using human and game information, especially psycho-physiological data collected during game play. However, the discussion of human game experience under different game contexts (like casual action game 'Snake' and strategic game 'Go') needs to be designed individually. Game experience of each particular person needs to be investigated individually, as former experience and skill levels contribute greatly to the differences of game performance and game experience including perception and cognitive process.

5.7.1 'Go' Game Experience of Professionals and Amateurs

In the first part, the 'Go' game performance and corresponding experience are investigated among professionals and amateur groups by using game performance data and self-reports on the entire human vs. computer 'Go' competition.

The Human versus Computer 'Go' Competition @ WCCI 2012 was successfully completed at the end of 13 June 2012. Besides the 'Go' game experiment designed in this chapter, which mainly focused on human players' game experience, there were 69 'Go' game sessions with different game settings that had been played by six 'Go' game players against computer 'Go' programs including MoGoTW, Many Faces of Go, Zen, Erica, Fuego, Pachi and Coldmilk. In summary, human players won 41 of the 69 game sessions. Thirty-two game sessions were played by professional players against computer 'Go', and 24 games were won by human players. Meanwhile, 37 games were played by amateur players, and 17 games were won. In large board game playing (19×19), all the professionals have given higher advantages to the computer programs as four, five or six stones of handicaps, while the amateurs gave none or two stones handicaps. Thus, the professionals generally played harder games due to the variable settings, but still had much higher winning rates compared to amateurs. The game results are summarised in Table 5.10.

Table 5.10: The Results of Human versus Computer 'Go' Competition

Board Size	**Number of Games Played**	**Professionals (number of winning games/overall number played)**	**Amateurs(number of winning games/overall number played)**
7×7	20	5/12	2/8
7×7 Kill-all	4	2/2	0/2
9×9	19	2/2	7/17
9×9 Blind	2	2/2	0/0
13×13	7	4/4	3/3
13×13 Kill-all	4	2/2	2/2
19×19	13	7/8	2/5

As shown in Table 5.10: 1) in 7×7 training board 'Go' playing, computer 'Go' programs won more of the games, even against the top professional players, especially when the computer side had conditions slightly in favour of humans in changing game variables. The results show the success of Monte-Carlo tree search with the use of 'Go' pattern recognition in building 'Go' AI [184]. 2) As board sizes became larger, the human players were stronger than the computer 'Go' programs built upon the most current AI technologies. This is shown as the increasing number of wins in both professional and amateur players group from 9×9 to 13×13 eventually to 19×19 game playing. Especially for the professional group, when the board size grew to 9×9 and larger, there was only one loss of the human players' side, which happened at 19×19 game playing when four handicap stones have given to the computer programs. 3) When games were played under special rules (e.g., kill-all and blind games), even though more complexities were imposed upon the human players which was uncommon in 'Go' game playing and learning (Kill-all games), or required great efforts to memorise the 'Go' steps (blind games), the human players still performed better than the 'Go' programs, especially in the professional group.

The opponent evaluation indicators derived from self-reports also support these conclusions. When evaluating their opponents, the human players have explained their advantages over the game programs as 'better skills', 'more experience', 'with overall picture in mind' and 'less mistakes made'. This shows the weakness of current computer 'Go' AI playing on bigger game board in forming strategies and making decisions. However, on a 7×7 small game board, the human players either found it 'very easy' as there were little variations in forming up strategies, or 'very hard' as the limited choices of the human players made it difficult for wining if the computer 'Go' programs have advantages over humans in Komi rules. This shows that in situations which require more computational than strategic skills, the computer 'Go' programs under current AI technologies out-perform the professional human players.

Comparing the self-reports from professional group (with professional rankings, more than ten years of playing experience and several local/international 'Go' competitions participated each year) and the amateur group (who have amateur rankings, more than ten years of playing experience, but seldom participated in 'Go' competitions), the results show great difference in game difficulty, performance, cognitive and affective experience during game play under different game variables.

The results are summarised as follows: 1) the professional group reported their self-confidence in winning the game as average or higher than average, and the amateur group reported average or below average, before the competition started; 2) two out of three professional players considered one of the main factors of winning a 'Go' competition as 'A peaceful state of mind', while none of the amateur players mentioned attitudes in answering the same question and all of them have listed 'Go game skill'; 3) all professional players considered 'complexity' and 'difficulty' of a

'Go' game as different notions, but all amateurs considered them as equivalent; 4) the professional group reported their self-performance during the competition as average or higher than average, and the amateur group reported average or below average, after the competition ended; 5) when evaluating the difficulties of all the game types under different game variables (7×7, 9×9, 13×13, 19×19, blind game and kill-all game) from 'very easy', 'easy', 'hard' and 'very hard', the amateur group generally chose 'hard' or 'very hard' for 13×13, 19×19 and blind game, while most of players in professional group chose 13×13 and 19×19 games as 'easy' and the blind game as 'hard'; 6) when evaluating the human players' advantages against computer 'Go' programs as opponents, all the professionals mentioned 'higher skill level' or 'longer experience'. The amateurs mainly considered their advantages in 'familiarity with larger game board playing' or 'overall thinking'; 7) both the professional and amateur group did not report strong emotional fluctuations during game playing, but one from each group have reported positive valence emotions (happiness, excitement and relaxation) after winning a game.

5.7.2 Perception and Memory in 'Go' Game Experience

As the most significant disparity between the 'Go' game concept and other games including the 'Snake' is the degree of game complexity, the second topic to discuss in this section is how a high degree of 'Go' game complexity influences game experience among different skill groups. Specially, the perception, working memory in cognition, and the long-term memory, which influences perception and cognition in the proposed game experience model, are focused on in this section.

The relative small number of cognitive studies in the game of 'Go' is related to the cognitive studies of the chess game as a research domain. The most cited works are De Groot's analysis on chess skills building upon perception, abstraction and memory [81], as well as Chase and Simon's work on chunking of chess information [59]. As the pioneer study of De Groot on chess players has pointed out, the master players of chess process chess information differently (and better) compared to novice players based on the experiments of solving given chess tasks. Thus, abstraction and inference of a given chess problem is replaced by perception in master chess players' information coding and processing system [80]. Building upon De Groot's work, Chase and Simon hypothesized chess information were encoded in chunks and tested this hypothesis using experiments conducted by chess players [58, 59]. A perception task where players reproduced chess positions in plain view and a short-term recall task where players reproduced chess positions after viewing it for 5 seconds were requested for chess players of expert and novice. The results found that chess skills were reflected by the size of chunks and the speed of perceiving chunks in chess playing.

Cognitive studies of 'Go' start with Eisenstadt and Kareev's work from 1975 discussing the internal representations of 'Go' game patterns [93]. Later on, Judith Reitman investigated the perception of information chunks in 'Go' games based on the replication of Chase and Simon's chess experiments [59] on 'Go' players [237]. Verbal protocols and eye tracking data were adopted in Saito and Yoshikawa's study in modelling 'Go' players thinking patterns [315].

Chess and 'Go' are the two best strategic board games in human history. However, compared with chess, the game of 'Go' has deeper strategic components and simpler rules without difference among pieces. From a cognitive science perspective, though information trunks and perception of patterns have been researched in the studies of chess, chess is more analytical which involves lower levels of pattern recognition skills. The 'Go' game, in contrast, focusses on information integration and pattern recognition skills in the entire process of learning and practising, though most of the teachers and players only have intuitive feelings of cognitive process in 'Go' playing. According to the nature of these two games, the game of 'Go', which has surprisingly few studies in the cognitive field, is a promising research domain to study the functions of perception and memory during game play.

This study is based on real 'Go' game play scenarios in a formal competition environment, compared with former works on Go-moku (much simplified version of 'Go') [93], recall and reproduction of 'Go' steps[237], and solving 'Go' problems[61, 227, 315]. According to former cognitive research of 'Go' game play, the hypothesis in this section is that there are differences of game experience between professional and amateur players especially in its form of perception and memory representations.

First, the comparison between game performance of professional group and amateur group within the design of this study are shown in Table 5.11. The number in the 'Game' section represents the number of Komi or Handicap in this game. The letter after the number represents the colour of stones the human player held in this game. So that, 7×7(K9.5W) means the human player played White on a 7×7 small training 'Go' board with the 9.5 Komi, 19×19(H6W) means the human player played White on a 19×19 regular board with six handicaps to the computer played Black.

Table 5.11: The 'Go' Game Durations and Results

Game	Skill	Time	Result	Game	Skill	Time	Result
7×7(K9.5W)	9P	15m	Win+Res	7×7(K9.5W)	6P	38m	Loss+Res
7×7(K8.5W)	9P	15m	Loss+Res	7×7(K8.5W)	6D1	5m	Loss-0.5
7×7(K8.5B)	9P	12m	Win+Res	7×7(K8.5B)	6D1	12m	Win+Res
7×7(K9.5W)	9P	11m	Loss-0.5	7×7(K9.5W)	6D1	12m	Loss-0.5
19×19(H6W)	5P	78m	Win+Res	19×19(H5W)	5P	70m	Win+28.5
9×9(K7W, Blind)	5P	40m	Win+Res	9×9(K7W, Non-blind)	5P	32m	Win+Res
7×7(H2K48W, Kill- all)	6D2	31m	Loss+Res	7×7(H2K48B, Kill-all)	6D2	12m	Loss+Res
13×13(H10K168W, Kill- all)	6D2	18m	Win+Res	13×13(H10K168B, Kill- all)	6D2	51m	Win+Res

The performance results show that in general, professional groups perform better than the amateur groups in a 'Go' competition environment. On a 7×7 small board playing, the performance between top professional players and amateur players has not shown great difference in both results and play durations. However, as board size becomes larger, the duration of play becomes longer, and the performance results of human players are better. The games with special variables (blind or kill-all) took longer for the player to play. In combined with the self-reports, these games are also evaluated as more difficult than others.

Psycho-physiological indicators, especially EEG features which reflected the central neural activities, were then analysed in the context of 'Go' game playing. The

EEG power spectrum density and power map of the professional 9P player during the four 7×7 small board playing are shown in Figure 5.6. The Window size for the FFT to transform the EEG signal from time to frequency domain is 256, with the overlap 128. The EEG power spectrum density and power map for one minute eye close and eye open baselines collected before game play are shown in Figure 5.7.

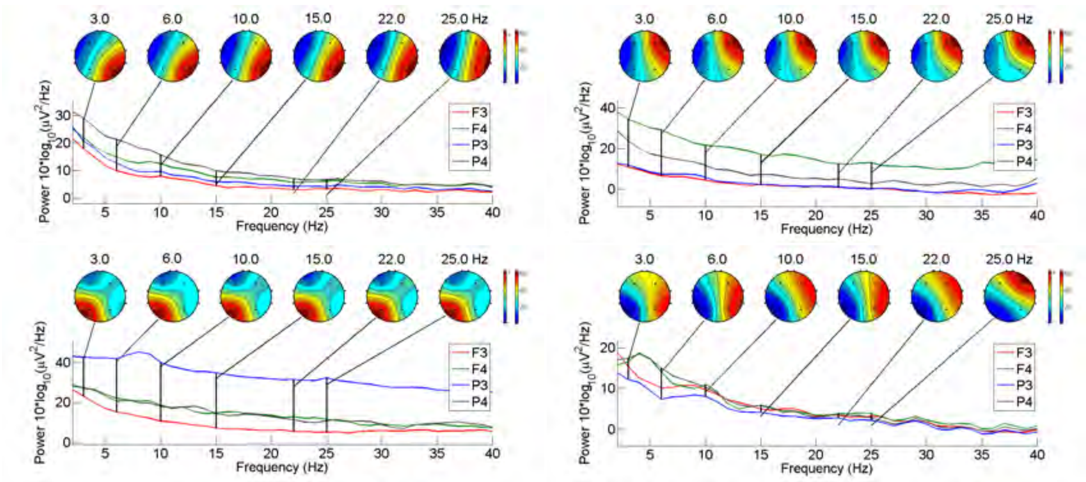


Figure 5.6: The EEG Power Spectrum Density and Power Map Calculated for Four 7×7 'Go' Game

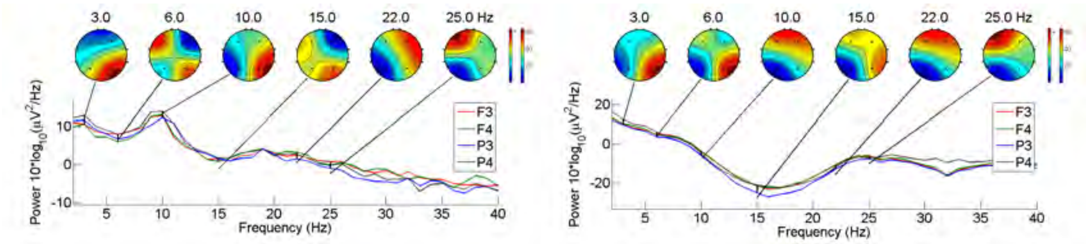


Figure 5.7: The EEG Power Spectrum Density and Power Map Calculated for Eye Close and Eye Open Baseline

As shown in Figure 5.6, except for the third game which has a strong P3 power, the dominant EEG power that reflects the electrical activities of neurons always lies in the right hemisphere, which may suggest right hemisphere dominance during 'Go' playing by the professional 9P player. The classic brain function location theory suggests the left hemisphere has a higher advantage in processing verbal-analytic abstract tasks than the right hemisphere, while the right hemisphere's functionality mainly focuses on spatial-synthetic imaginary thinking. 'Go' playing is a highly strategic task, which involves the integration and cooperation of both abstract and imaginary thinking, but compared with chess, which mainly relies on analytical functions, the key factor of 'Go' lies in spatial positioning. The results also suggest that professional players rely on recognition of spatial pattern forms to build up their playing strategies, which may support the former hypothesis of internal representation of 'Go' information as spatial patterns [93] and the recognition of information trunks of master players in both chess and 'Go' playing [59, 237].

Regarding the power spectrum density during games with the eye close and eye open baselines shown in Figure 5.7, there is a rapid absolute EEG power increase in alpha and beta bands during 'Go' game playing compared to resting states, since alpha and beta bands are the main dominant EEG bands when an adult is awake and exerting mental efforts, as reviewed in Chapter 2. The comparison between eye close and eye open EEG power maps shows the classic alpha attenuation from eye-close to eye-open stage discovered by Hans Berger [34].

The distribution of the power spectrum density and frequency map in Figure 5.6 are calculated at the time range of each game. The power map shows the EEG power distribution among four EEG positions (F3 F4 P3 P4) at interested important frequency bands from 3Hz to 25Hz. As shown in the figure, especially in lower frequency bands, the EEG power collected from the parietal lobe (P3 P4) during Game 1 to 4 are generally higher than the pre-frontal cortex (F3 F4). The main function of the parietal lobe is to integrate sensory information from various modalities, and P3 P4 positions are vertically on top of the lateral intraparietal (LIP), which have its functions on perception of visual information, recognition and attention of spatial locations, as well as understanding the spatial relationships. The high electrical responses from LIP region during 'Go' competitions, especially from right hemisphere, supports the former hypotheses that the professional 'Go' players focuses on the recognition and perception of spatial patterns during game play. This might be the neuron basis of the internal thinking representations proposed in former 'Go' studies.

The high electrical activities from LIP region, which are interpreted as the perception and integration process of visual spatial patterns in 'Go' game playing, especially for top professional players, may results from: 1) top professional 'Go' players may be good at remembering more chunks of 'Go' information as spatial patterns, similar to chess masters [59]; 2) the retrieval of former long-term memory on 'Go' knowledge and meaning 'Go' patterns helps the top professional player to recognise the current game state as an integration of spatial patterns, instead of processing it in an analytical way. Thus, long-term memory of professional players in 'Go' patterns may results in less mental efforts in solving current 'Go' problems, compared to amateur players.

Moreover, the Figure 5.6 shows that the second highest EEG power at different frequency bands (from 3Hz to 25 Hz) are collected from the right pre-frontal cortex, especially when playing harder games (game 2 and game 4). The pre-frontal cortex is the neural basis of central executive control in working memory models. It is one of the cortical association areas in the brain which has neural connections with all parts of cortex. The function of the pre-frontal cortex is to summarise all information for activity planning, to coordinate cerebral motor cortex, and to control and accomplish complex tasks. During tasks, the more information needed to be maintained in the working memory, the stronger are the activities in pre-frontal cortex. Besides the functionality of spatial thinking of the right hemisphere, the strong activation of the right pre-frontal cortex during a professional 'Go' player's playing harder 7×7 games may also shows: 1) the high requirements of maintaining large amount of information in working memory during harder game playing, since the retrieval of former 'Go' knowledge and patterns would not be enough in solving this hard problem; 2) the integration of information from different resources, including past knowledge and current analysis, which is in alliance with former research that the right pre-frontal cortex is more activated when maintaining integrated information than single information; 3) the involvement of episodic memory retrieval during tasks (e.g., spatial 'Go' patterns in memory). Cognitive scientists recognise that the left pre-frontal cortex is more involved in episodic memory encoding and the right pre-frontal cortex in retrieval.

Compared with the EEG features derived from top professional players, the EEG power spectrum are also generated for 6D2 amateur player playing four kill-all games 5.8, the 5P professional player playing Blind and Non-blind games 5.9 and 5P player playing two 19×19 large board games 5.10. In Figure 5.8, the top two diagrams show the EEG features during two 7×7 kill-all game playing, and the bottom two show the features during two 13×13 kill-all game playing correspondingly, as specifically explained in Table 5.11. In Figure 5.9, the left one illustrates the EEG power spectrum during blind game, and the right one demonstrates the spectrum during non-blind game with the same settings as the blind one. In Figure 5.10, the left one shows the features when playing against Many Faces of Go with six stones of handicaps, while the right one is against Pachi with five stones of handicaps.

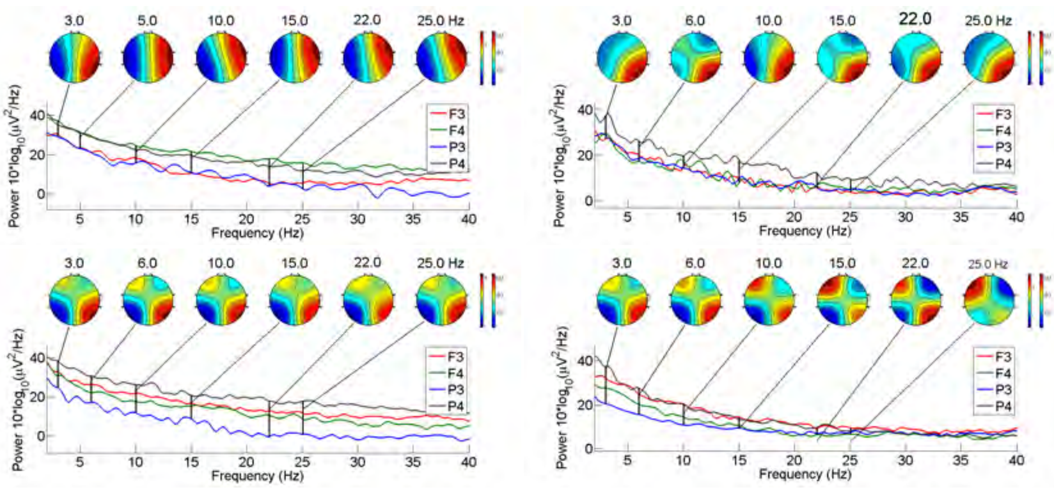


Figure 5.8: The EEG Power Spectrum Density and Power Map Calculated for 6D2 Player Playing Four Kill-all Games

Compared with the EEG indicators derived from power spectrum of 9P professionals 5.6 and 6D2 amateur player 5.8: 1) playing on a small 7×7 game board, the computer program performs equivalent or better than the top human 'Go' players.

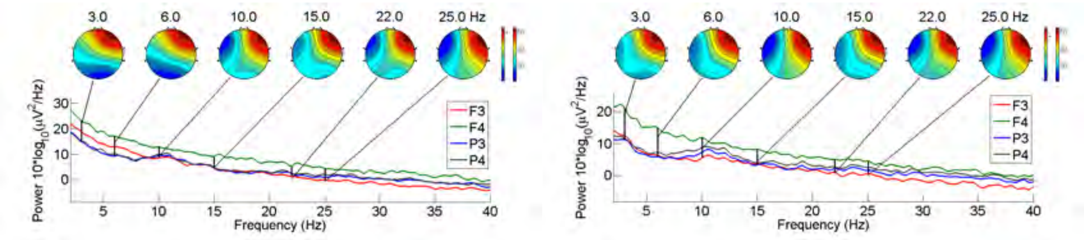


Figure 5.9: The EEG Power Spectrum Density and Power Map Calculated for 5P Player Playing Blind and Non-blind Games

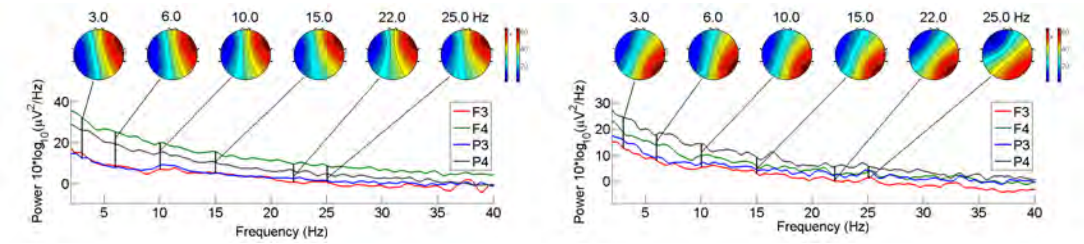


Figure 5.10: The EEG Power Spectrum Density and Power Map Calculated for 5P Player Playing Against Different Opponents on 19 $\times$ 19 Large Game Board

Both the 9P professional and the 6D2 amateur player demonstrate right hemisphere dominance in all frequency bands from delta to high beta; however, 2) on a larger 13×13 game board playing, even though human players are more skilful compared to computer programs, it still requires higher degree of strategic thinking and 'Go' playing skills. This shows as high EEG power on left pre-frontal cortex in all frequency bands, which supports high level analytical logical thinkings, together with the high electrical activities at right LIP region, which reflects the perception and processing of visual patterns in human brain. Unfortunately, in the 'Go' experimental design, there was no psycho-physiological data collected for the 9P professional players playing 'Go' games on the larger game board. Thus, the features derived from 6D2 amateur player are again compared with the 5P professional player playing against different computer 'Go' programs on 19×19 standard competition board, as shown in Figure 5.10, which shows as high right hemisphere dominance during both games. This difference among professional and amateur 'Go' players may indicate that the general 'Go' knowledge and long-term memory of 'Go' patterns of professional 'Go' players changes the play experience of 'Go' as a highly strategic board game, from computational/analytical cognitive process to perception and recognition of 'Go' patterns, especially when the overall complexity of games increases as the game board becomes larger.

When playing the blind game and the controlled non-blind game on a 9×9 board, the topographic EEG power maps of the 5P professional have not shown a great difference, both regarding the time the player had highest EEG power collected from right pre-frontal cortex. However, during the blind games, which are shown on the left, a much higher absolute F4 power on right pre-frontal cortex was collected across all frequency bands compared to that from the controlled game on right. This may indicate high degree of mental efforts exerted in blind games to memorise the steps, to retrieve the memory and to reconstruct the mental pictures of the 'Go' patterns and the current 'Go' game, which requires functions of right pre-frontal cortex (not the right LIP as the player was not receiving meaningful visual information). Note that for 'Blind Go' games, the players are not required to close their eyes during playing. They would be given an empty 'Go' board and a researcher would help to call out the steps taken by the computer programs verbally (just once immediately after the computer 'Go' makes that step). During games, they are expected to memorise each step and imagine 'Go' patterns with the empty board as an assistive tool.

Compared with the existing study about the EEG analysis of expert and novice chess players in solving same chess tasks [298], which showed that the relevant cortical areas of chess experts were located posterior and more in the right hemisphere than those of the novices, both the professional and amateur 'Go' players showed right hemisphere dominance in all frequency bands when playing on small 7×7 'Go' game board. However, when playing on larger 13×13 'Go' game board, the relevant cortical areas of 'Go' professional were still located in the right hemisphere but those of amateur moved to left frontal and right posterior areas.

The results confirms to the hypothesis in this section that professional 'Go' players and amateur 'Go' players have different internal perception and representations towards 'Go' playing and 'Go' patterns, resulting in different game experience, which could be traced by psycho-physiological and performance indicators.

The main results can be summarised as : 1) 'Go' game playing requires a high level of information integration and pattern recognition skills because of its playing strategies; 2) the psycho-physiological measurements, especially EEG collected from central nervous system, could indicate the processes of a human information processing system based on the functional specialisation of the brain; 3) compared to the game of 'Snake', 'Go' game players, both professional and amateur, have the same kind of playing goals due to the complexity of the game, but the game experience is different, especially in perception and cognition processes; 4) the long-term memory of professional players, in its form of professional 'Go' knowledge and recognised meaningful 'Go' patterns, transforms the focal point of the 'Go' game experience from computational/analytical cognitive processing into recognised/retrieval/integration of 'Go' information and 'Go' patterns in both perception and cognitive processes; and 5) the amateur player, in contrast, as the overall complexity of the game increases (the game board becomes larger), demonstrates a higher level of focus on computational/analytical cognitive processes than the professional players.

5.7.3 Affective Process in 'Go' Game Experience

In this third part, the affective process, especially affective arousal in 'Go' game experience is investigated using both subjective measures and objective psycho-physiological indicators, mainly from the perspective of the professional 'Go' player.

As defined in the 2D emotional model, most human emotions can be classified into valence and arousal as two independent variables [244]. As the arousal level of players from weak to strong is considered to have a relationship with task performance by Yerkes-Dodson Law [314], and the valence level during 'Go' game playing is seldom varied due to the strategic nature of the game; the affective arousal is discussed in this section, mainly by analysis of top professional 9P players playing four 7×7 games. The analysis is performed from two aspects: first, the possibility to identify arousal as having two levels, based on the game performance and game setting, is assessed; and then, the possibility to classify arousal into two levels based on the subject's psycho-physiological features is investigated. The analysis is designed to study the relationship among subjective and objective indicators in reflecting affective arousal during 'Go' game play. The success of the proposed design may lead to such future applications as finding the optimal arousal level during 'Go' playing for professional 'Go' game player training.

The affective arousal level has long been considered to have a relationship with task performance. The Yerkes-Dodson Law is one of the most 'stable' psychological laws which has stood the test of time from 1908 till now over a hundred years of psychological fashions [288]. A scientific law is used to distinguish the basic causal relationship in nature that always occurs when given conditions are present [267]. The Yerkes-Dodson Law explains that performance is a non-monotonic function of arousal, as shown in Figure 5.11.

Within this analysis, the game variables, game performance and self-reports of

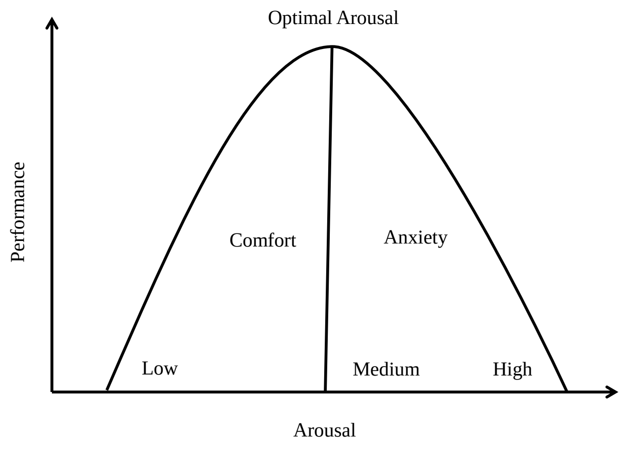


Figure 5.11: The Yerkes-Dodson Law

the 9P player playing four 7×7 games have been listed in Tables 5.12 and 5.13.

Table 5.12: The Game Variables and Performance of 9P Player in Playing Four 7×7 Games

Side	**Easy**	**Hard**
Attack	Game 1 (Komi 9.5) Win The computer resigned	Game 2 (Komi 8.5) Loss The human resigned
Defend	Game 3 (Komi 8.5) Win The computer resigned	Game 4 (Komi 9.5) Loss The human lost 0.5 point

As seen in Table 5.12, the Komi in the game variables is the points of scores added to the White player to compensate for playing second. The higher the komi, the more advantages the White player will get. The lower the komi, the more advantages the Black player will get. The changing of the komi rule among games adjusts the game difficulty level, and makes it either easy or hard for the human player.

As the player holding the Black stone always put the first stone on board,

Table 5.13: The Self-rated Game Difficulty and Performance of 9P Player in Playing Four 7×7 Games

Self-reports	**Game 1**	**Game 2**	**Game 3**	**Game 4**
Self-rated Performance (1low - 5high)	5	3	5	3
Self-rated Difficulty (1low - 5high)	1	5	1	5

the player is playing 'defend' strategies when holding Black, and playing 'attack' strategies when holding White. The four games are counter balanced between different game strategies in two game difficulty levels.

The result of the experiment shows that in 7×7 games, when getting little advantage in their Komi rules, the MoGoTW won all the games, even when playing against a top professional 9P player. Compared with the game results of the 6P professionals and 6D amateur players playing the same 7×7 games, the computer 'Go' program always won when it had little advantage in its komi rules, no matter what the rankings of the human 'Go' players were and whether he or she is a professional 'Go' player. From the results of the experiment, the difficulty of the hard 7×7 games is quite strong, even for the 9P player. It is also shown in the final questionnaire as three players consider the 7×7 games the 'difficult' or 'very difficult' among all game types.

From the human player's perspective, the 9P player always won when the komi rule favoured the human player with a high satisfactory in his or her performance, and always lost when the komi rule favoured the computer player with a median satisfactory performance.

According to the Yerkes-Dodson Law, and the subjective, objective game environment and game performance indicators, it could be inferred that the human player was close to optimal median arousal when playing the Easy * Attack and Easy * Defend games (Game 1& 3), and had a relatively high or low arousal (not optimal) when playing the Hard * Attack and Hard * Defend games (Game 2& 4).

In order to test the above inference derived from subjective indicators and objective game environment and performance, psycho-physiological indicators including skin conductance and EEG features are analysed under these 4 games. The change of SC, ST, heart and Resp rate is controlled by the autonomic nervous system (ANS), which is part of the peripheral nervous system distributed in organs, the cardiovascular system and glands. It regulates the functions of internal organs, maintains the life process of human body, and usually works involuntarily. The ANS can be divided into the sympathetic nervous system, which regulates the responses to stimuli, and the parasympathetic nervous system, which maintains the normal regular activities of human body. SC is an important physiological parameter showing the excitement of the sympathetic nervous system. It is: 1) generally considered to be the most stable physiological indicator of orienting reflex; 2) recognised as linearly correlated with the subject's arousal level of emotional dimensions during tasks, which shows the intensity of emotions; 3) a well-known indicator of stress level. The frequency of EEG signals as reviewed in Chapter 2 and the 'Snake' game experiment, could also indicate the affective arousal of players.

The physiological indicators during playing show a continuous arousal increase during consecutive playing of four 7×7 games as an increase of SC and a slight drop of ST. To normalise the features using the data collected at the first two minutes of each game as a baseline, the normalised SC and ST is shown in Figure 5.12 and Figure 5.13.

The segmented linear regression shows a trend of increase of SC during the first game played by the 9P professional player and a decrease of ST during the first game and the third game, which are easier games and the human player won. Conversely the SC decreases and the temperature increases during the second and the fourth games, which are harder games and the human player lost. It may be assumed that the human player is more mentally and emotionally activated to win during the easier first and third games, and is deactivated to lose and to resign in second and fourth games. According to the SC features, it may be inferred that the player has higher arousal when playing Easy * Attack and Easy * Defend games than playing Hard * Attack and Hard Defend games.

For the last game in which the human player lost by just 0.5 points, the steep increase of the SC at about 600 seconds may suggest an increased amount of mental efforts in the final stage to win that game.

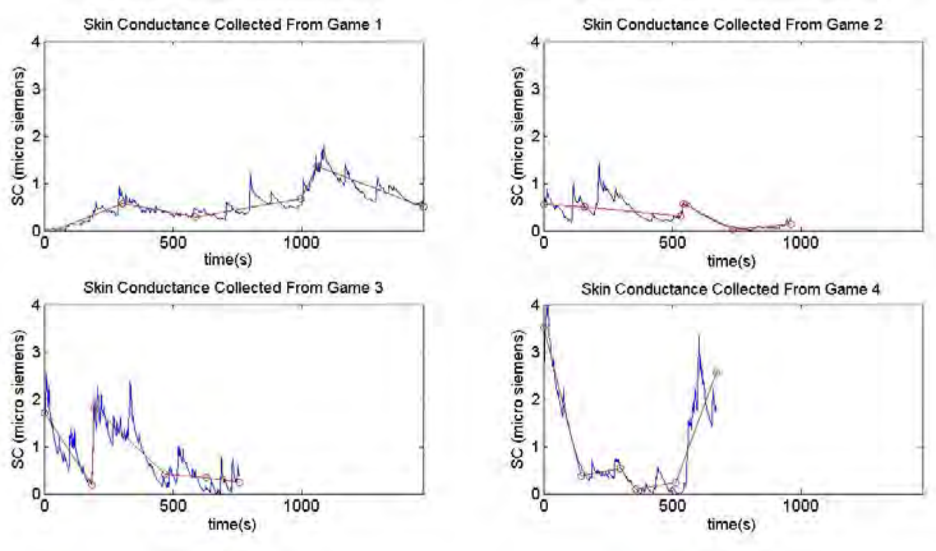


Figure 5.12: The SC of 9P Player

The EEG total power and power spectral density as indicators derived from four EEG channels (F3, F4, P3 and P4) are calculated for four games, as shown in Figure 5.14. The results show stronger EEG power from all four channels during Easy * Attack and Easy * Defend game playing (game 1& 3), and lower EEG power for Hard * Attack and Hard * Defend games. The high EEG power may shows as an indicator of high arousal and excited for games 1 and 3.

Figure 5.15 show the normalised EEG power spectrogram during the four game playing. Normalisation is achieved by Equation 5.1, in which the 'μ' and 'σ' represent the mean and standard deviation of the EEG power of particular channels throughout the time of game session.

$$P_{Norm} = \frac{P - \mu}{\sigma} \tag{5.1}$$

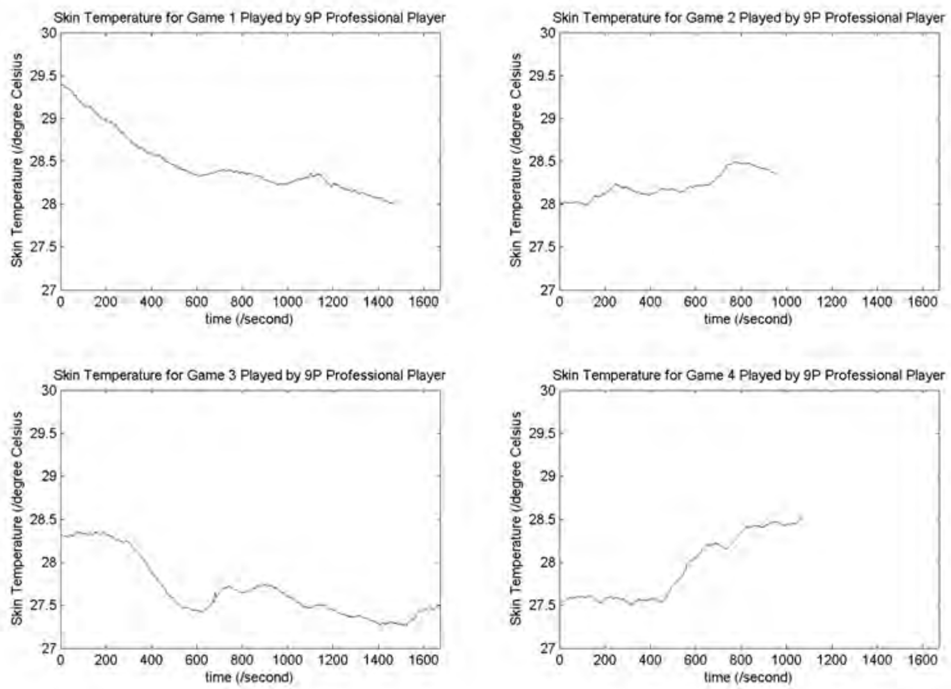


Figure 5.13: The ST of 9P Player

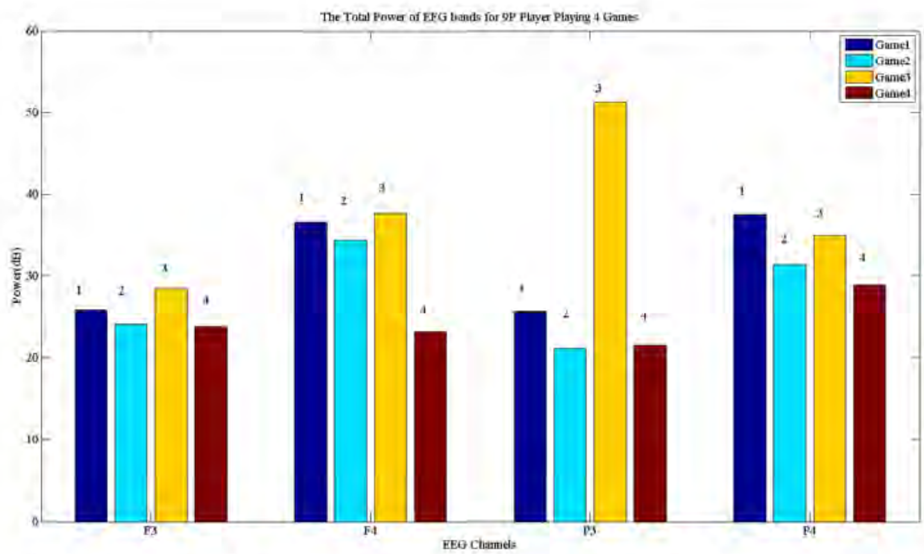


Figure 5.14: The EEG Total Power from all Bands (2Hz – 40Hz) Computed from Four Channels during Four 'Go' Game Playing Experiments

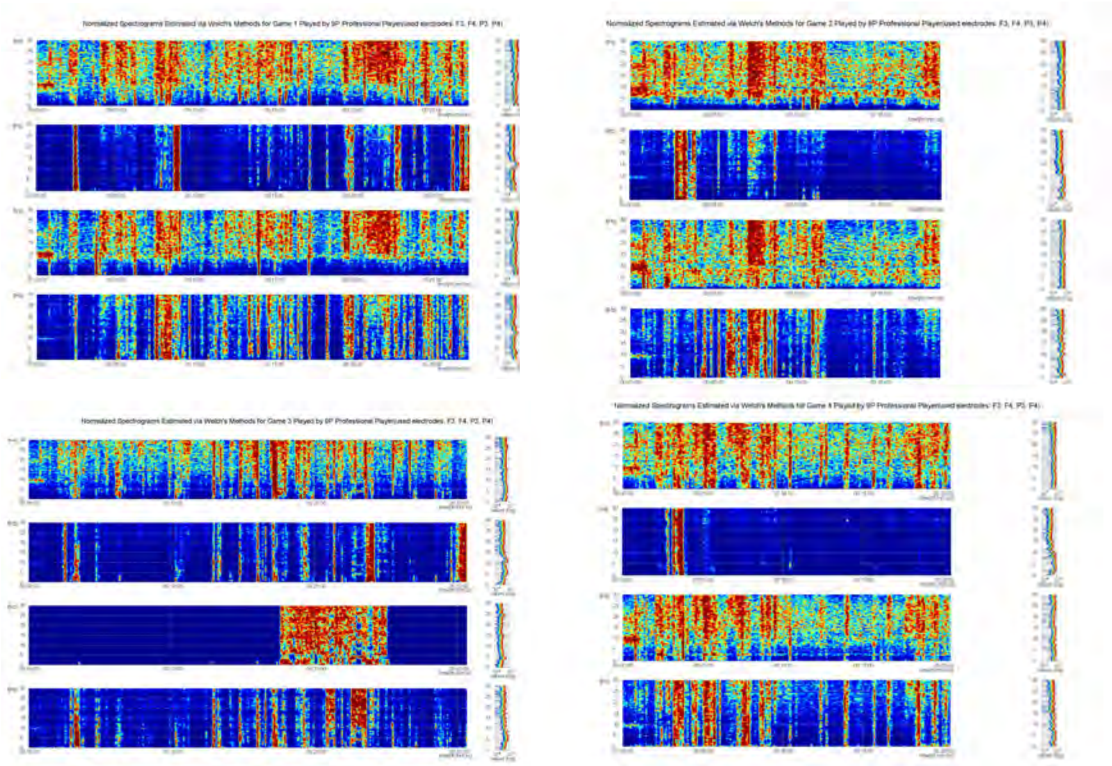


Figure 5.15: The Normalised EEG Power Spectrum of 9P Professional Player Playing 7×7 Games

Figure 5.15 shows that dominant frequencies during most of playing time range from 10 to 30 Hz, which lies at the alpha and beta bands. The activation of EEG power for four EEG channels(e.g., 4 to 7mins, 20 to 25 mins during the first game playing) is correlated with the rise of SC level shown in Figure 5.12. This correlation may indicate extraneous stimulus perceived (an unexpected move from the computer opponent), or the increase amount of mental efforts and affective arousal as game experience during this stages of game play.

In this case, the subject-dependent classification is used to test whether it is possible to classify arousal into two levels based on the subject's psycho-physiological features extracted. The classification is performed to assess if psycho-physiological features could be used to indicate affective arousal of professional 'Go' player during 'Go' game playing, which correlates with task performance. From the game performance analysis, it may be assumed that when playing Easy * Attack and Easy *

Defend games, the player was more likely to maintain an optimal median arousal, and correspondingly a higher or lower arousal when playing Hard * Attack and Hard * Defend. From the statistical physiological and EEG signal analysis in the former paragraphs, it is more likely that the player was in low arousal state when playing the high difficult 'Go' games.

Mean Skin Conductance (SC) levels, mean Skin Temperature (ST) levels, mean Heart Rate (HR) and mean respiration rate (RR) are used to calculate at one second windows during four games to make the classification. The features extracted when playing the first two games were used to train the support vector machine (SVM) to classify the features into two groups: optimal and low arousal. Then, the features extracted when playing the next two games are used to test the SVM models. After that, a cross-validation classification using the whole dataset was performed. The classification accuracy is shown in Table 5.14.

Table 5.14: The Affective Arousal Classification of 9P Player in Playing Four 7×7 Games

	SC	**ST**	**HR**	**RR**
Training Set	68%	67%	62%	65%
Testing Set	60%	34%	54%	53%
Cross Validation	65%	62%	57%	62%

The results show that it is possible to classify 9P professional human player's arousal levels during 'Go' game playing by using physiological features, including SC, ST, HR and RR. The results show that there are differences of physiological features collected from different game plays, which is expected to have two different levels of affective arousal.

The SC level as arousal indicators are also shown for 6D2 amateur players playing kill-all games and 5P professional players playing blind games, as shown in Figures 5.16 and 5.17.

As shown in Figure 5.16, the SC levels of the 6D2 player as indicators of arousal, were constantly increasing during the four kill-all playings, as the players are more

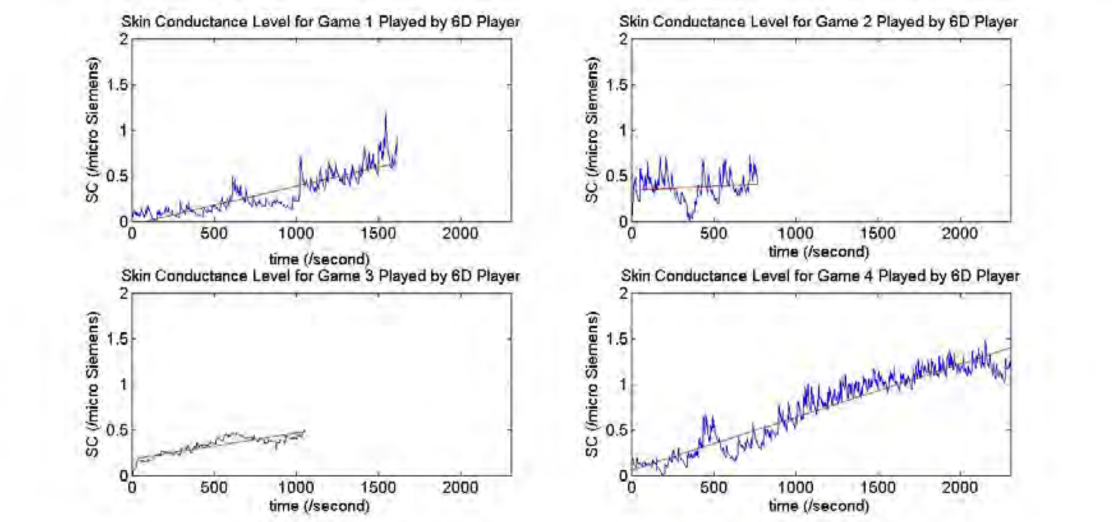


Figure 5.16: The SC Level for 6D2 Player Playing Four Kill-all Games

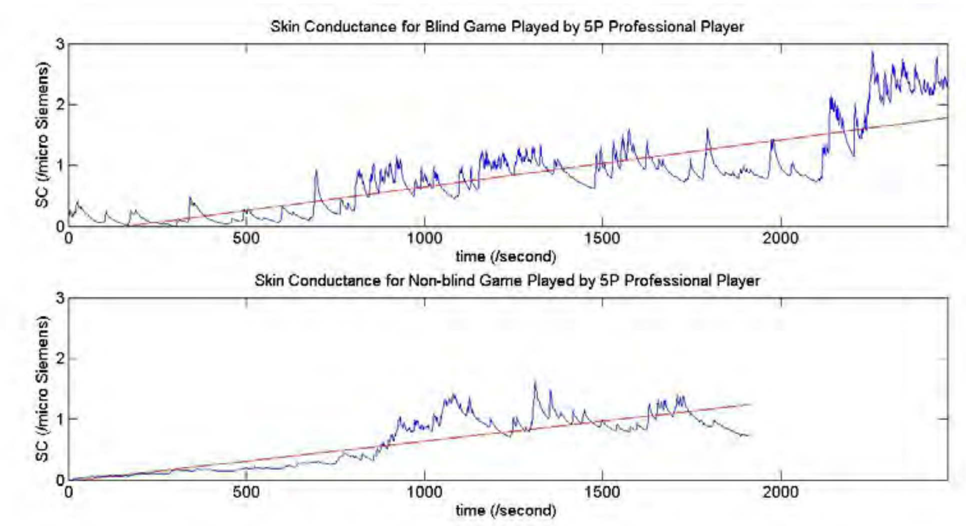


Figure 5.17: The SC Level for 5P Player Playing Blind and Non-blind Games

aroused at the middle and at the end of the game play compared to the beginning. This trend is the same with the 5P player playing blind and non-blind games, but is different from the arousal levels of the 9P players playing four 7×7 games, in which the player was more aroused in easier games in compare with harder games. This shows that the trends of arousal levels during 'Go' game sessions from beginning till the end are not fully dependent upon the overall difficulty of the games and the overall perceived difficulty of the games. The most influential factors on arousal might be: 1) the self-efficacy and playing goals, which characterise the players; and 2) the difficulty of games at certain steps, which needs to be investigated in future works.

An analysis and classification towards arousal level during human versus computer 'Go' playing using psycho-physiological signals collected from the human players, are explained in this section. Game features and human responses features were examined when the player played 'Go' games with two different difficulty levels: easy and hard. The results confirms that affective arousal as game experience in the 'Go' game context could be reflected by multi-indicators derived from human and game information, when the game context and individual difference is considered. The main results are: 1) both SC levels and EEG features are psycho-physiological indicators of affective arousal during 'Go' game playing; 2) the arousal level during 'Go' game playing could be estimated through game environment and game performance, but the changes in affective arousal levels among subjects during game play are not fully dependent upon overall game difficulty and self-perceived difficulty. More factors other than overall game difficulty, including individual differences and the difficulty of games at each step need to be considered; and 3) the arousal level during 'Go' game playing could be classified into two levels based on the subject's psycho-physiological features, which confirms that physiological features indicates affective arousal under 'Go' game contexts.

5.8 Conclusion

In this chapter, the proposed game play and game experience model has been evaluated using a second game concept — the game of 'Go', as a highly strategic board game originating in Asia and popular in every continent of the world. The use of this game and the experiment were chosen to demonstrate how this high level of game complexity influences the game experience of different skill groups under different game variables, by analysis of both subjective and objective indicators.

The main results in this chapter are listed as follows. The difference in skill levels of 'Go' game playing results in different game play and game experience, reflected in self-reports and performance, as professionals have stronger confidence in their skills and have higher winning rates, even when the game variables were set harder than for amateurs. The difference in skill levels of 'Go' game playing results in difference in psycho-physiological metrics collected from players, which may reflect the different internal perception and representations of 'Go' game players due to long-term memory, experience and knowledge. The psycho-physiological features under different game variables may reflect the difference in mental effort exertion and affective arousal during 'Go' game play. Finally, the psycho-physiological features, especially EEG features, may indicate the effects of human information processing systems based on the functional specialisation of the brain.

By answering the proposed research question, the subjective and objective indicators collected from human professional and amateur 'Go' players could encode the 'Go' game playing experience as an information processing system. However, game environments and individual differences, especially prior game knowledge and experience of same kinds of games as skills, influence the individual game experience of 'Go' game players.

Chapter 6

Interactive Evolutionary Computation Controlled Via EEG Signals

AI can have two purposes. One is to use the power of computers to augment human thinking, just as we use motors to augment human or horse power. Robotics and expert systems are major branches of that. The other is to use a computer's artificial intelligence to understand how humans think. In a humanoid way. If you test your programs not merely by what they can accomplish, but how they accomplish it, you're really doing cognitive science; you're using AI to understand the human mind.

Herbert Simon, interviewed June 1994 by Doug Stewart [276]

The two fields of cognitive science and AI overlap with each other. Though cognitive science tends to research human intelligence, and AI deals with machines or software, these two disciplines have never been separate. Taking the metaphor of the human brain as a computer information processing system, as Herbert Simon has pointed out, the development of cognitive science and AI benefits both fields in enhancing understanding of human thoughts and in creating computational artificial thoughts. In modern cognitive science and AI domains, much research has occurred and continues to build computational models of cognition of humans solving problems, then mimicking the model using symbolic processing in computer systems, using Alan Turing's computability theory [291]. The study of AI not only applies the proposed computational cognitive model to technical use, but also helps to elucidate the cognitive processes in the brain.

As explained in the two experiments, the focal point of the last two chapters lies in the game experience analysis of human systems under different game contexts. However, as proposed in Chapter 3, the game play model involves interactions of both human and computer system. In this chapter, my research focus moves to the computer part of this thesis: to study how computer systems could respond to human interactions during game play by utilising findings from the former chapters.

In the previous chapters, the game experience of human players using the simple game 'Snake' and the complex game 'Go' was evaluated using indicators derived from three aspects: the game inputs and outputs, the self-reports and the psycho-physiological data. Among them, the academic game research usually focuses on self-reports to assess their proposed psychological notions under game contexts. The psycho-physiological measures have gained interest and attention in various fields with different motivations under strictly controlled environments, but seldom in game research. This is probably because digital games are difficult environments as they generally involve more than two modalities of sensory inputs and outputs, noises from physical actions and environmental factors, and complex mental processes in different time scales from seconds to hours. The game experience model has not been generally defined. From a psychological or cognitive science perspective, both of the experiments reported here have not discussed the exact psychological processes in small time scales under game environments. However, it has been established that multi-modalities of psycho-physiological signals could be used to derive indicators that are correlated with subjective self-reports and estimations from game inputs and outputs. They can then be used as a mediator between games and human players to reflect game experience.

Compared with subjective self-reports and objective game inputs and outputs, which are usually investigated in academic game research, the psycho-physiological measures are attractive in the design phase as they are objective, real time, continuous, non-intrusive, sensitive and precise [167]. In this chapter, an adaptation mechanism based on psycho-physiological signals generated under designed mental tasks will be proposed for use in interactive evolutionary computation environments as a simplified game environment. Specifically, the mechanism is used in an interactive genetic algorithm for the purpose of genetic parameter control via EEG signals. The system is designed and implemented to evaluate if EEG data collected from human players could be used as a bridge to communicate between games and players as an input channel.

The chapter is structured as follows. The introduction of evolutionary computation, interactive evolutionary computation and their relationships towards games and game research is discussed in Section 6.1. The methodology of the proposed system is explained in Section 6.3. The Experimental Design and procedure is illustrated in Sections 6.4 and 6.5. The results are discussed in Section 6.6, with Section 6.7 concluding this chapter.

6.1 Introduction

Just like the world of physics before 1900 (the birth of quantum mechanics), in the early days of computer science, the algorithm, software and programs were built in a very precise, logical and deterministic way, inspired by computational parts of problem solving modelled in cognitive science for algebra problems or simple games, including Tic-tac-toe and the Tower of Hanoi. However, this deterministic approach faces problems when dealing with more complex (I would argue more interesting) problems when the software programmer does not have the step by step solutions. Games, although designed as an abstraction of real world situations, strategies and interactions, are usually complex problems to challenge players to operate in an optimal game experience. Some games, though computationally complex for humans, are easy for computers to solve using analytical methods. However, in most cases, game problems are complex for humans and even more complex for computers to solve. Thus, computer systems functioning to represent the complex game problem space, and interact with players or perform as opponents (like the Go program in Chapter 5) require advanced AI technique to provide an optimal game experience for players.

In this introductory section, basic concepts and relevant studies in cognitive science, HCI, evolutionary computation, interactive evolutionary computation, genetic algorithm and parameter control are introduced. The reason for studying interactive evolutionary computation (EvC) as a human evaluated method in solving optimisation problems is explained in this thesis. Further, potential research topics and application domains based on this study are addressed at the end of this section.

6.1.1 Game and Evolutionary Computation

Game play is a playful activity to explore a well-defined problem space and to find optimal solutions. For players, due to the embodied characteristics of human cognition, the problem space is wrapped with social and material contexts for symbolic processing, adding meanings to the game play. For computers, the problem space could be simplified in a more abstract manner. Take a complex game play scenario for example: in a multi-player online game, five combat roles — a tank, two damage dealers, a healer and a supporter — form a team to fight a mini-boss in a dungeon raid. This game play activity could be simplified to a problem of finding the optimal solution (kill the boss monster with minimum damage to the players) using the given five operands when the target function (the mini-boss) is given. Though in reality to direct a team in fighting a battle in game is more complex than solving this optimisation problem using AI techniques, here in the realm of this chapter, to find optimal solutions in complex problem space could be viewed as one way of simplified simulations of computers' game play scenarios.

Bio-inspired evolutionary algorithms have been successfully applied to optimisation and learning problems over the last few decades to solve complex problems that are not easily solved by classical analytical methods [28]. The EvC originates from Darwinian evolution (outlined in Darwin's influential book *On the Origin of Species*, 1859 [79]), which was later explained by the heritability and mutability of genetics. The evolutionary process is the explanation of both similarities and variations within species in nature. Parents pass their genes to the offspring. Mutation occurs randomly during this process, which causes the natural variations within species. The variations that 'fit' the environment more will be favoured by the environment, and have more chances to pass these characteristics to their offspring.

The important notions of Darwinian evolution, including reproduction, mutation, selection of the fittest, and recombination, have been adopted in computer science to form a simplified biological model of evolution and natural selection. They have been called evolutionary algorithms since the late 1950s, as a supplementary to traditional analytical methods, based on a deterministic approach, to target solutions of complex problems where: 1) approximate answers are preferred to exact answers due to the computational cost or: 2) step by step determining methods do not progress towards solutions. The underlying idea is similar to the biological process of evolution: given a population of individuals, those who survive the pressure of natural selection according to their fitness have higher reproductive success, thus raising the overall fitness of the population. A quality function is defined as an abstract fitness measure. Based on the quality function, selection is achieved to choose individuals that maximise the quality function. Recombination operates on those chosen individuals to produce offspring and mutation randomly produces new candidates. The process is iterated until an individual with satisfactory fitness is found, which is defined as a solution [91].

6.1.2 Interactive Evolutionary Computation

However, instead of a static problem space, games constantly change through the interactions between the human and computer/opponents systems. The variations of games through interactions are the true essence of this new popular media. A good example is the game concept of 'Nomic', which is a game with changing /evolving rules, determined by a system of democratic voting, inspired by the process of law-making in government, with the characteristic of self-amendment in legal systems. The game concept of 'Nomic' was first proposed by philosopher Peter Suber in his book — *The Paradox of Self-Amendment: A Study of Law, Logic, Omnipotence, and Change* [278]. This concept, through its development throughout all these years, has been adopted in many modern sophisticated card games and commercial games including 'Democracy' (the board game) and 'Bartok' (the card game). The main idea of this game involves human preferences in altering the game problem solving processes during game play.

The game concept of 'Nomic', as well as other games that involve human selection during game play, has a simplified representation similar to the concept of interactive evolutionary computation (IEC) as a sub-field of AI, in which humans are involved in the initialisation, evaluation, selection or mutation stages in evaluating an evolutionary process of optimisation problems in a given problem space, just as artificial selection is combined with natural selection in biology. IEC is usually used when the fitness function of the algorithm is unknown or hard to obtain. This concept has been widely applied in various practical areas including user-contributed content in web searching [185], aesthetic selection in graphs [268, 269], music [199] and industrial design [165], facial image and expression generation [50, 190], and distributed projects like folding@home [182].

Games and serious games are good application domains for IEC. The interactive evolutionary process can be used as adaptive mechanism in game play to form desirable game scenarios for human players. This is specifically explained in Section 6.1.5.

6.1.3 Genetic Algorithm and Parameter Control

Among the various types of evolutionary algorithms, genetic algorithm (GA), introduced by Holland [148] in his pioneering 1975 book *Adaptation in Natural and*

Artificial System [149], which mimics natural selection, is one of the most popular search methods used in practice. GA uses the language of biology and describes the basic encoded individual under manipulation as *chromosomes*. The collection of those individuals is called *population*. The population process to form a new one is called *reproduction*, and the new population is called the next *generation*. The process for reproduction involves *recombination*, *selection* and *mutation*, as described before.

Parameter control of the GA is a critical area in any GA, because the success of this optimisation process depends largely on the design and selection of appropriate search operators and parameters [92], which comes to be the balance between two cornerstones of problem solving by search, exploration and exploitation [90]. Exploration avoids getting stuck in local optima, and exploitation helps to converge quicker. The balance of exploration and exploitation influences the success rate and efficiency in problem solving. This idea has already been addressed in Chapter 5. The Monte-Carlo tree search used for computer 'Go' is not an evolutionary algorithm, but it is a search algorithm that involves maintaining balances between exploration and exploitation in searching problem spaces.

In GA, exploration and exploitation are balanced by two important genetic operators: crossover and mutation. Obtaining a balance of these two genetic operators is an important issue in controlling the degree of exploration and exploitation in problem solving. To ensure the effectiveness of GA for a particular problem, parameter tuning before running the algorithm and parameter adaptation during the process of problem solving are both common methods used for parameter control [92]. With regard to the challenge of this balance, online parameter control has drawn more attention because of its adaptability under various conditions and in non-stationary environments [92]. Human evaluation for the online parameter control of interactive GA is also suggested [285].

6.1.4 Related Research in Human-computer Interaction

Real time EEG has been recognised as a new communication channel between human brains and computer systems by HCI and virtual reality communities. These EEG-based Brain Computer Interfaces (BCIs) have been firstly researched to help disabled persons in motor recovery and substitution; for example, the control of a wheelchair [286]. More recently this approach has been extended to create an immersive experience for healthy users and has been tested in game environments [186], from simple games like navigating a maze [297] and Pacman [176], to more complex games including flight simulators [209].

However, in classical BCI design, before successfully using the system, the subject needs to learn how to regulate their brain signals in a systematic manner by performing imaginary tasks. Some researchers rely on the subjects' own ability to control their mu and central-beta rhythm by will, so as to (for instance) move cursors on screens [313]. Others rely on machine learning algorithms to learn the subject-specific brain pattern before reliable control can be expected in BCIs [131]. This training stage may consist of several sessions. Further, the training time varies among subjects, which can last from several hours to many months [130]. The cost is high and the resulting control scheme is always subject-dependent.

Clearly, cost of training is a significant challenge in moving the current BCI research from lab experiments to real world applications. The problem is tackled by: 1) avoiding complex mental tasks that require particular 'skills' of the subjects to regulate their brain waves, instead focusing on simple mental tasks that would trigger certain brain wave patterns which have been long addressed in cognitive science; 2) using baseline tasks to overcome between-subject variability in performing these tasks to build up a mathematical model.

The experiment described here proves the success of this idea in reducing training time, as compared to traditional approaches to BCIs design. Further, the technique can also be applied in the application of BCIs for other purposes.

6.1.5 Potential Research Topics

A key limitation of IEC design is that the number of evaluations that users can provide is limited by human fatigue. While computer systems could evaluate as many fitness functions as possible, human users generally experience fatigue after evaluating certain generations of results through a user interface. This fatigue effect has constrained the design of IEC in applications. There have been several attempts to address the fatigue issue in IEC design, including speeding up the convergence [285] and reducing human effort by predicting their preferences using AI techniques [161]. An approach that combines eye-tracking data as an input channel to IEC design has also been presented [228].

A new way to model mental states of a human subject as inputs for task controls based on EEG signals is presented in this chapter to reduce user fatigue during evaluations. Online parameter control in GA is selected as an example to demonstrate this work with regard to BCI. The application of BCI in GA parameter control is important for individuals and families of individuals who have physical limitations to use GA based applications. It is also important in developing future interfaces with better communication quality and larger bandwidth between healthy individuals and machines.

Moving from the abstract representation of problem solving into realistic situations, the potential research could also be extended to evolutionary music and graphics, entertainment and games, educational software, serious games and simulations, creative and industrial designs.

6.2 Objective

The objective of this experiment is to test if EEG signals collected from human player in real time could be used to interface human and games. In this case, an adaptive mechanism based on EEG signals collected from carefully designed mental tasks is designed as inputs for parameter control in an optimisation problem, which could be considered a simplified game play problem solving fully under control. The application alone could be further developed in HCI to solve more complex problems or complex games, as explained in Section 6.1.5. In the realm of this thesis, the research question asked for this experiment is:

IEC Experiment Research Question:

Could computer systems actively responded to human EEG responses as a modality of input?

This work is the first attempt to link the EEG-based BCI research and GA parameter control to balance the trade-off of exploration and exploitation in evolutionary computation. Proving the concept opens the door to extend the work to other applications that require real time control.

Real time EEG signals are collected from a human expert as inputs to control parameters in GA, when solving a benchmark problem. The results of how the mental tasks performed by the human expert change the crossover and the mutation rate are shown, to drive the evolutionary process. The aims of this study are to discover: 1) if a framework of using EEG brain signals as inputs to control genetic parameters is feasible; 2) if the technique of using baseline tasks to reduce training time is applicable in proposed framework.

6.3 Methodology

The methodology proposed in designing the experiment is explained in this section. Specifically, the general framework, the interactive GA design, proposed mental tasks, and the control functions using indicators derived from EEG are illustrated in the following subsections.

6.3.1 The Proposed Framework

The framework has a human expert involved in the system. The human expert observes/evaluates the problem and controls the parameters of the GA online during the process of problem solving. The system by itself takes care of the GA, the EEG recording and the mental states identification as parameter control inputs. The framework of our purposed system is illustrated in Figure 6.1.

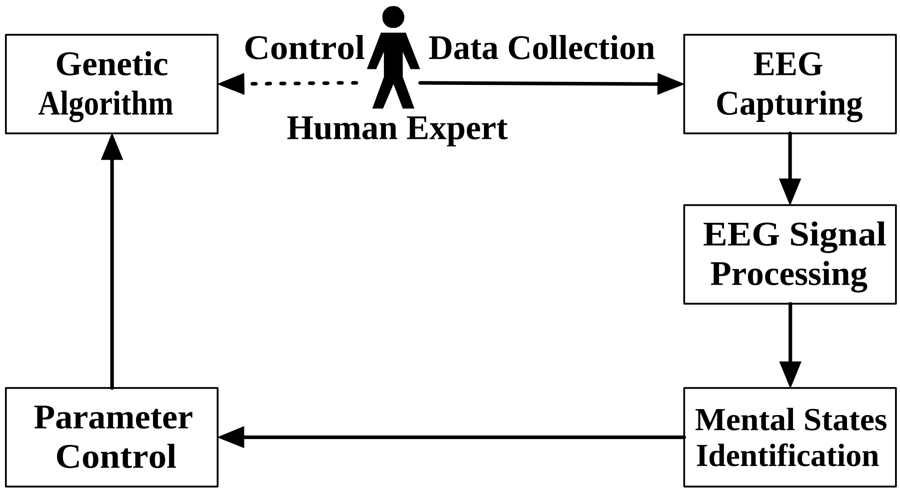


Figure 6.1: The Framework of the Interactive Evolutionary System with Parameter Control

As shown in Figure 6.1, the system is composed of five main components: the GA, the EEG collection, signal processing, mental states identification and the mapping of mental states to the changes in genetic parameters. EEG signals are collected from the human expert after he or she has evaluated the problem and made a decision for parameter control, process the signal to extract features, identify mental states in real time using these features, and lastly map the mental states to parameter control functions. The functions feed back to the GA main program to process and to display results, again for the human expert to evaluate. This loop continues until the GA has provided a satisfactory result.

The tasks for the human expert are to identify the test problem visualised on the screen, and to control parameters accordingly by performing simple tasks (close eyes, open eyes, close eyes to do computation, open eyes to do computation) for a given period of time. The tasks for the system are to capture and process the EEG signals during cognitive tasks chosen by the human expert, to identify the control messages according to the physiological features extracted from baseline tasks, which have to be accomplished before the control sessions, and then to control the optimization process of the task problem.

This framework of the interactive GA system is processed in real time so as to obtain instant control messages. Besides a quick baseline session that takes just several minutes, no training stage is required, as in classical BCIs design. This design makes the framework neither algorithm-dependent in choosing GAs, nor subject-dependent in choosing the human experts as subjects.

6.3.2 Genetic Algorithm and EEG Controlled Parameters

A detailed explanation of the designed interactive GA system is shown in the flow chart in Figure 6.2. The system consists of a standard GA with Roulette wheel selection and an EEG parameter control component.

The algorithm starts with the initialisation of population, which covers the entire search space. The population is randomly generated with a seed and is represented as chromosomes. In this case, chromosomes are created with a length of two. Each element has its value between '0' and '1'. If the parameter control function is enabled, the system will collect EEG data and calculate mental states for controls. The components will be further discussed in the following subsections.

If the parameter control is not enabled, the fitness of each member in the population will be evaluated and the selecting function among population will be performed. When selecting good parents to breed, the Roulette wheel method is used in this design, so that the members with greater fitness will be more likely to be selected.

The crossover stage will be performed after selection. The crossover operator takes selected two parents to produce a pair of children by one-point crossover. The

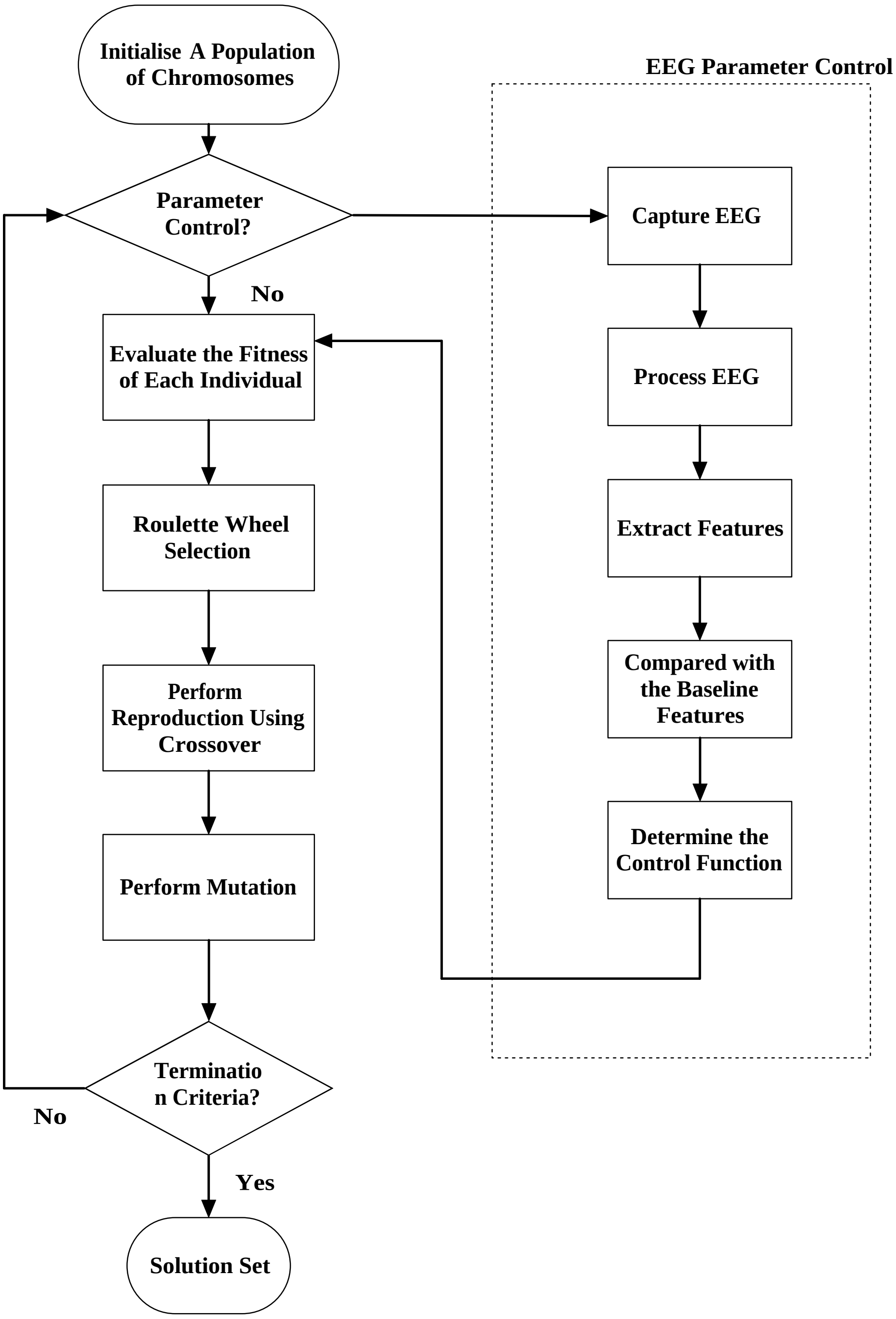


Figure 6.2: The Implementation Diagram of GA with EEG Parameter Control

resulting children chromosomes are the swap between two parents' chromosomes beyond the crossover point. The rate of crossover is defined as the crossover rate (CR), which is one of the parameters used for controlling the GA process.

The mutation operator changes the chromosomes entirely by replacing the targeted chromosome with chromosome generated from random values in the search space. The rate of mutation is defined as the mutation rate, which is another controlled parameter.

When the EEG parameter control is enabled, the system will collect EEG data, calculate mental states, and control the crossover and mutation rate accordingly by the resulting control functions. If not enabled, the GA will follow the standard way of evaluation, selection, reproduction and mutation without changing parameters.

6.3.3 Mental Tasks Design

The mental tasks are designed such that when the human expert completes the mental tasks, this results in the corresponding control changes in the GA — changes of crossover and mutation rates during the problem solving. The control functions are determined by features extracted from EEG signals captured during the tasks. To avoid the tedious process of BCI training, these tasks need to be designed to be simple enough for the human expert to identify and remember, but also diverse enough to generate distinguishable brain signal patterns that can be identified by our constructed cognitive model.

The mental tasks were designed by reviewing studies on EEG signal patterns under various thinking tasks. Two brain phenomena could be captured by EEG - the spontaneous activities, which are the event-related rhythm oscillation modulated by underlying functions of the brain; and the event-related potentials (ERPs), which arise in response to external stimulus. The spontaneous activities consist of the main electrical responses of the brain captured; and the ERPs need training to be isolated and extracted from the spontaneous activities. The tasks focus on spontaneous activities of the brain to avoid excessive training.

The increasing frequency of information transmissions between neurons is an electro-physiological indicator of excitement and activation of the corresponding cerebral functional area. Conversely, decreasing frequency is an index of attenuation and inhibition of the cerebral functional area. This implies the correlation between spontaneous brain activities, which could be shown as relative EEG power, and its corresponding underlying brain functions.

The mean power level of EEG alpha band has long been recognised as an important measure of resting state arousal under eyes-closed and eyes-open conditions. Recently, the topographic changes between eye-close and eye-open states has also been studied and identified [32]. During eye-close and relaxation stage, the temporal-occipital region is activated with an attenuation of the frontal region. Attenuation of temporal-occipital region and activation of pre-frontal region are observed during eye-open relaxation mode. The dorsolateral pre-frontal cortex (DLPFC) is the neural basis of the brain's central executive control function in most of the working memory models. It is one of the cortical association areas in the brain which has neural connections with all parts of cortex. Research has proven the activation of the DLPFC region while doing computational tasks. The function of the DLPFC is to summarise all information for activity planning, to coordinate cerebral motor cortex, and to control and accomplish complex tasks. The more information needed to be retained and to be processed in working memory, the higher the activity levels observed from DLPFC region will be [202]. Counting backwards is used as a simple and effective method for mental arithmetic in the former research [129] as computational tasks to activate DLPFC region.

Four mental tasks are designed for the human subject to control genetic parameters, as listed in Table 6.1, based on the EEG features and the brain functions explained above. The tasks are labelled as eye-close (EC), eye-open (EO), eye-close computation (ECC) and eye-open computation (EOC). The corresponding genetic parameter changes are also shown. The computational task is to count backwards from 100 at a step of three.

Before leveraging these mental tasks for parameter control, EEG baseline in-

Table 6.1: Four Human Mental Tasks

Mode	**Eye Status**	**Relaxation/ Computation**	**Period (Sec.)**	**Parameters**
EC	Closed	Relaxation	15	Increase Crossover Rate by 10%
EO	Open	Relaxation	15	Decrease Crossover Rate by 10%
ECC	Closed	Computation	15	Increase Mutation Rate by 2%
EOC	Open	Computation	15	Decrease Mutation Rate by 2%

formation needs to be collected from the targeted subject to allow for individual differences in EEG signals. Four baseline tasks were also designed to be the same as the four control mental tasks with the same durations. The four baseline tasks should be performed thoroughly by the subject before the control session started. The EEG signals collected from the four baseline tasks are processed to generate EEG signal patterns from each brain functional region to setup baselines for the control tasks.

6.3.4 Electroencephalography Signal Collection

The EEG signals are collected using a 19-channel EEG Nexus32 system. Twenty-one electrodes (including two reference channels) are integrated in an EEG cap following the international 10 to 20 system, as shown in Figure 6.3. The recordings of the EEG signal are continuous during the baseline session and the control tasks. The recordings are sent to the cognitive model for EEG data processing once the baseline tasks or control tasks has completed. The data is sent as a 19-channel EEG data stream at the sample rate of 2048Hz.

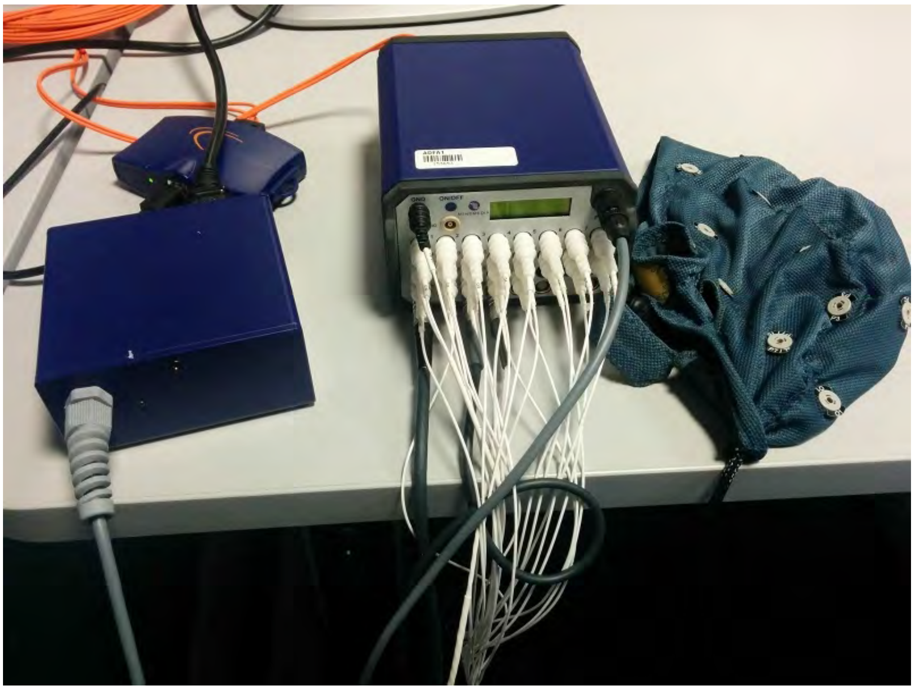


Figure 6.3: EEG Collection System and EEG Cap

6.3.5 Signal Processing and Cognitive Model

The collected EEG signals were processed by the cognitive model after the subject completed each baseline or control mental task. From former experiments on 'Snake' and 'Go', the results show that both the EEG frequency ('Snake') of certain channels and the EEG topography ('Go') that indicates the functional specialisation of brain could be used to derive indicators illustrating the user's perceptive, cognitive and affective states. In this cognitive model, both frequency and EEG topography are considered to focus on the estimation of the general mental states.

First, to find the EEG voltage readings, which represent the pure electrical activity at the targeted electrode positions on the scalp, the recorded EEG data stream, which is usually called the raw EEG data, needs to be re-referenced to obtain the relative measure between the targeted position and a reference position. The common average referencing method is used to provide a dereferencing solution for EEG data analysis, based on the assumption that the same electrical activities across all the sites spreading up the entire head could be considered as artifacts [87].

While on a theoretical basis this referencing system is suitable for a large number of electrodes, the test demonstrated that it was adequate enough for this task. The common average reference is mathematically represented by subtracting the mean of recordings from all electrodes in each channel.

The process is explained in Algorithm 1, in which $EEGSum$ represents the common average across all sites and EEG is the EEG data stream.

Algorithm 1 Common Average Referencing

```
for each second t of the duration of task do
    for each sample s in the second of t do
        EEGSum ⇐ 0
        for each channel c of EEG channels C do
            {C is the number of EEG channels}
            EEGSum ⇐ EEGSum + EEG[c][t][s]
        end for
        Average ⇐ EEGSum/C
        for each channel c of EEG channels C do
            EEG[c][t][s] ⇐ EEG[c][t][s] − Average
        end for
    end for
end for
```

The EEG signal is then filtered into eight frequency bands as in Table 6.2 using spectral analysis. An FFT transformation is performed on the re-referenced EEG signals to change the time domain signal into frequency domain using Equation 6.1. The relative EEG amplitude $A_{f'}$ and power $P_{f'}$ are also calculated by dividing those at the overall band as Equations 6.2 and 6.3. Note that the frequency bands of the signal below 1Hz and higher than 42Hz are filtered out.

$$X[m] = \sum_{n=0}^{N-1} x[n] e^{\frac{-imn2\pi}{N}} \tag{6.1}$$

where, $m = 0, 1, ..., N-1$, $n = 0, 1, ..., N-1$, $x[n]$ is the n^{th} input sample, and $X[m]$ is the m^{th} harmonic.

$$A_{f'} = \frac{A_f}{\sum_{j=1}^{42} A_j} \tag{6.2}$$

$$P_{f'} = \frac{P_f}{\sum_{j=1}^{42} P_j} \tag{6.3}$$

Where $f = 1, 2, ..., 42$, A_f and A_j represent the absolute amplitude, P_f and P_j represent the absolute power.

Table 6.2: The Eight Frequency Bands Of EEG Signals

EEG Bands	**Frequencies(Hz)**
Delta	1-4
Theta	4-8
Alpha	8-12
low Beta	12-15
Beta	13-21
High Beta	20-32
Gamma	38-42

EEG rhythmic activities can be classified within the bounds of each frequency band with a particular biological significance [89, 117, 151, 179, 279, 287], as shown in Figure 6.4. Introduced by Pope et al. [229] and further discussed by Freeman et al. [109], the engagement index $\beta/(\alpha + \theta)$ was tested as the most effective index in performance enhancement of adaptive automatic systems. The adaptation was achieved by keeping the control in manual mode when the engagement index decreased below baseline, and switched to auto mode when the index increased above baseline. This design is based on former research where beta bands power represents the increase of arousal and attention while the theta and alpha represent the decrease of this trend [100]. Former studies in neurofeedback training have represented that the power ratio instead of absolute power of EEG frequency bands (due to the individual differences of skull thickness and recording measures), is a better choice for adaptive automation system design [196].

However, as in the studies of Pope et al.[229] and Freeman et al.[109], the EEG signals were recorded and analysed only from four channels at the positions of the vertex and parietal lobe — Cz, P3, Pz, and P4 — which represent motor and sensory integration. As discussed in several studies on phase synchronisation between frequencies, theta and upper alpha coupling exists in working memory processes (e.g., memory scanning tasks) at the frontal cortex [168, 256]. In order to

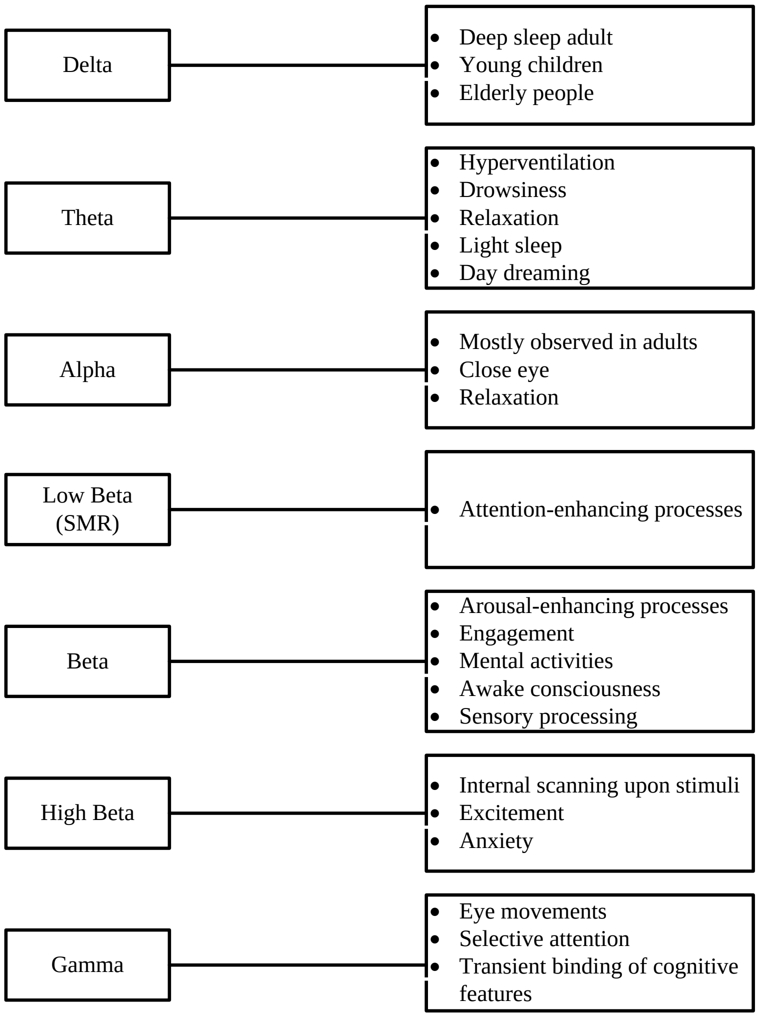


Figure 6.4: EEG Bands Interpretation

find a more general index, the theta/beta ratio (TBR), which has long been studied in the neurofeedback domain as an indicator of ADHD [213], and have been used successfully in our research group for an air traffic control context [14, 15], manifests as hyperactivity and inattention. There is consensus that the elevation of absolute and relative theta activity, together with suppression of beta activity, are likely associated with ADHD [226]. The child with widespread EEG theta to beta ratio greater or equal to 3:1 may indicate poor concentration [84].

However, the production of theta waves in eye-close state reflects relaxation and meditation[292], usually together with positive affective states. As the mental tasks discussed in these experiments are differentiated among eye-close/eye-open, and relaxation/mental arithmetic, the TBR value discussed in this experiment is presented as a robust EEG index to distinguish among those tasks.

The cognitive model is constructed as the averaged TBR value calculated within the given time period in the particular brain functional region, which is shown in Table 6.3. The TBR is calculated by dividing activities of the theta band and the beta band. EEG band activity is represented by band power, which is computed by accumulating power spectrum density within the given frequency range. The implementation process is explained in Algorithm 2, in which TBR represents the theta/beta ratio.

Algorithm 2 TBR Model

for each channel c in channels **do**
  for each second t in the task duration of T **do**
    $TBR[c][t] \Leftarrow \frac{ThetaAmp[c][t]}{BetaAmp[c][t]}$
  end for
end for
{Calculate indicators according to the channel position showing in Table 6.3}
$Attention \Leftarrow \sum_{t=1}^{T}(TBR[Fp1][t] + TBR[Fp2][t])/2$
$Planning \Leftarrow \sum_{t=1}^{T}(TBR[F7][t] + TBR[F3][t] + TBR[Fz][t])$
$\quad + \sum_{t=1}^{T}(TBR[F4][t] + TBR[F8][t])/5$
$SA \Leftarrow \sum_{t=1}^{T}(TBR[P3][t] + TBR[Pz][t] + TBR[P4][t]))/3$
$Language \Leftarrow \sum_{t=1}^{T}(TBR[T5][t] + TBR[T6][t])/2$
$Emotion \Leftarrow \sum_{t=1}^{T}(TBR[T3][t] + TBR[T4][t])/2$
$Visual \Leftarrow \sum_{t=1}^{T}(TBR[O1][t] + TBR[O2][t])/2$
$Motor \Leftarrow \sum_{t=1}^{T}(TBR[C3][t] + TBR[Cz][t] + TBR[C4][t])/3$
$Flexibility \Leftarrow \sum_{t=1}^{T}(TBR[Fz][t] + TBR[Cz][t] + TBR[Pz][t])/3$

Table 6.3: The Cognitive Model

Indicators	**Brain Functional Region**	**Electrodes' Positions in EEG Recording**
Attention	Pre-frontal Cortex	Fp1 Fp2
Planning	Frontal Cortex	F7 F3 Fz F4 F8
Situation Awareness	Parietal Lobe	P3 Pz P4
Language	Wernicke's Area	T5 T6
Emotion	Limbic System	T3 T4
Visual	Occipital Lobe	O1 O2
Motor	Motor Cortex	C3 Cz C4
Flexibility	Precentral Gyrus, Central Sulcus and Postcentral Gyrus	Fz Cz Pz

6.4 Experimental Design

6.4.1 Experimental Protocol

The experiments were conducted on a voluntary basis, with each participant completing their experiment, before another began. A background knowledge of GAs and parameter control were needed for the participants to take part in this experiment.

Before the experiment started , the researcher briefed each participant on the procedure of the experiment, the baseline tasks and the control tasks. The participant was given a printed table from the researcher during this stage, which showed the relationship between mental tasks and the parameter control results as in Table 6.1, so that he or she did not need to memorise them. The EEG sensor setup was done after the subject briefing. The baseline session was started if the EEG signal quality was satisfactory after sensor set up.

The baseline session consisted of four baseline tasks (EC, EO, ECC, and EOC) which needed to be performed one by one in sequence. The participant was required to be fully focused on the tasks during this stage. Twenty seconds of EEG recording were taken from the participant doing each baseline task, with five seconds for stabilisation and 15 seconds used for input to calculate features by cognitive model. The EEG recordings during the warm up period was preserved but not calculated. The researcher monitored the process and notified the participant of which task needed to be performed, the duration and the end of each baseline task. This session took two minutes.

After going through all four baseline tasks, the main session started . The participant was required to observe a test problem with unknown functions, but its global maximum position was shown on the screen. After identifying the problem, the GA started with the generation of an initial population and the first ten generations by the default crossover and mutation rate. The resulting values were plotted on the screen as coloured dots on the contour map of the task problem. The fitness function was also shown on the screen to help the participant to evaluate the problem.

After each ten generations, the GA stopped for the participant to decide if the genetic parameters needed to be changed (increased or decreased). The participant needed to first observe the current state of the problem solving process, evaluate the problem, make a decision (change the parameter or not, which parameter to change, increase or decrease), refer to the corresponding mental control task, clear their mind and relax for 20 seconds, and then start the selected control task for 20 seconds. The researcher informed the participant of the procedure above during this stage. If the participant decided not to change any parameters, both the relaxation and the control tasks stage were skipped.

The control tasks were processed in the same way as the baseline tasks — the system took a 20 second EEG recording, also identified the first five seconds as warm up and the next 15 seconds to obtain features in real time from designed cognitive model. The features derived then compared with the baseline features using similarity metrics, a control decision was made, the genetic parameter of GA was changed accordingly, and the results of the following ten generations generated under the changed parameters were shown on the screen for the participant to evaluate. If the participant decided not to change any parameters and the above control task stage had been skipped, the GA took the former parameters and generated ten generations under the former designated parameter value. The system was operated in real time exactly after the participant had finished the control task stage and the EEG recordings had been received.

Once the results of the following ten generations shown, the participant repeated the process of observe, evaluate, decide, relax and then start the control tasks. This process could be repeated as many times as needed. In this experiment, each participant was required to repeat this task five times (the first ten generations were generated on default value of parameters) due to the pilot study that after repeating five times, the fatigue effect of the participants had negative impacts on performing mental tasks.

6.4.2 Test Problem

A single-objective function was chosen as the test problem in this experiment. The function used *sin* to create several local maximum and a global maximum. The definition of the fitness function is described in Equation 6.4. The landscape of the fitness is shown in Figure 6.5.

$$\begin{gathered} f(x,y) = (15xy(1-x)(1-y)\sin(3\pi x)\sin(3\pi y))^2 \\ x \in [0,1], y \in [0,1] \end{gathered} \tag{6.4}$$

There are four local optima surrounding the global maximum ($f = 0.8789$) at point [0.5, 0.5]. It is a suitable example function in order to investigate the balance between exploration and exploitation in GA by changing parameters.

Figure 6.6 shows the results of GA evolutions with a fixed seed but different crossover and mutation rates. As shown in the figure, when the mutation rate is low (0.01), the solutions are stuck at the local optimal.

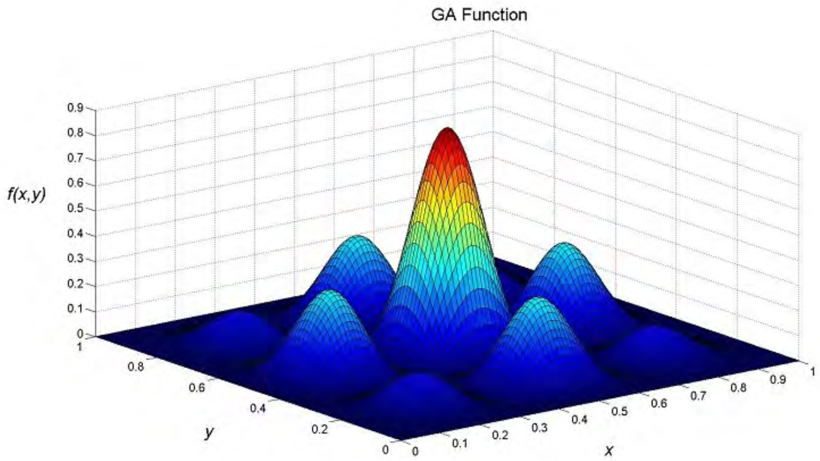


Figure 6.5: Experimental Protocol

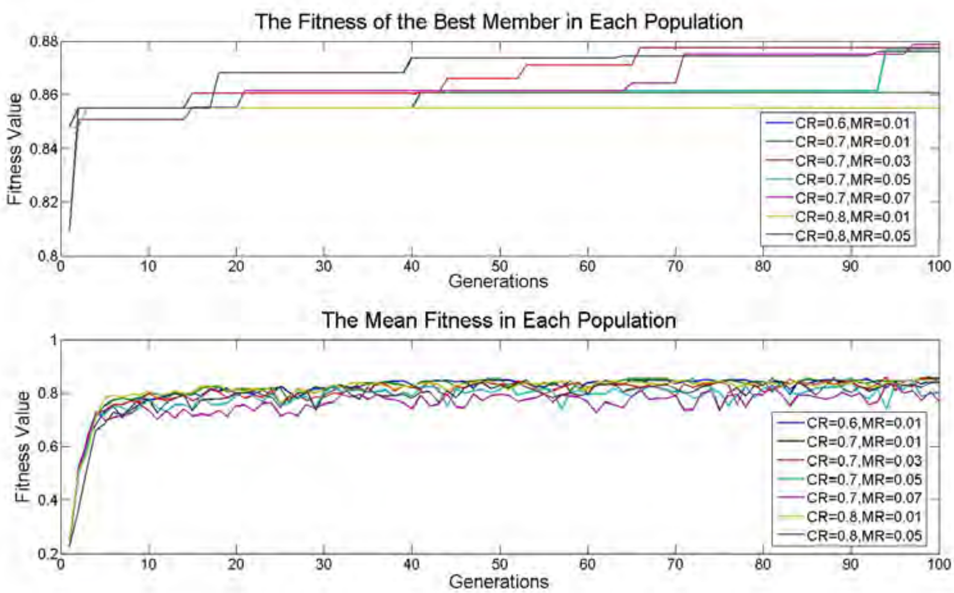


Figure 6.6: Fitness Values of the GA Populations, under EEG Controlled Parameters

6.5 Experiment Setup and Procedure

The experiment was conducted by strictly applying the experimental protocol. Six subjects, all professionals in computer science, aged from 20 to 30, including three males and three females, voluntarily participated in the experiments. All are right-handed. They all had average durations of sleep, of at least 7 hours the night before experiments. None had drunk alcohol, coffee or tea within 24 hours before the experiments.

The experiment consisted of a 50-minute test procedure. During the experiment, the subjects were required to remain seated on a comfortable chair in a closed, bright, and quiet lab environment. The EEG signal was captured using the Nexus-32 EEG system produced by the Mind Media. The procedure is illustrated in the following Figure 6.7.

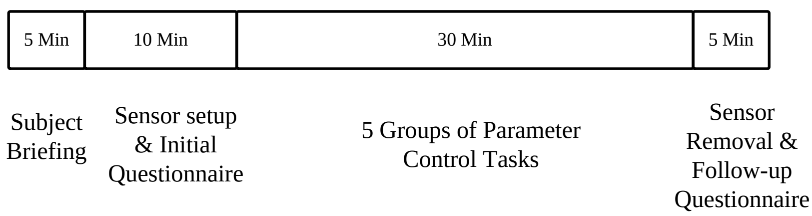


Figure 6.7: Experiment Setup and Procedure

6.6 Results and Discussion

The EEG topographic heat maps — which show relative activity by regions of the brain — are computed based on the interpolation of EEG power calculated from each channel. The topographic maps focused on the temporal changes are first presented. After detrending, topographic maps computed at five seconds, ten seconds, 15 seconds and 20 seconds of each baseline task are selected from one of the conducted experiments as an example, as shown in Figure 6.8. However, it could reflect the general relevant cortical areas of all participants in performing most of the mental tasks. The results in the figure show that during EC baseline, the visual cortex was shut-down as high EEG power presented in O1 and O2 positions. During EO baseline, the power at O1 and O2 positions attenuated, while the frontal, pre-frontal cortex and parietal lobe (which is associated with attention, planning and situation awareness) began to activate. During ECC baseline, the activation of the frontal cortex was not as great as seen during EO and EOC baseline, and also the visual cortex was activated, but not as strongly as in EC baseline. Finally during EOC baseline, the mainly activated areas were the pre-frontal and frontal cortex, which may indicate high engagement and planning. The results show that the four cognitive tasks are differentiable on the basis of the EEG power collected from 19 EEG channels.

The topographic maps of power at each frequency band are also shown in Figure 6.9, which are calculated by averaging the EEG power in the frequency bands across the duration of the given tasks in Figure 6.8. The colour map is scaled to the data range of each topographic map. The first column shows the total EEG power from 1 to 42Hz. In the following columns, the power maps calculated from frequency bands delta to gamma at each mental task are presented. As shown in the Figure 6.9, during eye closed tasks (EC and ECC), the delta and theta band power, especially at posterior part of brain, are greatly attenuated compared to EO and EOC tasks. During computational tasks (ECC and EOC), the beta and high beta band power, especially at the frontal and pre-frontal cortex, are greatly enhanced than relaxation tasks (EC and EO). The power changes among frequency bands could be depicted by TBR index calculated in the cognitive model. Specifically, during the EC task, the visual cortex was activated as high power at O1 and O2 from alpha to gamma bands. During the ECC task, the visual cortex was activated as in the EC task, and frontal cortex was also activated as an indicator of the attention and planning during computational tasks. During the EO and EOC tasks, the EEG power showed more slow-wave activities compared to EC tasks, and higher EEG power at frontal cortex

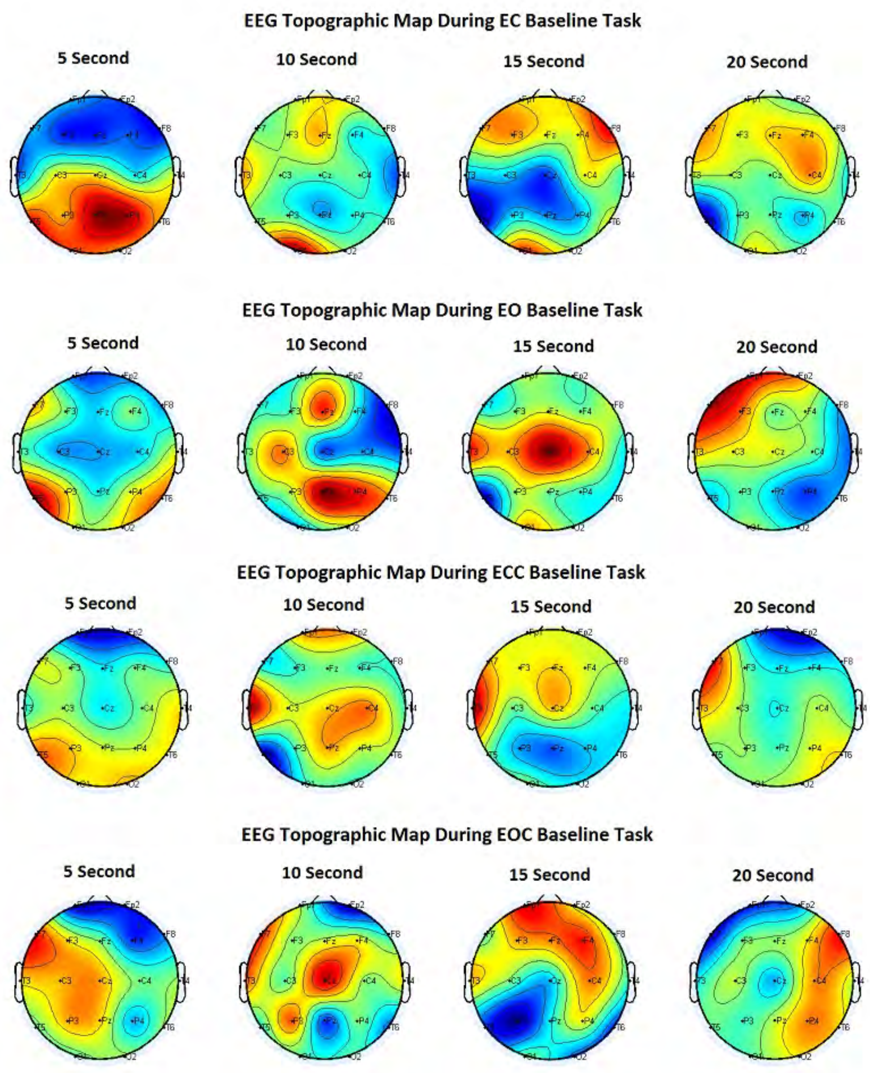


Figure 6.8: EEG Topographic Maps Computed for 4 Baseline Tasks on Temporal Changes

was shown during EOC task compared to EO task, which is in accordance with EC tasks.

The Euclidean distances of features between a control task and a baseline mode is calculated and then the minimum is found, which shows the maximum similarity between these two tasks. The mental state during the control task is classified the same as the baseline task with the minimum distance. The distance coefficients are calculated as Equation 6.5 for each baseline task.

$$D_{M,T} = \sum_{b=1}^{8} \sqrt{(I_b - B_{M,b})^2} \tag{6.5}$$

Where $D_{M,T}$ is the distance coefficient between a mental task T and a given base line of mode M, I_b is the task indicator of band b, and $B_{M,b}$ is the baseline of band b in mode M, as listed in Table 6.1.

In this experiment, the GA functions were tested five times for each participant, with each function including 100 generations and nine parameter control mental tasks. The first ten generations were generated by the default crossover and mutation rate set before the experiment(CR =0.6, the mutation rate (MR)=0.01). The mental tasks were performed at the step of ten generations. The subject did not use the skip function during the experiment. Therefore, a total of 270 mental tasks were processed and identified, and the results are shown in Table 6.4.

Table 6.4: Experimental Results

Tasks	Number	Accuracy	Numbers of Mapped Tasks			
			EC	EO	ECC	EOC
EC	74	81.08%	60	4	10	0
EO	67	68.66%	8	46	4	9
ECC	66	71.21%	10	7	47	2
EOC	63	76.19%	0	13	2	48
Total	270	74.44%				

One of the GA processes is shown in Figure 6.10 and Table 6.5. In this example, the identification of control mental tasks was performed with 100% accuracy.

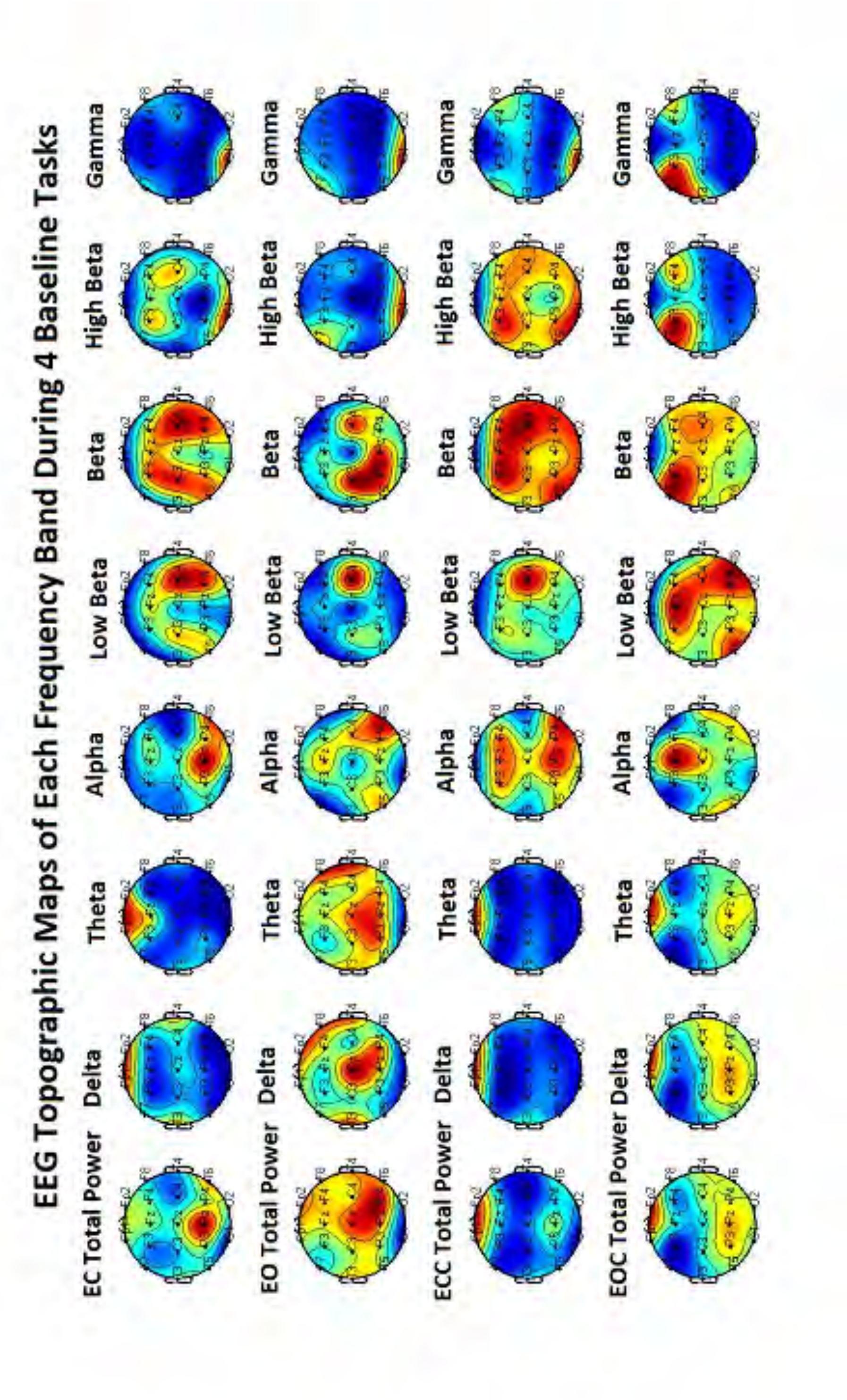


Figure 6.9: EEG Topographic Maps for 4 Baseline Tasks on Frequency Changes

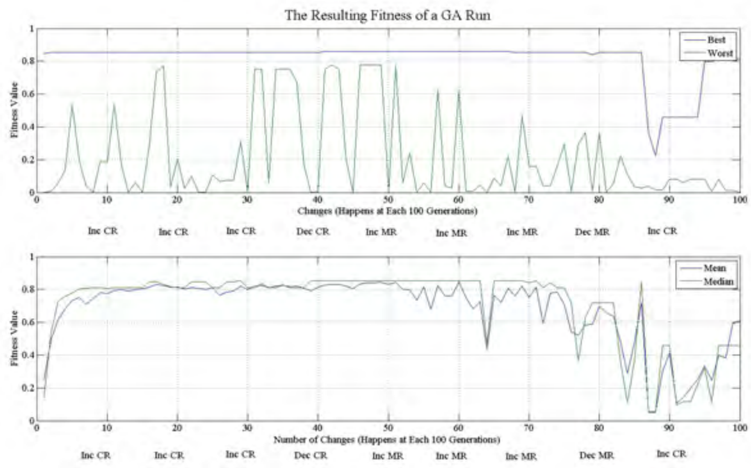


Figure 6.10: The Best, Worst, Mean and Median Fitness Value With Online EEG-based Parameter Control

Table 6.5: The Mental Tasks and Control Actions

Sequence	Mental Tasks	Control Actions	Parameter Values after Operation
0	Initialise	Default	CR=0.6 MR=0.01
1	EO	Increase CR by 0.1	CR=0.7 MR=0.01
2	EO	Increase CR by 0.1	CR=0.8 MR=0.01
3	EO	Increase CR by 0.1	CR=0.9 MR=0.01
4	EC	Decrease CR by 0.1	CR=0.8 MR=0.01
5	EOC	Increase MR by 0.02	CR=0.8 MR=0.03
6	EOC	Increase MR by 0.02	CR=0.8 MR=0.05
7	EOC	Increase MR by 0.02	CR=0.8 MR=0.07
8	ECC	Decrease MR by 0.02	CR=0.8 MR=0.05
9	EO	Increase CR by 0.1	CR=0.9 MR=0.05

The member values (x,y) for the test problem from generation 1 to 100 of the given GA processes are shown in Figure 6.11. The global optimal is at (0.5,0.5) and the colour of the scatter map is drawn based on the fitness value of each member in the population. The member values are drawn at the step of ten generations after each mental task. The figure shows a convergent result for our EEG-based interactive GA system.

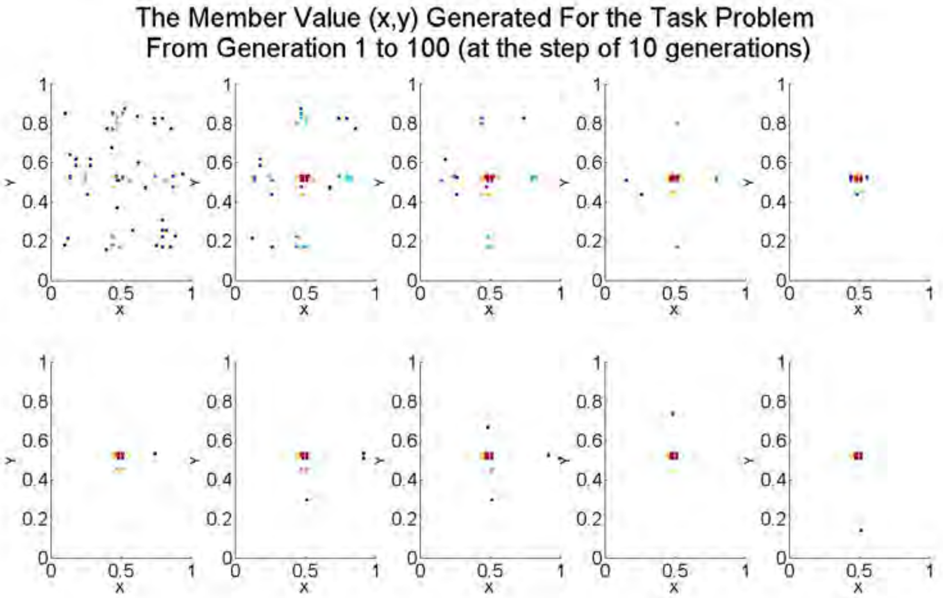


Figure 6.11: The Member Values for the Test Problem

As in the example, the test problem is a single-objective easy function, so the best, mean and median fitness increased quickly during the first ten generations under the default value CR=0.6, MR=0.01. The CR value increased up to 0.9 to generate the next 30 generations, and the fitness value increased steadily to try to reach the global maximum 0.8789. After 50 generations, the median fitness was close to the maximum. The increase of MR in the following stages added more variations to the population, so that the mean and median fitness value of each population generally decreased until the MR decreased at the end of 80 generations. There were sharp decreases of all the best, mean and median fitness values from generation 80 to 90 after the mutation rate decreased. That was probably because after the global maximum was almost reached, the mutation process in the population deteriorated the results. After increasing the CR at the end, the fitness value started to increase again.

All experimental results with mental task parameter control are shown in Table 6.4. The overall identification accuracy of the 270 control mental tasks is 74.44%., with 201 out of 270 correctly identified by the system developed. As shown in the table, the distance between mental index derived from EC and EOC is farthest among all the four tasks, so that none of the EC tasks has been wrongly classified to EOC, and vice versa. Among these tasks, the TBR index is better performed in distinguishing between eye-close and eye-open tasks, which is accordance with the former research [214]. Meanwhile, there are relatively more errors in distinguishing between relaxation states and computational states, in both EC and EO conditions. There are probably three reasons that lead to this result: 1) the computational task (counting backwards in steps of three during EC) is hard to control for both the researcher and the participant. For the researcher it is hard to identify from observation if the participant is faithfully doing the computational tasks or not. The participant may find it hard to focus on the tasks or to do the task in the right way; 2) counting backwards from 100 at the step of three may be too easy for some participants, so that not much attention and mental effort is needed to perform this task to distinguish between pure relaxation; 3) fatigue and learning effect may affect the results, especially when the participants have performed several tasks repeatedly.

Among all the four tasks, the correct classification rate of the EC task is the highest (81.08%) followed with the the EOC task (76.19%). The classification accuracy of the EO task and ECC task is relatively lower, with 68.66% and 71.21% accordingly. The results again support that the distance between the mental index derived from EC and EOC is farthest among all the four tasks, as the performing of an EC task is supposed to have most of the brain regions suppressed and the EOC task is, in contrast, supposed to have most of the brain regions activated, while both the conductions of EO and ECC tasks involve the activations of some brain regions and suppression of other regions. To achieve a better classification accuracy, a recognition of the brain patterns instead of the Euclidean distances of index features could be tried in future works.

6.7 Conclusion

This chapter focused on EEG signals as an input channel to interface between human players and computer games. IEC as a simplified game problem solving simulation was used as a test platform. A new concept of an EEG-based interactive GA was designed, implemented and tested in this chapter. The experiment showed 74.44% classification accuracy among 270 mental tasks performed by six professionals as subjects. The results proved that EEG brain signals could be used as inputs to control genetic parameters, and the technique of using baseline tasks to overcome some of the individual differences and to reduce training time in HCI design is applicable in the proposed framework.

To summarise, the introduction of game, EC, IEC and HCI was presented together with potential research topics based on this piece of research. A framework of designed system was presented based on, but not limited to, the current progress in both brain-computer interaction and evolutionary computation. The system has been implemented and a thorough experimental protocol has been designed to conduct the experiment. Experiments have been conducted and the classification accuracy was satisfactory.

To obtain a better identification rate, one possible improvement of the methodology would be to perform a thorough study on the most appropriate duration of the mental tasks, and the ratio of the warm up stage to the EEG recording stage. A longer time duration of EEG recording during mental tasks will likely provide more robust results. Further obtaining more than one baseline sample of each task would likely lead to an improvement. Similarly, more sophisticated classification algorithms to recognise the brain patterns instead of the Euclidean distances of index features could be tried. This is one area that could receive work in the future.

The results of this chapter, together with former chapters, indicate that both individual differences and game contexts are crucial in analysing game play and game experience. Mental tasks in this chapter are designed as a potential method in EEG-based adaptive interface design to overcome some of the individual differences by performing simple mental tasks, which have well-established EEG responses features among a wide range of humans. IEC in problem solving is used as a simplified game problem space that is fully under control to overcome some of the influence of game contexts. The idea to apply EEG signals under designed mental tasks as a bridge between human players and IEC problem solving is satisfactory. However, in designing an optimal game experience for particular human players playing particular games, the bridge needs to consider the more complex game context and the individual human experience model.

Chapter 7

Conclusions and Future Work

Accept the challenges so that you may feel the exhilaration of victory.

General George S. Patton

Motivated by the imbalance between the prosperous game industry and fledging academic computer game research, this thesis has presented a systematic study of game play and game experience from the human players' perspectives in this nascent multi-disciplinary field. In order to define, identify and analyse the human game experience, game information and human information before, after and during game play was collected to evaluate how they encoded the game experience of players. Among this information, psycho-physiological data (especially EEG signals) captured by current sensory techniques from players was identified as an objective, sensitive, real time, continuous, non-intrusive, and unobtrusive indicator reflecting game experience during game play interaction. Further, psycho-physiological data can also act as an input channel to interface between games and players to enhance future game experience.

However, to establish a sophisticated game experience theory, and to design adaptive games to provide optimal game experience based on psycho-physiological data, there are still significant challenges, as identified in this thesis. These challenges may arise from the multitude of factors that need to be considered in games, game play and game experience analysis. As for games, although there are commonly used game genres to categorise games from game play interaction, the categorisation still lacks consensus in game studies; the playability of games lies in the originality of the game design, which encourages games to be designed 'out of the boxes'. As for human players, regardless of the great variation in games, game play as an interaction between players and games has occurred in a particular place during particular period, but the game experience, as cognitive and affective process during game play is affected by more factors than the current interaction, but also player information before and after playing. Still, although psycho-physiological studies in multiple fields have accumulated indexing human cognitive processes, well-recognised consistent human cognitive processing models do not exist. Thus, the psycho-physiological data, which is collected and analysed during game play, is not sufficient to represent game experience on its own.

These challenges identified currently for game research do not mean that psycho-physiological data, especially EEG, cannot be used to facilitate adaptive game design or player-centric game experience research. In contrast, the studies in this thesis highlight its potential in these areas, if game contexts and individual human game experience models, based on human information before, after and during game play, are considered and well-designed.

7.1 Contributions of the Thesis

In summary, the main research question of this thesis is:

RQ1: What are the main challenges faced when using psycho-physiological data as a mediator for player experience in a computer game?

In order to answer the main research question, the thesis analysed the challenges in using player psycho-physiological responses for game play interaction from three aspects, which illustrated as 3 sub-questions:

- **RQ1.1:** What are the player-centric models of interaction in game play?

- **RQ1.2:** Could psycho-physiological data, especially electro- encephalographic (EEG) data, encode the game experience of human players?
- **RQ1.3:** Could EEG data be used as an input channel to control simplified games?

The main contributions of the thesis are summarised as follows.

- **Contribution 1**: Player-centric models of what is a game, game play, and game experience are proposed based on an analysis of, and identified weaknesses in the existing literature (Chapters 2 and 3), to address RQ1.1. The models were explained in Chapter 2 and Chapter 3. Games are defined as 'a system bounded by rules that involves problem solving and is designed to be fun'. Game play and game experience were modelled as the interactions between information systems in Chapter 3. These general models in theoretical game research, need to be integrated with game contexts and individual human models, as discussed, and could be used to facilitate player-centric game experience research, game design and enjoyable human-computer interface design.
- **Contribution 2**: Psycho-physiological signals during game play are proven to encode the game experience of human players during game play, as illustrated in Chapters 4 and 5, to address on RQ1.2. Proposed game play and game experience models are evaluated under two game contexts: the simple game of 'Snake' and the complex game of 'Go' within the realm of game problem solving. The results show that cognitive and affective processes of human players during game playing under the discussed game contexts could be reflected by psycho-physiological signals, especially EEG signals collected from the central nervous system, which demonstrates the potential of improving game experience using these signals.
- **Contribution 3**: EEG signals collected from human players could act as an input channel to control simplified game interfaces, as presented in Chapter 6, to address RQ1.3. To minimise the variability of game contexts, a framework

of interactive problem solving using evolutionary computation controlled via EEG signals was proposed, implemented, and evaluated. To overcome some of the individual differences, designed mental tasks which have well-established EEG response features among wide range of humans are used to identify EEG responses and to apply them as an input channel. A satisfactory control accuracy has been achieved by experiments designed under proposed framework. The result shows that games could respond to changes in brain activities at a systems level using EEG signals as input channel. This design could be used in BCI applications or sophisticated game environments once the contexts and individual models are considered.

7.2 Challenges Recognised in the Thesis

Further, the main challenges identified using psycho-physiological data to reflect game experience in game play, which are also main findings of the thesis, are summarised as follows.

- **Finding 1**: The human experience, and the human game experience in particular, needs to be investigated through an ensemble of indicators within the realm of multiple domains as 'human factors' research. This may be due to the empirical perspective that game experience is multi-faceted (e.g., high cognitive workload or negative emotions caused by game play does not necessarily mean bad game experience). To study the game experience of players, a sophisticated method might be to classify the indicators into those that are static during game play (long-time goal, former experience, former preference, etc.) and those that are dynamic though playing (short-term goal, gaining experience, preferences in playing, etc.), and to investigate accordingly.
- **Finding 2**: Game experience models must of necessity be game and context-dependent due to the complexity and variation of each game. In order to investigate game experiences under particular game contexts, the indicators

should be again investigated from both a macro-frame (overall game setting, main playing strategy, playing rules, escalation of challenges, etc.) and a micro-frame (each game scenario, strategy required in each decision making, adapted rules and challenges based on the playing skills, etc.) perspective.

- **Finding 3**: EEG signals can interface between human players and games to facilitate game design. However, as discussed in this thesis, EEG signals alone can not solely represent game experience, to allow design of adaptive games to optimise game experience. To optimise game experience, which is an optimisation problem far more complex than finding the global maximum (as shown in Chapter 6), but also has an unknown problem space, a more sophisticated adaptive mechanism based on game context and individual human model may be considered.

7.3 Future Work

As discussed at the beginning of this thesis, games are simulations, so that no current established discipline can cover game research as a sub-domain; neither can any of the current disciplines in principle be excluded from this domain. The omni-directional feature of games makes game research as a domain greatly intriguing, as if connecting games with other domains or viewing games from other domains' perspectives, there could be hundreds of game-based research domains. Some of them have already been defined and are well researched, like game-based learning. Some are just starting as inspired ideas, like 'gaming' the past (connecting games with research in history) [205]. There are still more others under defined and under developed, that could potentially be greatly fascinating.

Within the realm of this thesis, challenges are identified in using psycho- physiological signals as a mediator to interface between games and players. However, these are great opportunities too. In particular, to address these challenges, my future work lies in context-based player-centric adaptive enjoyable interface design, based on individual models constructed from both the static and dynamic indicators discussed in this thesis, using psycho-physiological signals as an important source of information to interface between humans and computer interfaces.

Game started, and it will not end here.

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