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Believable Exploration:
Investigating Human Exploration Behavior to Inform the Design of Believable Agents in Video Games

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CERTIFICATE OF ORIGINAL AUTHORSHIP

I certify that the work in this thesis has not previously been submitted for a degree nor has it been submitted as part of requirements for a degree except as part of the collaborative doctoral degree and/or fully acknowledged within the text.

I also certify that the thesis has been written by me. Any help that I have received in my research work and the preparation of the thesis itself has been acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

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List of Publications

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Abstract – By nature, human beings are curious about their environment. Arriving in a new place, they observe, recognize and interact with their surroundings. People collect information about the new place, and locate objects in that space that help them to make further decisions. This is a typical scenario of spatial exploration. Spatial exploration is common human behavior, where humans explore unknown environments to acquire information and resources. It is pervasively seen in real-world and virtual environments, from exploring new living/working spaces to charting the oceans or venturing beyond the boundaries of our planet. Just as humans explore 'real' environments, they also investigate artificial environments in video games. Computer agents, which perceive surrounding environments with limited visual range, often appear in exploration activities, acting as tools or partners for explorers. Despite the broad range of human activities that employ exploration behavior, this element has been insufficiently investigated and understood. Additionally, even though it is commonly accepted that believable agents benefit people in human-computer interaction systems, the research into creating computer agents with believable exploration behavior has been neglected. To solve these issues, I extract the patterns of human exploration behavior in virtual environments, and explore the methodologies of developing believable agents, which explore spatial environments in human-like ways. In the pursuit of this goal, this thesis makes the following four contributions to the emerging field of believable agent exploration: 1) I employed video games as a testbed to investigate human behavior of spatial exploration. Human players played specialized exploration games, verbalized their behavior during playing and discussed their thoughts in the post-play interview. Behavioral patterns were extracted based on replays of playing, think-aloud data and interview data via thematic analysis. 2) Differences of exploration behavior between human and computer agents were identified through a third-person-observation assessment of believability. 3) A *heuristic agent* was developed, which mimics human exploration methods reflected via the behavioral patterns. Three heuristics, as components of the *heuristic agent*, were designed to filter potential options when the agent decides where to explore in each step. 4) An *integrated agent* was developed by filling the behavior gaps between human and computer agents, where an integrated architecture embedded expectations of human-like exploration from mid-level players. Both the *heuristic agent* and the *integrated agent* passed the third-person-observation assessment of believability. Therefore, findings in this thesis contribute to fill the gaps in the fields of understanding human exploration behavior as well as developing believable agent.

Index Terms – autonomous exploration, spatial exploration, real time strategy (RTS) games, Turing test, believability assessment, human-like intelligent agent, believable bot, thematic analysis, heuristic method.

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Chapter 1. Introduction

1.1 Spatial Exploration

Human beings have a long history of exploration in the search for resources and knowledge. Notable human exploration stories, such as the Greek exploration of Northern Europe and Thule (Markham 1893), the Chinese exploration of Central Asia (Wood 2004; Wriggins 1998) and the Vikings (Fitzhugh & Ward 2000) have featured in many books and films. Exploration rose dramatically when European explorers sailed and charted much of the rest of the world in pursuit of power and material wealth (Parry 1981). Since then, much major exploration has occurred for reasons mostly aimed at information discovery.

In the recent years, modern techniques enable humans to reach places they could not have reached independently. These techniques have increased the desire to explore deep waters and outer space. Taking the deep-dive ability of bathyscaphes, explorers measure the depth of trenches in the deepest parts of the ocean (such as the Mariana Trench) (Chan & Villagomez 2010), explore shipwrecks (Wall 2010) (for example the Titanic, which sank in the North Atlantic Ocean in 1912), and discover deep marine life (Johnson 2013). In terms of outer space, scientists observe the universe (Sparrow 2006) (such as stars, planets, galaxies and nebulae), detect the terrain and landforms in other planets (Adler & Trombka 2012) (for example craters on the Moon), and collect samples of materials (for example samples of soil on Mars) (Editors 2012). Humans fulfil the desire to explore by using special devices or deploying them to automated or semi-automated machines.

Many exploration-based tasks in human societies are also carried out with the assistance of machines to save labor, reduce risk and decreasing the risk of contamination. They are applied to save lives, study archaeology and conduct military operations. These applications often occur in environments which are dangerous or difficult to assess without additional technology (Thrun et al. 2004), such as using drones for aerial surveillance (Cavoukian 2012). For civil usage, autonomous robots are sent to scan unmapped places to construct digital maps (Celmins 2000) and into otherwise inaccessible places, which are inconvenient for people to move in, for search and rescue missions (Tadokoro 2009). They are also applied in military scenarios to scout the environment and assess hostile strength (Carpenter 2016). In many of these cases, machines explore the environment, collect information and transfer the data to humans. Oftentimes, they execute operation commands from humans for further exploration or other exploration-based behavior. In such ways, humans and machines complete these tasks collaboratively.

Exploration is not only a kind of group activity, but also a type of common behavior of individuals. A newly enrolled member of staff explores his or her working environment (such as office areas, laboratories, lounges, café, shops nearby etc.) Tourists explore roads, landmarks, museums, resorts and scenic spots when they arrive in a new city (Maitland & Ritchie 2009). Even a renovated shopping mall that is near to home is valuable for humans to explore to discover new opportunities and entertainment.

1.2 Insufficiently Studied Spatial Exploration

Exploration is a common discovery-based activity that players perform in modern video games (Hamari & Tuunanen 2014). In some games, like Journey (thatgamecompany 2012), the game can be simply about exploration. In other games, ranging from adventure games to first-person shooter (FPS) games, exploration is a core game mechanism that is essential for players to advance in the game (Fullerton 2014; Schell 2015). The most common type of exploration in games is spatial exploration, which includes:

- mapping environments
- collecting bonus items
- discovering locations, landmarks and specific game items.

Mapping game environments is a design manifestation of the spatial exploration mechanics in games, where players must reveal unknown environments by travelling on them (for example, uncovering the fog of war in a real-time strategy (RTS) game (Hagelback & Johansson 2008; Si, Pisan & Tan 2014a)). In these scenarios, players normally explore the game world to cumulatively build up their knowledge of the map, which makes it easier for them to navigate between locations to find game objects of interest. Often, exploration also adds to the variety of gameplay, for example, rewarding players when they uncover hidden trap doors to secret levels, or finding secret game items with special abilities (Wang & Sun 2011).

Although spatial exploration is an essential activity of human beings, human behavior in performing this type of exploration tasks is insufficiently understood. Behavioral patterns and types of human exploration have not been fully investigated. Exploration is involved in many aspects of human life but there is no uniform scenario which reflects all kinds of exploration behavior. Rather than examine these real-life scenarios, video games can be used as a virtual abstraction of the real-world to sample human exploration behaviors (Garris, Ahlers & Driskell 2002). To achieve this, the settings of virtual environments could be flexibly customized to seamlessly fit into real environments. In this manner, this research employs RTS games as a testbed to generate knowledge reveal how humans explore spatial environments.

Prior work has devised several player types, which have been shown to effectively reflect the behavior features of different groups of players (Bartle 1996; Bateman, Lowenhaupt & Nacke 2011). Although the player typology derivations and findings are highly valuable to game design, they are lacking in terms of their consideration of player exploration behavior. Human exploration behavior even in virtual worlds has not been fully studied.

Investigating how human players explore virtual game environments contributes to better game design, for example, how game objects are hidden and distributed around the map as well as the design of believable non-player characters (NPCs) that use human-like exploration techniques. It is also essential to develop an exploration component for computer agents in both real-life and virtual worlds. Within the exploration scenario mentioned above, computer agents that are capable of doing exploration play an important role in assisting humans. Hence, better exploration agents can improve the ways that humans explore.

In this thesis, I utilize computer agents to represent computer programs that autonomously control a unit to conduct spatial exploration in virtual environments. They have a certain intelligence where they can also be regarded as a kind of intelligent agent. They are differentiated from humans since they do not have actual human intelligence. They can also be regarded as machines in the Turing test

(Turing 1950) scenarios as a means of distinguishing them from humans. Given the fact that experiments run in the video game environment, they also include computer game playing agents ("bots") (Hingston 2009), which represent the software programs that play video games. In later chapters, I will consistently use computer agents to represent the terminologies of intelligent agents, machines and bots in the fields I focus on.

1.3 Research on Autonomous Exploration

Developing autonomous exploration agents is an active research area in the robotic field (Thrun 2002). Researchers design exploration algorithms to fulfil mapping and searching and to conduct tasks in unknown environments. The test beds mainly employ robots working on a setup scenario of the real world or a computer-simulated environment. The testing methods normally get a set of algorithms to run for the same exploration task several times. Indicators such as time utilization, travelling distance, map coverage and goal achievement are collected for each run of the experiment. In general, the algorithm with less time expenditure, less travelling distance, more map coverage and more goal achievement is evaluated as the best one (Amigoni 2008).

Those experiments assume the best algorithm is one that can achieve the goals of tasks efficiently and independently. In many cases, however, people cannot wait until the whole environment has been explored before making further decisions (Schenker et al. 2003). The exploration tasks can sometimes be endless. It is common that there are no explicit boundaries for unknown areas. Hence, exploration agents are required to continuously supply valuable information to provide support to humans, in time-constrained missions (Schenker et al. 2003). Intermediate results—including procedure, strategy and preferences of exploration—should make sense to people. One possible way to achieve this goal is to make exploration agents believable.

1.4 Believable Agent

Research on believable agents has been an active field crossing several areas of artificial intelligence (AI), human-computer interaction (HCI) and game research. Insights from virtual environments indicate that believable characters enhance player experience by playing with or against human players (Umarov & Mozgovoy 2012). They are key factors in constructing believable virtual environments. Believable agents can aid in improving the efficiency of work environments as well as quality of life by collaborating with and assisting human users. One of the first definitions of believability is an "illusion of life" (Bates 1994). Believability is a cognitive sensation created by virtual characters, which makes the people, whom the characters are interacting with, believe that these characters are thinking, feeling, intelligent and realism. It represents different meanings in different scenarios. A chat-bot illustrates believability by expressing a range of emotions (Bates 1994). Johansson et al. (2013) believed that emotions, social positioning and interaction of deliberating entities are three factors to create believability for NPCs in multiplayer games. Avradinis, Panayiotopoulos & Anastassakis (2013) focused on human intentions which reflect on decision making as the source of believability. In this thesis, the believability discussed refers to human-likeness, or the degree to which the agent credibly and consistently demonstrates human-like behavior. The meaning of the word "behavior" varies among different researchers. Several studies focused on the behavior illustrating the sense of believability in different means such as gaze (Poel et al. 2009), facial expression (Malatesta et al. 2009; Sloan, Cook & Robinson 2009), gesture and posture (Corradini et al. 2004). The behavior, however, refers to navigation behavior and its domain-relevant extensions in this thesis.

The Turing test provides the foundation for believability assessments, which is a benchmark in assessing the intelligence of computer programs. In the Turing test, participants were asked to distinguish humans from computer agents by textually communicating with them via a computer. The way that invites human judges to interact with, observe and compare the exhibitions of human and computer agents, which is presented by Turing, comes the basic theory to evaluate believability. Video game characters use more than just textual or verbal means in their interactions with players. In many cases, their believability is primarily exhibited via their behavior. Even though human players normally cannot converse directly with these characters, the actions exhibited by them that players observe directly enhance the gameplay experience (Iskander & Maxim 2012). A range of literature (Choi et al. 2007; Glende 2004; Taatgen et al. 2003) has demonstrated that human-like characters in the virtual world enhance players' feelings of immersion and increase the enjoyment of digital game play. This phenomenon encourages both game researchers and AI researchers to investigate and develop believable characters (for example, Reidl and Stern's interactive narrative system for storytelling (Riedl & Stern 2006)).

Several game AI competitions, such as Super Mario AI (Shaker et al. 2013; Togelius et al. 2012) and the 2K BotPrize Competition (Hingston 2009), encourage participants to develop believable AI (Livingstone 2006) bots. These competitions provide several promising directions for creating believable computer agents. The applied, practical approaches vary from scene to scene. For example, in Super Mario, where the core gameplay is focused on moving and jumping to collect coins and avoid obstacles, A* (Hart, Nilsson & Raphael 1968)(a popular path finding algorithm, which solves problems by searching the solution with the smallest cost among all possible paths to the solution. It firstly considers possible paths that appear to lead most quickly to the solution by using a heuristic distance-evolution component.) and other rule-based path finding strategies normally form the basis of the participants' approaches (Shaker et al. 2013). In FPS games, such as Unreal Tournament used in the 2K BotPrize Competition, learning to use weapons is largely the focus of the participants' approaches when developing gameplay agents (Hingston 2009).

Even though developing believable agents has been investigated in many other game activities and genres, believability in reconnaissance and exploration in unknown environments has not been fully studied. Enabling gameplay agents to have believable exploration contributes to developing believable gameplay agents where game environments need to be explored. Reconnaissance and exploration in an unknown environment is a popular activity in terms of gameplay in a variety of digital games (for example searching for hidden portals in Role Playing Game (RPG) and spying on enemy forces in RTS games). Therefore, developing believable exploration agents can be of considerable benefit in creating believable gameplay agents.

1.5 Research Questions

The background introduced above reveals that understanding how humans do spatial exploration and developing believable spatial exploration agents benefit many fields, such as understanding humans' spatial recognition and navigation systems, designing digital navigators, designing game environments and developing general human-like computer agents. These two problems, so far however, have not been sufficiently researched and so this thesis aims to fill that gap.

The objectives of this research are to understand how humans do spatial exploration and to investigate ways to develop believable spatial exploration agents. The medium which I employ to achieve these goals is a virtual environment in the RTS genre. The overarching research questions are:

Q1. How do players explore virtual environments? What behavioral patterns do they exhibit?

Q2. What behavioral differences exist between normal players and automated exploration agents?

Q3. How do the behavioral patterns of human exploration contribute to believable exploration?

Q4. How do we bridge the gap between human and computer agents' exploration via a computer agent?

The four research questions presented follow the logic that understanding human behavior in terms of exploration presents a valid assessment method to evaluate human-likeness in exploration, and then design exploration computer agents by mimicking human behavior and evaluating it with the assessment method presented. The four research questions are answered in the four chapters (from Chapter 3 - 6) separately. In Chapter 3, the game environments (three exploration games) are developed, which are used as the testbed. The patterns of how humans explore spatial environments identified in Chapter 3 are used to develop human-like agents in Chapter 5, which contribute to creating heuristic option filters. The four-phase thematic analysis developed in Chapter 3 is also used in subsequent chapters to analyze the verbal data collected from experiment participants. In Chapter 4, a believability assessment method is developed, which is used to identify the behavioral gaps of humans and computer agents, and to evaluate the developed exploration agents in Chapter 5 and Chapter 6 respectively.

1.6 Experimental Environments

Real or simulated robots are normally employed to test autonomous exploration algorithms. However, it is difficult to record the data of human explorations in such environments. Additionally, the interactive interfaces are not suitable to compare and distinguish exploration behaviors between human and computer agents. These environments, hence, are not suitable to conduct the experiments within this thesis.

I selected the RTS game – StarCraft (Entertainment 1998) as the testbed, due to a number of experimental and practical considerations. The primary reason is that the StarCraft platform enables researchers to easily develop rich experimental environments by providing a virtual world editor. Researchers are able to customize the virtual terrain, import extra models and modify the attributes (such as moving speed, damage and armors etc.) of units. They have even been authorized to design game scenarios. This provides opportunities to gamify the exploration tasks, which, in turn, simplifies the process of conducting user studies. For the requirements of understanding human behavior in exploration tasks and of evaluating believable behavior, a game platform needs to be convenient, agile and comprehensive. StarCraft offers the capability to conduct tests in its RTS game platform.

Another reason is grounded in the consideration of the strategic purposes of either real world applications or virtual world functions. Exploration for constructing digital maps, searching specific items and scouting opponents acts as a foundation to support further strategic actions. The mechanism of RTS games is a vivid simulation of strategic battle scenarios. Making use of this mechanism, the output of the exploration module could be designed by involving the strong correlations with other modules. Normally, almost all other modules (such as battle management module, unit production module and building construction modules etc.) are affected by the information gained from scouting about terrain and opponents.

Finally, the main application goal of this research is to make a contribution to developing believable characters, especially human-like gameplay agents, in RTS and other relevant games. After it was released in 1998, StarCraft was one of the most popular RTS games during the past 20 years. The game mechanism, design and implementation influenced the conceptualization of RTS games in players' minds and pervasively affected the development of successor RTS games. Thanks to the StarCraft AI Competition, first hosted by the Artificial Intelligence and Interactive Digital Entertainment (AIIDE) Conference in 2010, StarCraft has become a notable testbed for evaluation of AI agents (Ontañón et al. 2013) and so in keeping with this existing literature I also utilize it for our experiments.

1.7 Contributions

This thesis generates broad contributions ranging from identifying behavioral patterns of human exploration to developing believable exploration agents in different ways.

1. Identify behavioral patterns by revealing four behavioral archetypes: *Wanderers*, *Seers*, *Pathers* and *Targeters* when humans explore virtual environments. *Wanderers'* movements do not exhibit a definite destination or purpose. *Seers* aim to aggressively expand their visibility span when exploring unknown environments. The *Pather* archetype is characterized by elaborately structured cognitive maps of environments. And the *Targeter* archetype is objective-oriented towards terrain features.

2. Understand how humans explore virtual environments by analyzing the four behavioral archetypes through the lenses of *strategy*, *reasoning*, *perception* and *hesitation*.

3. Explore how g*ender*, *weekly gameplay time* and *real-life navigation abilities* contribute to the determination of players' behavioral types in exploring virtual environments.

4. Develop an experimental framework based on a third-person-observation method to evaluate the believability of computer agents in exploring virtual environments.

5. Build structured models to represent behavior differences extracted between human players and computer agents on aspects of *interaction with*

environments, *game-goal orientation*, *navigation* and *sense of the mechanism*, in exploration contexts, which construct a framework of believability criteria.

6. Use heuristic methods to develop a computer agent to play exploration games. It mimics the way of humans explore and passed the third-person-observation assessment of believability. Meanwhile, it performed well in completing exploration tasks efficiently.

7. Develop a believable exploration agent by integrating components which bridges the behavioral gaps between humans and computer agents in terms of believability.

The listed contributions filled gaps in the field of human behavior and believable agent. They also provide guidance for game design, believability assessment, and development of believable agent.

1.8 Thesis Outline

In this thesis, I employed an action-based research methodology, where human exploration patterns are exacted based on the analysis of their gameplay, and development and evaluation of believable agents are based on the gameplay of exploration games. In Chapter 2, I give an overview of the research on believability in games, RTS and gameplay AI, spatial exploration, human navigation and exploration and gamer types. Human behavior in exploring virtual environments is investigated in Chapter 3 and behavioral patterns are identified. In Chapter 4, an experimental framework is developed to evaluation believability of agent and identify the framework of believability criteria in exploration games. Chapter 5 presents a *heuristic agent* mimicking human exploration based on behavioral patterns identified in Chapter 3, where its believability and efficiency are evaluated. In Chapter 6, I develop an *integrated agent* which bridges the behavioral gaps between humans and computer agents identified in Chapter 4. Finally, I conclude with the findings and lessons of this thesis, and present future work extending this thesis in Chapter 7.

Chapter 2. Literature Review

In this chapter, I review literatures in fields of believability, RTS and gameplay AI, spatial exploration, human navigation and exploration, and gamer types. In reviewing each of the field, I identify gaps that this thesis contributes to. I also highlight ideas, methodologies, trials and conclusions from previous research which support our work.

2.1 Believability and Believable Characters in Games

Improving the subjective feeling of enjoyment while experiencing games (i.e. playable) is a reasonable way to improve gaming (Nacke et al. 2009). The playable feeling is mainly grounded in feeling immersed (Jennett et al. 2008), presence and flow (Weibel et al. 2008). The implementation of the immersed feeling most likely relies on the techniques of computer graphics, which is outside the scope of this research. Flow represents a mental state that a person has with a feeling of energized focus, full involvement and enjoyment when performing an activity. Strong feelings of presence and flow can be elicited in playing against a human-controlled opponent (Weibel et al. 2008). That motivates our research direction to develop gameplay agents with believable behavior (human-like) for enhancing the feeling of enjoyment.

2.1.1 Turing Test

Turing (1950) proposed the question "Can machines think?", from which he presented the famous Turing test to analyze the intelligence level of computer agents. The typical form of Turing test is that an interrogator in one room uses a computer to play a question-and-answer game with two subjects who are in another room. One of the subjects is human while the other is a computer agent that attempts to fool the interrogator into thinking it is human. The task of the interrogator is to determine which is which. If the interrogator is unable to tell, then the computer agent must be considered intelligent (Figure 2.1).

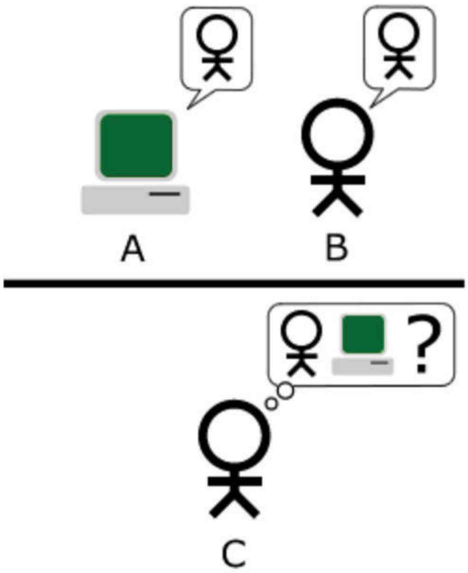


Figure 2.1 Turing test (Turing 1950)

The Turing test encouraged researchers and developers to create a computer agent for passing the test. Turing test based competitions were also organized, providing a platform for practical Turing tests. The Loebner Prize (http://www.loebner.net/Prizef/loebner-prize.html) was first held by Hugh Leobner in 1991, which became an annual Turing test event. During the competition, the programmers were required to create a conversational program (called *chatterbot* or *chatbot*). The interrogator acted as a judge, who chatted with both the program and a human ("confederate"), and then made a determination as to which one was human and which one was the program. The format of the competition has changed over the years, so that the conversational restriction decreased while the chatting time was extended. The competition has awarded the bronze medal every year for the computer system that, in the judges' opinion, exhibits the most "human likeness" among the year's participants. The silver and gold prizes have never been won so far. The silver prize is granted to the first *chatbot* that judges cannot distinguish from a real human. The gold prize is rewarded the first *chatterbot* that judges cannot distinguish from a real human in a Turing test which includes deciphering and understanding test, visual and auditory input.

Aside from high endorsements, the Turing test has also has been widely criticized. The most renowned criticism was John Searle's paper (Searle 1980), in which the "Chinese Room" was presented. He argued that the Turing test could not be the criterion for whether a machine could think. Searle noted that a conversational machine could pass the Turing test by simply manipulating symbols which it did not understand at all. Within that, it could not be identified as "thinking" in the sense that people think.

Getting rid of the criterion of the "thinking" machine, the assessment theory that was implied in the Turing test could be used to reflect the human-likeness of programs' conversational behavior. Human-likeness itself is meaningful in several applications.

2.1.2 Definition of Believability

Human-likeness of artificial entities that can think, feel and behave like humans is, grounded in the idea of believability. The first published page that describes believability is about Disney animation (Thomas, Johnston & Rawls 1981), starting with the words:

> "Disney animation makes audiences really believe in … characters whose adventures and misfortunes make people laugh - and even cry. There is a special ingredient in our type of animation that produces drawings that appear to think and make decisions and act of their own volition; it is what creates the illusion of life."

The definition of believability as the "illusion of life" is widely adopted in the field of interactive agents. Believable agents refer to software programs "that provide the illusion of life, thus permitting [an] audience's suspension of disbelief." (Bates 1994). Riedl & Young (2005) present a precise definition of it: "Character believability refers to the numerous elements that allow a character to achieve the 'illusion of life,' including but not limited to personality, emotion, intentionality, and physiology and physiological movement."

In video games, human players commonly play with or against players who are controlled by AI. To apply believability to these cases, do we still have to pursue the goal of "creating characters to achieve the 'illusion of life'"? Since video games themselves are running in a virtual environment, the feeling of "illusion of life" that human players are likely to get is, actually, the illusion of being controlled by humans (Livingstone 2006; Tencé et al. 2010). Therefore, the fulfilment of believability in video games is transferred to create a gameplay agent, which can make players believe that a human is controlling the agent.

2.1.3 Believability Criteria

Understanding the criteria of believability is a pre-requisite for designing believable agents. Laird & Duchi (2000) designed an in-game observation and questionnaire-based assessing environment to explore the believable criteria with component-scaled Soar in the FPSgame – Quake (Software 1996). They found that decision time and aiming skills affect whether believability is convincing where bots with 0.1 second decision time and mid-level of aiming skill were mostly regarded as human players. Soar is an AI architecture in which long-term procedural knowledge is encoded (Laird, Newell & Rosenbloom 1987). The Hingston (2009) study showed that gameplay bots which applied pseudo-randomness and incorporated skill errors achieved success in performed believability. The judges' comments suggested that measurements such as increasing the range of human-like behavior, eliminating obvious stupid behavior, increasing bot's apparent aggression levels and exhibiting sound tactical play could increase the level of bots' believability in FPSgames. Reynaud, Donnart & Corruble (2014) proposed that efficiency was another factor contributing to believability. In social scenarios, a study from Demeure, Niewiadomski & Pelachaud (2011) indicated that appropriate emotions and variable social-cognition could create high perceived believability.

Tencé et al. (2013) proposed ten requirements for believability. First, the believable agent should react reasonably to other players and the variants of the virtual environment (Livingstone 2006; Wetzel 2004). The reaction time needs to be controlled as long as the human players react (Laird & Duchi 2000; Livingstone 2006). Repeating the same action and behavior undermines the illusion of being human-controlled, which requires the agent to change their actions in different ways and even surprise players with unpredictable behavior (Bryant & Miikkulainen 2006; Isla 2005; Laird & Duchi 2000; Livingstone 2006; Loyall 1997). It is necessary to have similar perception ability to players with whom it interacts (Cass 2002). It should memorize what was presented (Loyall 1997), understand players' behavior (Isla 2005; Pinchbeck 2008) and be able to plan autonomously to avoid possible mistakes (Livingstone 2006). Finally, the agent has to evolve and adapt its behavior via interacting with the environment and players (Gorman & Humphrys 2007; Thurau, Paczian & Bauckhage 2005). The ability to evolve should also appear to be felt by the human players (Tencé et al. 2013).

2.1.4 Believability Assessment

Inheriting from the traditional Turing test, believability assessments are conducted through experiments where judges interact with both *chatbots* and humans in a first-person view and then evaluate the human-likeness of the entities that they communicate with. This approach is called first-person assessment, where a human player (judge) is engaged in a video game against two opponents, which are controlled by another human and an AI system separately. The judge's task is to identify the human among the opponents (Hingston 2009).

Gilbert & Forney (2015) designed an assessment environment where judges chat with 3D virtual *chatbots* and both the AI and psychological factors were evaluated. French (2012) showed that assessing the computer agents' ability to process information and interact in a meaningful way is more crucial than just fooling a human. Karniel et al. (2010) organized a version of the hand-shaking assessment, in which judges physically shook hands with a mechanical arm, which was either controlled by a human or a program. Then, judges attempted to distinguish which was which.

Many scenarios of video gameplay do not require players or characters to interact consistently with each other. In 2K Botprize (Hingston 2009), the judges joined into the game but acted as bystanders. They used a voting gun to shoot and mark the characters which were reckoned as human players. Two potential weaknesses of the method are 1) it is difficult for judges to spend even time on each of the subjects, and 2) in-game operation may disturb the observations.

Togelius et al. (2012) introduced a third-person assessment approach to evaluate Mario AIs, in which judges did not stand in the scenes of gameplay but watched video clips. Llargues Asensio et al. (2014) compared the first-person and third-person assessment methods in the context of BotPrize competition. The results suggested the third-person approach is more demanding than the first-person evaluation in the behavioral context.

Selection of judges is also an important aspect of believability assessment. Within an assessment, keeping both human players and computer agents attempting to be a human that judges expect could reduce recognition errors and increase the accuracy of the Turing test (Warwick & Shah 2015). Hence, judges' expectations of human-likeness involve assessments, which means that whether bots successfully convince judges relies on how much their behavior can match the judges' expectations. Hingston (2009) believed AI and psychology experts who have a thorough understanding of the inner mechanism of AI were the ideal judges for these types of evaluations.

An alternative approach is to employ automated analysis algorithms, which can analyze a series of stored action sequences, performed by human-controlled and AI-controlled characters, referring to 'believability attributes' (Umarov & Mozgovoy 2012). One example is automated believability testing applied in detecting cheating bots in Quake 2 (Pao, Chen & Chang 2010). The authors developed an algorithm to classify any given player as a human or an AI system by comparing the trajectories of characters with pre-recorded trajectories of human players and bots.

2.1.5 Alternatives to Believability Assessment Solutions

Motivated by the Turing Test, a lot of effort has been put into the research of exploring ways to produce computer agents that can operate their intelligence like humans and behave in a humanoid manner. The pre-condition is to have a practical and valid assessment methodology to indicate whether a computer agent is believable or not. In addition to validating the believability of a computer agent, the assessment also provides a deliberative guideline to develop human-like agents.

The review of the literature above provides valuable trials in constructing a holistic approach that can be pervasively applied to believability assessment. Believability itself, however, is a complex trait for any entity. One potential approach is the divide-and-conquer idea, in which believability is tested in environments of different centric concepts, such as achievement, exploration, and sociability might be a potential direction to work. Accordingly, believability criteria within the central, established concepts can be extracted from the believability tests.

The primary assessment methods observe and compare the behavior of subjects within in-game environments. Even though they are valid in assessing candidates of believable AI competitions, the efficiency is not good when they are used as a benchmark in the development of believable agents. In this scenario, both judges and participants need to be present for the experiments in person. Configuring in-game environments for each individual participant and recruiting sufficient number of participants presents a significant disadvantage in scaling up this mode of assessment. Alternatively, standard online questionnaires which are easily distributed with interfaces to label the behavioral differences between human and agents under development might be potential solutions to this problem.

2.2 Real-time Strategy Games and Gameplay AI

2.2.1 RTS Games

Real-time strategy (RTS) is a subgenre of strategy video games that emphasizes strategic challenges (Geryk 2008). Many of them provide economic challenges and exploration. Instead of operating in turn, players play the games in a real-time manner. They are required to have skillful thinking and planning to achieve victory in real-time conditions (Rollings & Adams 2003).

RTS games can be viewed as simplified military simulations, where a player plays against a hostile counterpart within a conflict context. In a typical RTS game, a player orders multiple units and buildings to gather resources, construct expansions, build armies and battle against opponent players' units. The winner is the player who eliminates all the enemy units. Gameplay operations progress in a real-time environment, where players conduct as many actions as they are physically able to make simultaneously, instead of taking turns (Ontañón et al. 2013; Robertson & Watson 2014). In RTS communities, people use Actions Per Minute (APM) to measure the number of actions a player can perform in a minute (Cheung & Huang 2011). It reflects a player's skill, which indicates he both knows what to do in the game and has manual dexterity to carry it out. Novice players have low APM counts, often below 50. Professional e-athletes (electronic athletes, refer to people who join formal video-game competitions) usually have average APM scores around 300. Due to the fact that computer-controlled gameplay transfers instructions directly to the game without any physical operations, the APM count that a computer agent has can be far beyond human players, even at a million or billion level.

Utopia (Daglow 1981) and Cytron (Software 1992) have been controversially considered as the first game of the RTS genre. Later, BYTE, in December 1982, first used the words - “real-time strategy” in describing the Cosmic Conquest as a “real-time space strategy” game which possesses elements of management and war-gaming (Sartori-Angus 1982). The real prototype for modern RTS games emerged with Westwood’s RTS game - Dune II: The Building of a Dynasty (Studios 1992), which featured all the core concepts and mechanics still used in today’s RTS games (Walker 2010). Total Annihilation then introduced 3D units and terrain. Some notable modern RTS games include Company of Heroes, Rise of Nations and the StarCraft, Warcraft, Command & Conquer and Age of Empires series.

Figure 2.2 An example of beginning scenarios in RTS. In an opening scenario, a player has a base building and several basic units which are useful to gather resources and construct other buildings.

Figure 2.3 An example of gameplay of RTS. As the game proceeds, a player deploys his units distributed around the map.

An official game starts with players joined into two camps with an equal number of players. In the base area (Figure 2.2) of each player, a base building accompanying with basic facilities and units are located. Players start constructing buildings, collecting resources and manufacturing units. As the economy grows, players construct more buildings, produce multiple units, research new techniques and expand their force to another resource site. Upgrading and constructing key facilities may unlock advanced units to be produced and techniques to be researched. For balancing purposes, units for each player are not allowed to exceed a pre-set upper limit. Until existing units are eliminated, new units could be produced and refilled. Army forces and defense facilities are usually strategically deployed in many areas outside of the player's base point (Figure 2.3). They functionally help for the purposes of offence and defense. A player (or a camp) wins a game when all the buildings, facilities, and units of the opponent are eliminated. In some games, a player's remaining units will be forfeited when all the buildings are destroyed. Often, players terminate games by spontaneously claiming to give up when they feel they have little chance to win.

RTS games require players to order many units, operate with multiple game objectives and switch among dynamic scenarios and tasks. Several training studies have shown that playing RTS games can improve cognitive functions such as reasoning and visual short-term memory. Basak's (Basak et al. 2008) research suggested that training old people to play RTS games significantly improved their cognitive functions such as task switching, working memory, visual short-term memory, and reasoning, where they used Rise of Nations*:* Gold Edition (Games 2003) as the training tool. Comparing groups of students who were trained in environments of StarCraft and StarCraft II (Entertainment 2010) respectively, Glass, Maddox & Love (2013) found that gaming conditions that emphasized maintenance and rapid switching between various information and action sources leads to the enhancement of cognitive flexibility in fulfilling non-game tasks. Dobrowolski et al. (2015) compared cognitive abilities (measured by task switching and multiple object tracking) of two video game player groups of specific genres (FPS and RTS). The results indicated that players of RTS games demonstrated better cognitive abilities, especially in terms of object tracking, compared to players of FPS games after similar playing times.

2.2.2 RTS Game AI

Video games are commonly regarded as test platforms for advancing Artificial Intelligence (AI) via virtual environments simulating the real world, and a set of rules abstracted from real life. In that sense, AI techniques could be developed and evaluated within RTS games which can then be applied to solve real-world problems (Schaeffer 2001). Buro (2003) encouraged AI research based on RTS games, where the achievements would contribute to solving real-world decision tasks. He highlighted problems that RTS games provide to AI research: resources management; decision-making under uncertainty; spatial and temporal reasoning; collaboration; opponent modelling and learning and real-time adversarial planning. A server-client RTS system is presented (Figure 2.4) that aims to establish a sandbox environment to develop RTS game AI.

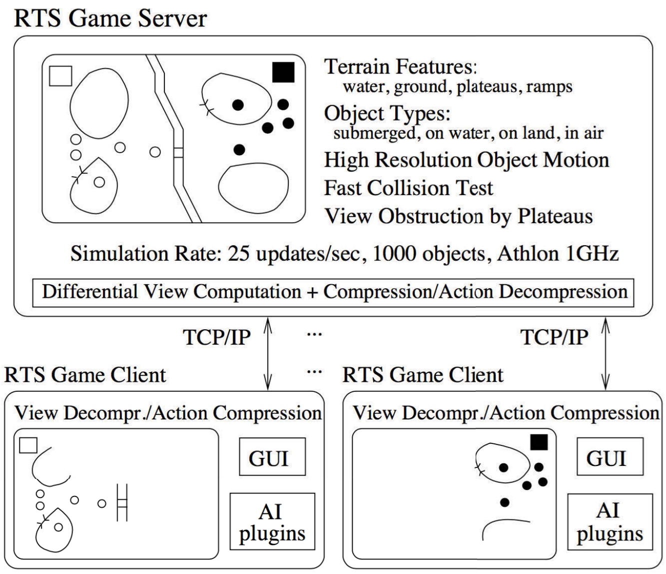


Figure 2.4 Server-client RTS game architecture. Clients connect to a central server which sends player views, receives actions for all objects, and updates the state of the world (Buro 2003)

RTS games require players to balance multiple tasks. Players need to deploy military forces to attack domains of opponent players, while at the same time they need to arrange resources, research new technologies and construct new buildings and units. Resources and time limitations force players to choose between keeping an army with myriad but weak units and building one with a small group of advanced units. Thus, they need to deliberate about allocating time and resources to develop the economy, upgrade technologies and build military forces, all of which requires long-term decision-making and planning, often called macro-management

(Justesen & Risi 2017). I define strategic decision-making as macro-management in this thesis.

In addition to strategic decision-making, players must maneuver units in a specific local scenario. They sometimes format a group of military units to surround and annihilate an enemy troop (Hagelbäck 2012). Many times, they retreat one specific unit with a low health point, apply the power of a unit to a specific object (a group) or control a specific unit to attack enemies that are in a weak situation (Zhen & Watson 2013). These operations are usually called micro-management (Szczepański & Aamodt 2009). Tactical decision-making includes operations of maneuvering specific units for specific purposes, which also refers to micro-management in this thesis.

2.2.3 Strategic Decision-making

Previous research in strategic decision-making has approached this problem as a planning problem, a machine learning problem or a hard-coding behavior problem.

Most commercial RTS games actively use hard-coding behavior approaches. Finite state machine (FSM) is acknowledged as the most common techniques (Houlette & Fu 2003). FSM divide AI behavior into manageable states, such as "attacking", "retreating" and "launching magic," and then bind conditions to these states. When the game process meets the specific conditions, the states are triggered and corresponding actions are taken. Hierarchical FSM is also an active approach applied in commercial games, in which states are composed of hierarchical structures (Houlette & Fu 2003). These hard-code approaches, however, are challenged by issues of encoding dynamic, perceiving and exploiting by opponent players.

Planning techniques organize AI behavior and produce adaptive plans for winning. One important approach is case-based planning (CBP), where AI analyses the case of the current situation and retrieves solutions from the past or hand-crafted similar cases. The first trial of applying CBP into RTS games was by Aha, Molineaux & Ponsen (2005), who developed a CBP system where complex states are abstracted and a set of actions are generated for each state. The ability to match states was then improved over multiple games. Ontañón et al. (2007) combined a behavioral language (ABL), introduced by Meteas and Stern with CBP to generate a real-time case-based system in playing Wargus (https://wargus.github.io/index.html) (a clone of Warcraft II (Entertainment 1995)). Cases are extracted from human-annotated game logs, which can then be composed to formulate in-game strategies for winning the game. Mishra, Ontañón & Ram (2008) extended their work by adding a decision tree model which is used to assess situations when selecting cases (Figure 2.5). That helps to skip unnecessary attribute matching and emphasizes a relevant attribute, which in turn creates a better and faster version. One of the difficulties with CBP systems is retrieving and reusing cases where there are a large number of cases that need to be searched.

Hierarchical-planning methods group similar cases together to solve problems in RTS gameplay. One example is the hierarchical task network (HTN), which maintains task goals, sequences and potential solutions. High-level tasks are decomposed into simple tasks that are stored in successor levels (Muñoz-Avila & Aha 2004). Laagland (2008) implemented a hand-crafted HTN into an open source

RTS game, named Spring.

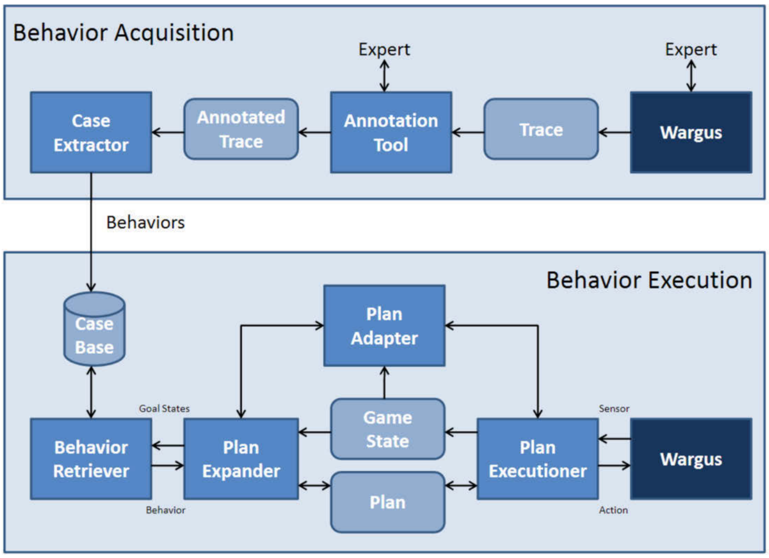


Figure 2.5 An example of implementing case-based planning in Wargus (Mishra, Ontañón & Ram 2008)

This review of literature also includes automated planning, in which a start and a goal state, as well as a set of actions, are given to a gamebot. Normally, heuristic state-space planning with domain knowledge is used to search an action path leading to the goal state from the start state (Robertson & Watson 2014). The full round of RTS gameplay, however, has complex domain knowledge and varying situations. It is even difficult to tell whether achieving goals is going along with the plan, or whether the plan has failed. Therefore, planning to achieve a simple and single goal is a grounded direction. For example, Chan et al. (2007) and Churchill & Buro (2011) employed an automated planning method to find an optimal plan for constructing a particular set of buildings and units in a minimum amount of time.

Regarding making strategies via machine learning techniques, Weber & Mateas (2009) employed supervised learning techniques to develop a strategy learning system, which learns strategies from labelled human-performed replays via a data mining approach in StarCraft. Dereszynski et al. (2011) constructed a gameplay state transition graph and employed Hidden Markov Models (HMM) to estimate the probabilities of building construction sequences and the most probable behavior models in StarCraft. Hostetler et al. (2012) extended their work by adding a dynamic Bayesian network model, where the probabilities from scouting opponent players are considered to identify the strategies. Synnaeve & Bessière (2011) presented a Bayesian semi-supervised model to learn gameplay opening (early game strategies) patterns by observing replays. Then, they presented an unsupervised Bayesian learning model to learn replays, which was capable of predicting selected upgrades in the tech-tree (a tree-shaped diagram which provides a hierarchical visual presentation of what upgrades a player can take) based on observation (Synnaeve & Bessière 2011).

2.2.4 Tactical Decision-making

Tactical decision-making in RTS games is a gameplay behavior where decisions are made for specific game matter, including terrain analysis, reasoning about the formulation of a group of units, corresponding spatial information (terrain and position) and the military abilities and health circumstances of units in battlefields.

Terrain analysis helps AI build up a structured map representation, which provides information for decision-making. A tile-based terrain representation system has been used in BANG – an RTS game (Pottinger 2000). In this system, game maps are separated into many small tiles, which are quad-shaped small spaces. Then tiles are grouped into two types of areas, the convex area and the non-convex area. After generating convex areas and non-convex areas, area connectivity is determined, which is essential for tracking routes in the game.

The qualitative spatial reasoning (Forbus, Mahoney & Dill 2002) technique is used to analyze game maps. Forbus, Mahoney & Dill (2002) introduced soft constraints into the design of the heuristic path-finding method, in which game units achieve dominant positions due to domain knowledge embedded in the algorithm. Compared to traditional map representation in path-finding scenarios, the qualitative spatial reasoning description defines a specific area into three different types—free travel space, narrow path and fire field—by using image processing techniques and Voronoi diagram computation methods (Figure 2.6). A Voronoi diagram is a distance-based region decomposition method.

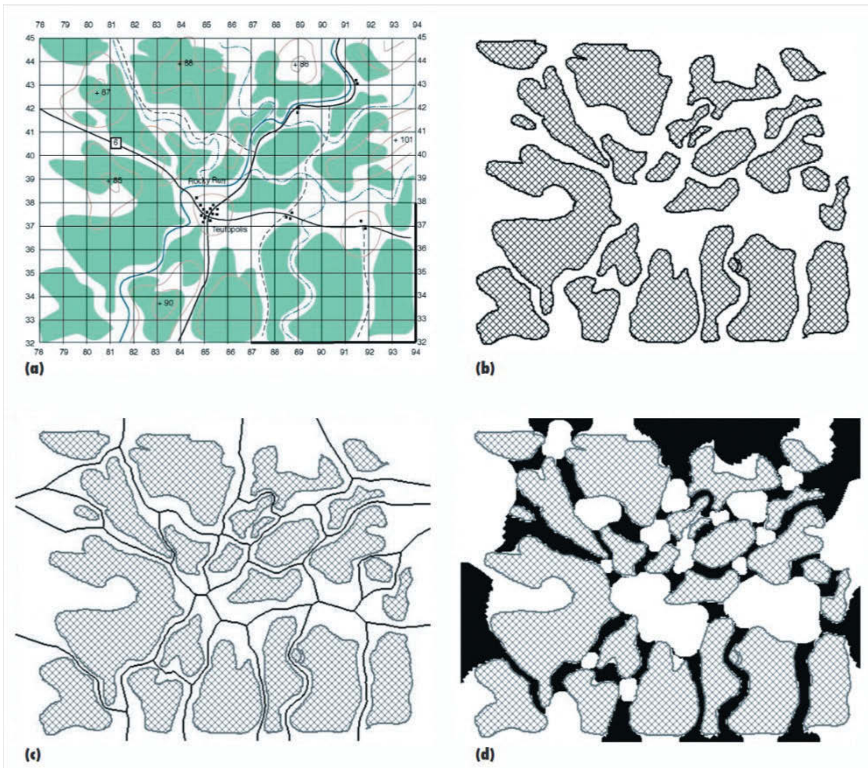


Figure 2.6 Detection of choke points and regions: (a) a map used in an online tactical decision game; (b) terrain that is severely restricted for armored units; (c) a Voronoi diagram; (d) free-space regions (white) and paths (black) (Forbus, Mahoney & Dill 2002).

Perkins (2010) extended the Voronoi diagram by introducing choke points. A choke point is a narrow space that links two expansive regions. Region nodes are identified from the Voronoi diagram, which has the maximal radius in one specific region. Then, the algorithm generates choke point nodes. The army that holds a choke point can easily defend against an enemy army which intends to pass through. Each choke point node is located between two region nodes with the shortest radius. Finally, obstacles and choke points, which are on each region node, are looked up to identify the edges of each region's polygon. The novel process from Perkins was including pruning operations. To reduce invalid computation, Voronoi diagram pruning, adjacent region merging and choke points walling off are done before the next operations.

The automatic-growth mesh technique is another way to do region partition. Hale, Youngblood & Dixit (2008) proposed the algorithm - DEACCON (Decomposition of Environments for the Creation of Convex-region Navigation-meshes) which begins by seeding small quads in each field of the map. The quads grow on each edge until they encounter obstacles. Three different conditions are considered and handled. If an edge of a quad encounters an edge of an obstacle, the current edge stops while other edges go on growing. If an edge comes across a vertex of an obstacle, two new quads are seeded on each end of this edge with other edges extending. If a vertex encounters an edge, the current vertex will be deleted by generating two new vertices on the interaction line. The process is repeated until the whole map is covered by convex regions. Hale & Youngblood (2010) expands this automated navigation mesh generation method into 3D scenarios.

Machine Learning and game tree search are the two most important approaches for tactical decision-making. Hladky & Bulitko (2008) employed hidden semi-Markov models (HSMM) and particle filters for tracking game units in FPS games. Kabanza et al. (2010) combined HMM-based hostile task tracker and HTN-based strategy encoding for predicting the plan and intent of opponent players. Sharma et al. (2007) combined case-based reasoning (CBR) and reinforcement learning to develop a plan-evolvable-and-reusable tactical component. They sped up the learning process of RL by grounding the simulation in a simple scenario and gradually increasing the complicity. Cadena & Garrido (2011) employed fuzzy CBR for strategic and tactical planning.

Reinforcement learning (RL) is an important machine learning technique in maneuvering a small group of units. Shantia, Begue & Wiering (2011) implemented RL to control units in small scale battle, in which artificial neural networks are used to automatically formulate an expected reward for an action of a particular unit in a particular game state. Human assistance is introduced to RL by Judah et al. (2010) to accurately and efficiently learn to control units in a skirmish in Wargus. Finally, Marthi et al. (2005) present hierarchical Q-learning to maneuver a group of units in a “one robot with multiple effectors” fashion.

Applying searching techniques to play complex RTS games is still a difficult problem. There are, however, several successful trials in playing abstracted RTS games or making tactical decisions by using search-based algorithms. Sailer, Buro & Lanctot (2007) implement the theory of searching the Nash equilibrium among a set of pre-defined strategies in a simulated adversarial environment. Churchill, Saffidine & Buro (2012) present the Alpha-Beta Considering Duration (ABCD) algorithm for controlling a group of military units in a simplified StarCraft, named SparCraft, which exclusively focuses on battle scenarios. Chung, Buro & Schaeffer (2005) applied Monte-Carlo planning to play a capture-the-flag simulation game with an open source RTS platform. To win the game, a player needs to maneuver a group of units, avoid obstacles and assaults from enemies, and take the flag from the opponent's camp to his own. Balla & Fern (2009) applied a more novel Monte Carlo tree search method – Upper Confidence bounds applied to Trees (UCT) – to the tactical battle planning scenarios in Wargus.

2.2.5 Holistic Solution

A human-level method is invited into SORTS - a RTS game AI (Wintermute, Xu & Laird 2007). Script-based AI programs extensively run well in FPS games (shooting games in which players have a first-person visual angle). However, features like dynamic environment, multiple goals, rich knowledge and a large amount of data make the drawbacks of scripted AI agents more significant. In the SORTS system, the authors design an integrated AI agent with a perception module and an execution module, which are built on two platforms – Soar and the Open Real Time Strategy (ORTS) which is an open source RTS game engine developed at the University of Alberta. In the perception module, human perception helps to form unit groups and to focus attention. While in the execution module, both micro-management and global coordinators employ FSM to handle unit behavior and make decisions separately. Additionally, McCoy & Mateas (2008) made progress on aspects of integration and of a component specialist. They use ABL to combine modules in the AI agent. The authors develop five specialist competencies—strategy manager, income manager, production manager, tactics manager and recon manager—in which expert high-level strategic knowledge is incorporated to cope with the multi-task environment in RTS games. These manager components interdepend on each other with the assistance of ABL. With the removal of one of them, the entire agent falls into a disadvantaged state, due to a lack of key information or partially uncontrolled facts.

EISBot (Weber, Mateas & Jhala 2011) is a kind of transformation and extension of McCoy and Mateas's work. EISBot is a StarCraft AI agent, which inherits the ABL-based architecture. In terms of improving the ability of the reactive planner, the authors augment working memory by adding beliefs of the game environment, integrate external goal formulation with the enabling agent to pursue a new goal in parallel with the currently active goals, interface with the external goal planner and incorporate a case-based behavior activator.

Unlike ABL-based agents, Young et al. (2012) present a hierarchical architecture by dividing the action space into macro-management and micro-management. In the macro-management part, a belief management system is used to model the opponent and create strategies, while the task–based architecture organizes game units to achieve different goals, such as constructing buildings, assaulting the enemy, defending the enemy and scouting. Tasks are generated, evaluated and monitored while being executed. The behavior of each unit is handled in the micro-management layer. A combat evaluator helps the unit to analyze the environment around it, to decide when to attack or retreat.

2.2.6 Game Bots

Within the StarCraft AI competitions, gameplay bots are developed and submitted for competition. Ontañón et al. (2013) selected a set of brief structured bots: Broodwar, BotQQ, Nova, UAlbertaBot, Skynet, SPAR, AIUR, and BTHAI, from the annually held AIIDE and the Computational Intelligence and Games (CIG) StarCraft AI competitions. They read and analyzed the source code of gamebots, and then diagrammed out components and architecture for each bot (Figure 2.7).

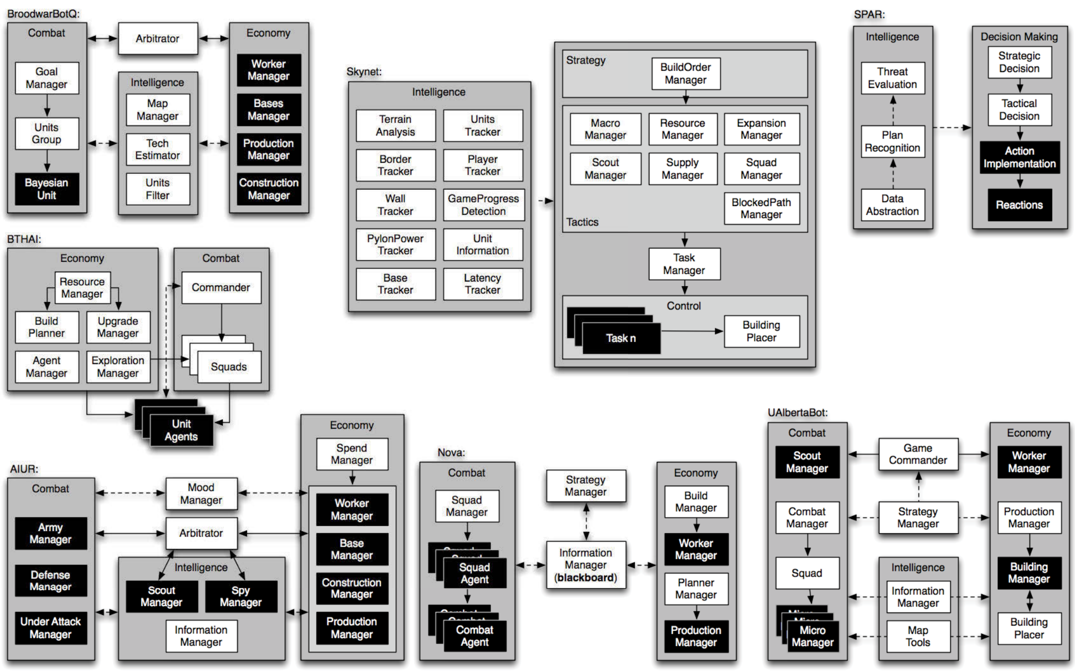


Figure 2.7 The architecture of 7 StarCraft bots obtained by analyzing their source code. Modules with a black background sent commands directly to StarCraft. Dashed arrows represent data flow, and solid arrows represent control. (Ontañón et al. 2013)

The design of game-bots (Kaminka et al. 2002) (in Figure 2.7) solve problems in playing StarCraft by decomposing problems into sub-problems where each of them focuses on a specific aspect of gameplay. By analyzing the architecture of the bots, they put forward two main ideas behind the design.

1. Abstraction: complex tasks can be abstracted hierarchically, where each task is put into different hierarchical layers. A simple multi-layer structure is a dual-layer of the strategic layer and tactic layer. For example, a strategy of launch "Zealot Rush" (Zealot is a kind of basic combat unit of the Zerg race

in StarCraft. Since training zealots does not require high technology and it costs very less resources for training one unit of zealots, it is possible to train a zealot army with an appreciable quantity at the beginning time of a game. “Zealot Rush” represents a strategy where Zerg players train a zealot army to destroy opponents’ base at the beginning time when opponent players do not get a chance to build up a defense force.) should be divided into two layers of tasks. In the strategic level, the task means to schedule resources to produce a sufficient zealot army and launch the rush in the right timing, while tasks of how to build a zealot army and decisions about what kind of army formulation would be required when rushing would be solved in the tactic layer. Correspondingly, the problem solvers are structured in hierarchical levels within the bot. For achieving a goal using a high-level module generating a series of abstracted actions and sequences, the actions determined by higher-level modules are considered as the goals of the lower level modules (Ontañón et al. 2013).

2. Divide-and-conquer: Due to the complexity of RTS, gameplay requires fulfilling tasks on different functional facets, such as developing economies, scouting, harassing, constructing buildings and producing armies. Completing each of these tasks is relatively independent behavior. Each module is designed to focus on one specific facet. Modules occasionally collaborate to complete tasks, when a task relies on other tasks to be completed or processed in a particular timeframe (Ontañón et al. 2013).

2.2.7 Open Areas of RTS AI

The review of RTS AI literature indicates several open areas:

Automated Learning and Evolving

Developing RTS game-bots commonly involves implementing domain knowledge (Aha, Molineaux & Ponsen 2005; Ontañón et al. 2013; Ponsen et al. 2007). Domain knowledge that the AI developers have will determine the quality of gameplay bots, which are manually implemented (Ontañón et al. 2007) or learning (Weber, Mateas & Jhala 2011) from labelled gameplay examples. The development relies on the scope of an existing set of playing knowledge: strategies, tactics and tricks. Hence, the limitation of existing human-discovered knowledge has restricted the development of gameplay AI, let alone the constraints of knowledge representation and implementation. Gameplay bots can only be improved by playing knowledge being increased and implemented. Enabling AI to learn and improve their playing skills via consistently playing is a promising direction. Even though reinforcement learning (Judah et al. 2010) has been applied to maneuver units in small-scale scenarios, it is still a long way to go to extend it into formal full-round RTS game playing.

Collaborative and Adversarial Play

Playing with or against other players is commonly supported in RTS games, and many other video games such as FPS and RPG. A player needs to adaptively adjust his strategies to strategically collaborate with allies or beat opponents by taking advantage of their weaknesses. This process requires the player to continuously observe other players' behavior, normally scouting opponents' deployments due to the "fog of war" mechanics. In RTS games enemy units, and terrain are normally hidden from the player by a shade layer called fog of war. It is revealed when the area is explored, but the information is often fully or partially rehidden when the player does not have a unit in that area (Adams 2014). Based on acquired information, a player could guess the strategies they are using and predict the next actions they will make. Many times, the information is incomplete. The player should make predictions with imperfect information while simultaneously devising scouting strategies to acquire information which is urgently needed.

Player modelling techniques have been applied to predict the opponent's opening strategies (Synnaeve & Bessière 2011) by observing their constructed buildings. Handling the situations of strategies changing and consistently scouting is still not solved. In many cases, AI players' behaviors are observed by their allies or opponents. Making the behavior believable could enhance the gameplay experience (Togelius et al. 2012). It is still an area which has not been sufficiently researched in RTS AI.

Integration

Playing a complex RTS game requires fulfilment of many concepts of tasks, such as resource gathering, determining building orders, placing buildings, expanding and deploying defense forces, scouting, harassing and attacking. In the review of literature above, many efforts are put into solving a specific task. It is common that optimal solutions for different tasks need different techniques. This leads to inconsistency in knowledge representation, architecture construction and information communication among components. Integrating different components is still an open problem in RTS AI research. Alternatively, borrowing ideas from other fields like Go AI (Silver et al. 2016), to apply techniques holistically for conducting all the tasks might be another possible direction.

Believable Gameplay Agent

Techniques that allow the gameplay agent to learn strategies directly from the playing records of humans or employ the cognitive architecture that models how humans solve problems are actively applied in the literature. In this sense, researchers tend to approach AI's playing to a human-level, which means making AI players beat human players without cheating. However, the direction of developing a believable gameplay agent is neglected in the RTS genre. As discussed in 2.1 Believability and Believable Characters in Games, gameplay agents that exhibit believability can enhance the experience of human players. Therefore, having RTS AI with believable behavior is a promising but under-researched direction.

2.3 Spatial Exploration

In RTS games, the fog of war covers the detail of terrain and enemy units. Players can only notice the enemy units and map patches when these objects fall into the visual range of their own units. To capture information about enemy and terrain, AI agents assign scout units to detect the game environment. Therefore, how to plan the scout path to get more information is a difficult problem for the scouting agent. The scouting task shares common problems with spatial exploration where an entity with a limited visual range explores in a totally or partially unknown environment to map the terrain or to search for specific items.

2.3.1 Terrain Exploration

Building map information incrementally by gathering spatial environment data is a new approach for analyzing game terrain. The challenge is how to navigate scout units in the right way; in other words, gathering more terrain data in a short time, and avoiding damage. One potential field technique (Hagelback & Johansson 2008) has been used to deal with fog of war in Wargus, to reveal the covered map. Park et al. (2012) presented a heuristic navigation tactic for scout units to collect opponents' information. They devised a navigation method where a scout walked around the enemy base. There is still no accepted algorithm to solve the unknown territory detection problem in the RTS game field.

The primary goal of scouting strategies is to collect the spatial data in a particular area. It is similar to robotic exploration of unknown terrain. For robotic research, the problem is that computing an exploration path is a sub-field of the area-mapping problem, in which a robot equipped with a detection sensor with limited visual range explores in an unknown planar environment to completely collect all the map information (Choset 2001). Since searching an optimal path for a map coverage robot (i.e. start from one point, then completely explore the map space and go back to the origin point) is still an NP-hard (non-deterministic polynomial-time hard) problem (Arkin, Fekete & Mitchell 2000), some algorithms are developed to fulfil the task approximately. For instance, wall following strategies are simple ways to collect segments of the movement space border, which are presented in (Lee & Recce 1997).

Kim, Zhang & Egerstedt (2010) present a trajectory-based exploration strategy by constructing Voronoi diagrams. This solution relies on the pervasively distributed obstacles in the exploration space. Due to the incomplete knowledge of the space, there are many uncertainties in planning a path within several steps. A promising approach is to select the next-best-view (NBV) in each step, where less distance is taken, while a big step achieves the final goal (i.e. collecting more territory information). Normally, the NBV is chosen from either observable position in a current view or explored locations in previous steps. A coverage-map-based strategy is presented by Stachniss & Burgard (2003), which formulates the map into occupied grids with a probability model. Amigoni & Caglioti (2010) present the theoretical aspects of the criterion for determining the best observation positions, in which entropy theory is employed to calculate the expected information gathering (Figure 2.8). A multi-criteria decision-making (MCDM) strategy for choosing NBV is presented by (Basilico & Amigoni 2009) by using Choquet Integral (Grabisch & Labreuche 2010) to combine criterion utilities.

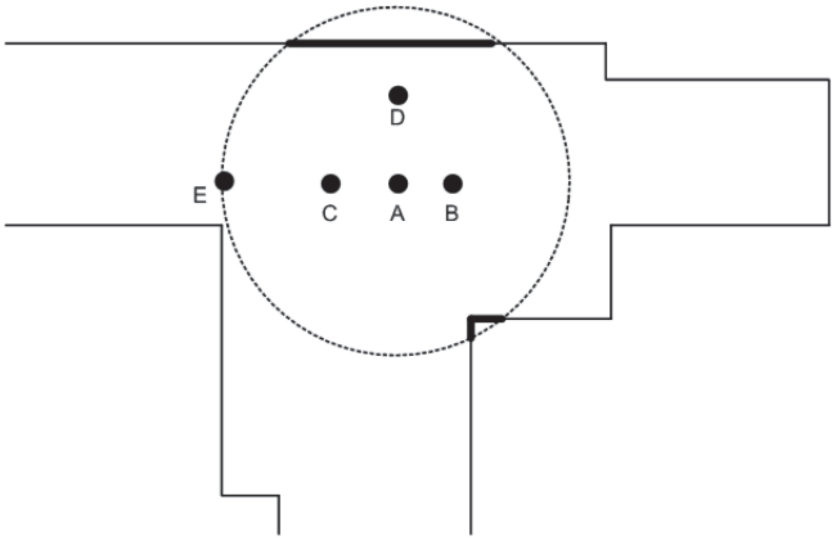


Figure 2.8 Observed candidate positions (Amigoni & Caglioti 2010)

Tovar et al. (2006) present a one-step-look-ahead strategy by generating a search tree from candidate positions during exploration. Li, Amigoni & Basilico (2012) formulate finding exploration paths in the planar grid environment as a search problem, in which the occupation state of global grids is tested when doing next step planning. As investigated, the frontier-based map representation method proves to be an effective way to filter candidate positions for evaluation (Amigoni 2008). Compared to grid-based map presentation, choosing the next potential points along frontiers intuitively provides more chances to gather knowledge of unknown areas.

2.3.2 Coordinated Exploration

The efficiency of exploration can speed up by assigning a group of units, which work collaboratively with each other. The agents can share their visual range, gathered information and data. In multi-entity cooperative scenarios, one fundamental problem that the system confronts is how to organize the entities, distribute sub-tasks and coordinate them while avoiding the overlap or redundancy. Three types of network organization architectures are presented in the state-of-the-art literature. They are centralized, hierarchical and decentralized (Rone & Ben-Tzvi 2013).

In centralized architectures, there is an inner or outside controller which processes all communication and computation (Howard, Matark & Sukhatme 2002). The control entity is allowed to access the global states, and to manage all the entities. The entire system is a failure if the controller fails.

Hierarchical architectures can be named as centralized hierarchical architectures, in which a single entity at the highest level, controls a group of other entities, and then each unit in this group coordinates another group of units. Units in the lowest level simply perform tasks. For instance, Nieto-Granda, Rogers & Christensen (2014) present a branching-reserve strategy, in which the original exploration tasks are distributed by a unit at its higher level when new possible branches are detected.

Decentralized architectures provide the greatest flexibility by not having controllers. All the entities compute and plan individually and communicate with others. There are many coordinated models within this architecture. A market model is introduced for developing a redistribution of assignments mechanism (Zlot et al. 2002). In this approach, each agent has a set of priced targets generated from explored areas. Agents can trade their goals to maximize revenues, which, in turn, manage to achieve the global target effectively. The free-market approach has also been widely used in various multi-agent systems (Choi, Brunet & How 2009; Khan & De Silva 2014; Stentz & Dias 1999). Decentralized architectures are useful in performing cooperative tasks across different systems. With the free-market model, it is a promising architecture to solve the problem of coordinated exploration among the various players.

2.3.3 Reconnaissance

The potential field (Hagelback & Johansson 2008) technique is used to deal with fog of war in Wargus. The terrain map is represented by blocks of 4*4 terrain tiles. The visited flag of each tile determines whether a certain block has been explored. A distance based piecewise function is used to calculate the exploration potential of unknown blocks. The value of potential field determines which block should be visited in the next step for scout units. The distance-based navigation tactic just makes the reconnaissance (or recon) unit avoid repeating the exploration of known blocks. However, the most interesting areas are not explored prior to this.

Park et al. (2012) present a heuristic navigation tactic for recon units. Motivated by the behavior of human players, who almost always control their scout unit to walk around the enemy base to capture more information, the authors developed an algorithm to assign the recon units to move around the enemy buildings they detected. The recon units modified their move direction when a new enemy building was found. The movement direction is perpendicular to the vector, which is calculated by setting the position of the recon unit as the start point and the location of the building as the end. If there is more than one building, the building vector is the sum of them. Although these two recon algorithms contribute to the scout opponent's buildings and units, there is still no efficient method to detect game terrain and to organize terrain areas that have been found.

In terms of high-level planning for reconnaissance, the fact is not all terrain information is useful for the AI agent to make a decision. Experience shows that the areas from friendly base to opponent's base are repeatedly reached by both sides of the units. The resources that are arranged to scout are very limited. Therefore, when to scout, where to scout and which units are assigned to scout are three difficult problems for a scout agent. Chung, Buro & Schaeffer (2005) employs the Monte Carlo method to create a planner for combat scenarios in RTS games. To simplify the experimental conditions, they create a flag capture game (two groups of units fight against each other to capture their opponent flag) based on ORTS.

First, the planner generates a game plan for each AI player randomly and executes it. Second, an evaluation function is developed to record the result of the execution. Third, the first two steps are repeated a number of times. Finally, the planner chooses the best plan for the AI agent based on the statistical result. Regarding evaluation function development, three classes of factors are calculated. These are the hit points (health) of the army, exploration, and visibility (whether the flag has been captured).

Another promising algorithm (Balla & Fern 2009) – UCT is used to make a tactical assault plan for RTS games. They aim to develop group-based planning rather than individual units. Two actions for planning are joining several army groups into a large group and uniting a friendly group to attack a certain army. In state formulating, hit points, friendly group action and current game time are calculated. Naves & Lopes (2012) present a stochastic search and planning method to solve the production planning of resources. The actions–collecting resources, construction building and unit producing—are described as consumers and producers (i.e. each action needs to consume some resources or produce some resources). There is still no strategy planning in spatial exploration or other related areas. However, the abstraction methods described above might be useful for us to describe states and actions when the scout planner is designed.

2.3.4 Generating Believability in Movement

Navigating the movement of scout units in a believable manner is an indispensable part of generating a human-like scouting agent. Several experiments have been made to simulate plausible movement behavior. Henry et al. (2010) employed inverse reinforcement learning to train a navigation agent in a crowded environment. Its weakness to maintain a plausible behavior in a crowded environment is that both the environment and the training data are generated by simulation. A genetic approach is used to evolve an artificial neural network that implements dynamic obstacle avoidance while following a direct path (Graham, McCabe & Sheridan 2005). In the video game field, research in developing plausibility is of more interest in the FPS genre, in which behavior in low-level movement such as changing direction, changing speed and jumping, as well as game actions like aiming and firing, are considered. One proposed global architecture combines independent and hand-tuned neural networks for delivering human-like control (Gamez, Fountas & Fidjeland 2013). Thurau, Bauckhage & Sagerer (2003) developed a learning structure for the agent to learn primitive actions from the state of position and relative position of the enemy, by using self-organizing maps and artificial neural network approaches. Tomai, Salazar & Flores (2013) employs spline representation to model human-player movements. Combining the human-controlled movement data collected from a simple massive multi-player online role-playing game (MMORPG)-like game and the spline, an algorithm is developed to mimic human-like movement in open world games.

2.3.5 Human-like Exploration

Automated exploration (AE) and human-controlled exploration (HCE) are the two primary ways that computer agents act as assistants to help humans reach somewhere humans themselves could not easily reach and gather spatial information that is totally unknown or incomplete to them. The advantages of these two approaches are grounded on different points. AE benefits humans with labor saving and focuses on the completeness of exploration in an acceptable time span, while HCE helps to effectively capture the spatial locations that humans are more interested in. In other words, these two ways are functionally complementary to each other. It is meaningful to unify their benefits in one system. A possible direction is to make human and computer explorers collaborate with each other in a better way, where human assign high-level tasks (for example, seeking source of water around) to computer explorers, meanwhile computer explorers are capable of automated exploration in a human manner. That means they could not only autonomously fulfil exploration tasks but also prioritize gathering information that humans care more about. It requires intelligent explorers to make exploration decisions in a human-like way.

Spatial exploration is a core concept of the design of video games. It is pervasively implemented in the playing of many game genre, including RTS, RPG, FPS and especially adventure games. A commonly focused area is to develop intelligent gameplay bots that play with and against human players. The philosophy is that enabling gameplay bots to be human-like (believable) can enhance the experience of players. Developing believable spatial exploration AI, which exhibits human-like exploration behavior, is a fundamental step to building human-like playing bots.

Finally, most of the previous work has focused on developing human-like movement models in low-level perspectives (for instance, navigating in crowed environments (Henry et al. 2010), learning to avoid enemies (Thurau, Bauckhage & Sagerer 2003) and moving in curve trajectories (Tomai, Salazar & Flores 2013)). It is still an open problem to develop an agent to handle high-level tasks, like scouting, while mimicking human-like movement in a believable manner.

2.4 Human Navigation and Exploration

Understanding how humans navigate and explore is an important step to develop believable agents which can explore unknown environments in a human-like way.

2.4.1 Human Exploration and Way-finding in the Real World

Understanding how humans explore and navigate in the real world is a well-explored research area. Knowledge construction was deemed to be an important aspect of exploration (Kuipers 1978; Kuipers, Tecuci & Stankiewicz 2003; Meilinger, Knauff & Bülthoff 2008; Viswanathan, Lees & Sloot 2015). In particular, the variations among how people construct navigational knowledge in the form of cognitive maps (Eichenbaum 2017; Hartley et al. 2014; Howard et al. 2014; Pfeiffer & Foster 2013; Wu & Foster 2014) remains an active research area. Lynch (1960) proposed that the cognitive map for navigation is composed of five components: paths, edges, districts, nodes and landmarks. The case with which people can navigate in new environments is influenced by the number of choice points, visual access, the degree of structural differentiation and other factors which determine how cognitive maps are created (Evans & Pezdek 1980; Gärling, Lindberg & Mäntylä 1983; Gibson 2009; Gopal, Klatzky & Smith 1989; Weisman 1981).

Pfeiffer & Foster (2013) firstly provided direct evidences for future-focused sequences of navigational activity in neurons (called place cells) of hippocampus in a realistic two-dimensional environment. Additionally, Wu & Foster (2014) presented that hippocampal replay captures the topological structures of learned environmental environment to support navigation. Furthermore, Howard et al. (2014) reported that hippocampal contains both the Euclidean distance and the path distance to goals as distance representations during navigation. Although these real-life navigational studies can provide some insight into how people explore virtual environments, our research scopes out a new area of study that focuses on exploration in a new way.

As state-of-the-art simulation techniques enable virtual environments to be sufficiently similar to real environments, it allows simulation-based experiments and testing of navigational memory. Viswanathan et al. (2014) explored the role of memory in real-life way-finding by investigating user behavior in their self-developed indoor virtual environment.

2.4.2 Human Exploration and Way-finding in Virtual Environments

Developing analysis tools to investigate players' behavior by analyzing gameplay data is a popular way to understand players' experience and inform game design in general (Chittaro, Ranon & Ieronutti 2006; Drachen & Canossa 2009; Moura, El-Nasr & Shaw 2011). ArcGIS (Esri 1999) was used by Drachen & Canossa (2009) in a video game context. It enabled researchers to visualize game metrics via multiple facets of data related to spatial environments. Chittaro, Ranon & Ieronutti (2006) developed a visualization tool named VU-flow, which presents visual components that allow users to observe and extract behavioral patterns from individuals as well as populations. In another work, Moura, El-Nasr & Shaw (2011) developed a visualization system that is capable of visualizing players' actions in an active way which is used to analyze telemetry data, extract gameplay patterns and identify design issues (Figure 2.9). It provides protocols to visualize the time spent in each area of game maps, identify active regions and extract players' navigation paths. Although these visualization tools provide a general solution for spatial analysis, they can only act in a complementary role when understanding human navigation and way-finding behavior, because experimental subjects vary from scene to scene.

Figure 2.9 The interface of a visualization system for way-finding data (Moura, El-Nasr & Shaw 2011)

Regarding human navigation, Moura & Bartram (2014) investigated how players responded to different visual way-finding cues in several scenarios: maze, climbing room, waterfall room and exit room, based on the 3D action-adventure game, The Lost Island. They found that proper feedback guidance was highly demanded throughout navigation, and players were very sensitive about missing cues.

Another study about developing a visual system for enhancing players' navigation experience was conducted by Milam et al. (2011), in which the relationship between visual load, camera and motion attributes was investigated. Moura & El-Nasr (2015) summarized a set of design techniques that are currently used in navigation systems of 3D action-adventure games which include three aspects: navigation aids, level design choices affecting navigation and game mechanics related to navigation. Biggs, Fischer & Nitsche (2008) also attempted to understand players' construction and comprehension of small-scale environment patterns in procedural environment generation applications. Their results showed that players who interacted with structured patterns tended to be goal-oriented and preferred to construct cognitive maps.

Using a different approach, Badler & Canossa (2015) designed experiments in a Tropical Island demo to analyze players' camera movement and gaze displacement. They found that players' gameplay gaze behavior resembled that of real-life activities.

On the perspective of player personalities, the five factor model (FFM) (Goldberg 1993) framework has been broadly used to analyze exploration behavior. van Lankveld et al. (van Lankveld, Schreurs & Spronck 2009; van Lankveld et al. 2011) presented links to preferences of an exploration map with the activity facet of the extraversion type in FFM. Yee et al. (2011) concluded that non-combat exploration and exploration with curiosity behavior could map to the agreeableness and openness personality traits respectively. Canossa et al. (2015) introduced players' behavior of interacting with doors as a variable into game metrics when conducting correlation analysis between exploration behavior and the big five personalities which indicates that an explicated personality correlates with the type of the in-game environment as well as the behavior that the play is conducting, while Spronck, Balemans & Van Lankveld (2012) located triggers in optional areas of the experimental environments to test the openness of exploration behavior. Although it appears that current research has discovered several interesting connections between exploration behavior and players' personalities, behavioral patterns of exploration remain to be explicitly identified.

Category	Literature	Contribution	Sub-field
Real-life navigation	Evans & Pezdek (1980) Gärling, Lindberg & Mäntylä (1983) Gibson (2009) Gopal, Klatzky & Smith (1989) Weisman (1981)	The number of choice points, visual access, the degree of structural differentiation determine how cognitive maps are created.	Construction of cognitive map
	Lynch (1960)	Cognitive map is composed of five components: paths, edges, districts, nodes and landmarks.	Structure of cognitive map
	Wu & Foster (2014)	Hippocampal replay captures the topological structures of learned environmental environment to support navigation.	
	Pfeiffer & Foster (2013)	Provided evidences for future-focused sequences of navigational activity in neurons of hippocampus.	Planning
	Howard et al. (2014)	Hippocampal contains both the Euclidean distance and the path distance to goals as distance representations during navigation.	Distance-measurement instrument
	Viswanathan et al. (2014)	Investigated the role of memory of real-life way-finding in indoor environments.	Memory
Navigation in virtual environments	Moura, El-Nasr & Shaw (2011)	Developed a visualization system which could actively visualize players' actions to analyze telemetry data, extract gameplay patterns and identify design issues.	Visualization and analysis software
	Moura & Bartram (2014)	Investigated how players responded to different visual way-finding cues in several scenarios: maze, climbing room, waterfall room and exit room, in a 3D action-adventure game.	Environments effect navigation behavior
	Milam et al. (2011)	Investigated the roles of visual load, camera and motion attributes in enhancing navigation.	Navigation enhancement
	Moura & El-Nasr (2015)	Summarized a set of design techniques navigation aids, level design choices affecting navigation and game mechanics related to navigation applied in 3D action-adventure games.	Game design for in-game navigation
	Badler & Canossa (2015)	Found that players' gameplay gaze behavior resembled that of real-life activities.	Similarity of navigation in virtual environment and real-life way finding
	van Lankveld et al. (2011)	Discovered the connection between the extraversion type in FFM and preferences of exploring a map.	Connections between exploration behavior and personalities
	Yee et al. (2011)	Mapped non-combat exploration and combat exploration to agreeableness and openness type respectively.	

Table 2.1 Key contributions in the fields of human navigation behaviors.

2.4.3 Archetypes of Spatial Exploration in Virtual Environments

Discrete spatial systems of human cognition and behavior such as spatial memory, orientation, and navigation have aroused the interests of researchers and encouraged them to study them. However, the research area is still shrouded in darkness in terms of understanding people's variations in using their systems. There are differences in their abilities, disabilities and preferences. Identifying archetypes and categorizing people into different spatial navigation types will contribute to better understanding. As the review of literature above shows and Table 2.1, exploring human behavior in terms of navigation and way-finding in real-life has been a subject of interest to researchers for some time but it is still an open area in virtual environments. Studies, in the literature, emphasized on general navigation and path-finding behavior. Spatial-exploration behavior, as an independent activity, has not been fully investigated. It would be much interesting to open the box of spatial-exploration behavior and categorize them into different types, which will enable us to have a better understanding human behavior of spatial-exploration.

2.5 Gamer Types

The broad field of research in classifying player behavior has drawn much attention from game user researchers for two essential reasons. The first reason is that understanding players' personalities helps to design better games, which enhance players' experiences. A deeper understanding of players' needs and desires can be used for better game design, balancing game content, structuring experiences and selecting virtual goals (Charles et al. 2005). Another reason is it benefits the development of "gamification" for the game market, where research subjects (gamers) are potentially the consumers (Hamari 2013).

The categories of typology studies of gamers' internal segmentations are the psychographic basis and behavioral basis, which differ from external segmentations including *geographic factors* (where gamers live) and *demographic features* such as age, gender, education and occupation (Hamari 2013).

2.5.1 Psychographic Basis

The psychographic approach tries to group players according to their independent attitudes, interests, values, and lifestyles. Ip & Jacobs (2005) presented a two-type model, where players are divided into hard-core players and casual players. Compared to casual players, hard-core players as described by Ip & Jacobs are people who prefer to deliberate over their gameplay. They deliberately try to game in different ways, acquire comprehensive knowledge about games, play longer and more often, and actively participate in game-related forums. This model, however, has been criticized (for example Bateman, Lowenhaupt & Nacke (2011)) as too simplistic.

Reviewing the research on human personalities which is embedded in game research, researchers have used both type-based models, such as the Myers-Briggs Type Indicator (MBTI) (Myers, McCaulley & Most 1985), and more recently trait-based models, such as the FFM (Goldberg 1993). Type-based models assume that each personality is mutually exclusive. Myers, McCaulley & Most (1985) developed MBTI, using four bipolar axes to distinguish personality types in four dimensions. In each bipolar axis, two opposite psychological types are marked on the ends. The four groups of dimensions are: extroversion and introversion, sensing and intuition, thinking and feeling, and judging and perceiving. Different permutations of these dimensions classify individuals into one of sixteen types. On the other hand, trait-based models emphasize measuring traits, which can be defined as patterns of individual preferences in behavior, thought and emotion (Kassin 2003). The Five Factor Model (Goldberg 1981) includes five personality traits - *openness*, *conscientiousness*, *extraversion*, *agreeableness*, and *neuroticism*. The FFM is currently a leading model in personality psychology (Goldberg 1993). Correlations between players' gameplay patterns and the FFM have been an active research area (Canossa et al. 2015; Spronck, Balemans & Lankveld 2012; Tekofsky et al. 2013; van Lankveld, Schreurs & Spronck 2009; van Lankveld et al. 2011; Yee et al. 2011).

Bateman & Nacke (2010) offered insight into the underlying neurobiological mechanisms of gamer types and presented an interim gamer model – BrainHex, via a top-down lens. This model includes seven-gamer types: *Seekers*, *Survivors*, *Daredevils*, *Mastermind, Conquerors, Socialisers* and *Achievers*.

Seeker – The Seeker type is interested in the game world and obtaining fun experiences through exploring environments.

Survivor – These people enjoy experiencing the feeling of terror. For example, they gravitate towards environments with a horror context.

Daredevil – Players of this type are thrill seekers and enjoy taking risks.

Mastermind – This type enjoys solving puzzles, devising strategies and making more efficient decisions.

Conqueror – Players that fit this type like challenges and winning easily does not satisfy them.

Socialiser – Players who come under the *Socialiser* archetype enjoy interacting with other players in games. They like talking to other players, collaborating with them to fulfil game tasks and attacking other characters intentionally or unintentionally.

Achiever – Players of this type are motivated by the game goals. They especially focus on achieving long-term goals.

Founded on neurobiological theories and validated with a large number of participants (50, 000 players (Bateman, Lowenhaupt & Nacke 2011)), the BrainHex model attempts to provide a more generalizable typological model across game genres.

2.5.2 Behavioral Basis

Behavioral approaches devote attention to identifying patterns of gameplay behavior within one or across several game genres.

Some research looks into the essential nature of playful experiences. Efforts have been made to develop types of game mechanisms that surprise players. Barash & Caillois (2001) described four playful behavioral patterns, choosing words from different languages in order to reach the original concept. *Agon* referred to games that provide the challenge of direct competition. *Alea* described games with chances and randomness. *Mimicry* was used to describe the play as someone or something else. *Ilinx* described games with sensory stimulations.

Lazzaro (2008) focused on the discovery of emotional patterns of fun when observing player studies. The result demonstrated four distinct patterns, which were termed the Four Fun Keys. *The hard fun* comes from achieving a goal when playing, where a player fulfils a goal of the game or meets a challenge that they come across. It is related to the desires of BrainHex's *conqueror* and *achiever* archetypes. *Easy fun* reflects the curiosity of virtual arts, unknown environments, well-designed mechanisms and dormant entities, which stimulates explorative play. *Serious fun* is related to immersive experiences, in which players find it exciting to engage in the game world. *People fun* is generated from the relationships with other players. For example, players have either competitive or collaborative sessions with others in multiplayer games.

A direct way is to recognize patterns via observing gameplay behavior and analyzing data from playing. Drachen, Canossa & Yannakakis (2009) observed a set of players engaged in the adventure game *Tomb Raider: Underworld* and identified four types (*Veterans*, *Solvers*, *Pacifists* and *Runners*) of players that significantly correlated with the total number of deaths and the completion time. *Veterans* have the most reasonable playing style, where they have a rare number of deaths and complete the game very quickly. *Solvers* spend relatively little time on solving puzzles encountered during the play. *Pacifists* complete the game very quickly but at the expense of dying frequently. *Runners* skip over the details of playing and play the game swiftly.

Bartle's (Bartle 1996) research is one of the most cited works in terms of player typology. Observing players' behavior in the multiplayer strategy game Multi-User Dungeons (MUDs), he described a qualitative model with four player types (*Killers*, *Achievers*, *Socialisers* and *Explorers*) via a two-dimensional factor of playing, namely acting vs. interacting, and player vs. world (Figure 2.10). *Achievers* are players who are focused on fulfilling the tasks designed in the game, such as gathering reward points and seeking treasures. They prefer actions and world-oriented activities. *Explorers* are interested in revealing how the game mechanics work, which illustrates their preference to interact with the game world. *Socialisers* are more interested in interacting with players than the game world itself. They are motivated to know other players, formulate a relationship with them and play with them. *Killers* engage in playing competitively with other players, where they get satisfaction from beating others, and in many cases showing off their intelligence and skills. This type is more oriented towards action and other players.

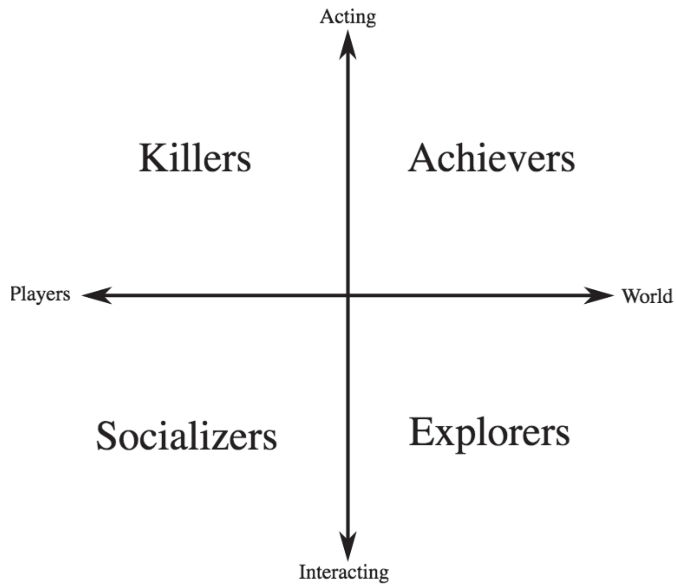


Figure 2.10 Bartle's player type axes (Bartle 1996)

2.5.3 Behavioral Types of Games' Central Concepts

Video game user research has focused on classifying players based on their preferences, but has not sufficiently accounted for the actual behavior of players when fulfilling specific game tasks and interacting with the game and other users. This behavior could be included in the core concepts of games: *Achievement*, *Exploration*, *Sociability*, *Domination*, and *Immersion*. Many models include some of these concepts. For example, Bartle's *Achiever*, *Explorer*, *Socialiser*, and *Killer* map to *Achievement*, *Exploration*, *Sociability* and *Domination* respectively. Yee's model covers *Achievement*, *Exploration*, *Sociability* and *Immersion*. It is, however, necessary to discover a player's typology in each concept. That means it is inadequate, for example, to reach conclusions about player achievement and sociability separate from the other dimensions in terms of overall categorization of players.

Chapter 3. Understanding Players' Map Exploration

In this chapter, I investigate how players explore game maps and identify the behavioral patterns of players. To achieve this, I answer **Q1**:" How do players explore virtual environments? What behavioral patterns do they exhibit?" by finding the answers to its three sub-questions.

Q1.1 What behavior do players exhibit in exploring these virtual environments?

Q1.2 Can we classify and extract types of exploration behavior?

Q1.3 What factors affect exploration behavior?

To answer the three questions, I organize gameplay experiments, in which thinking aloud (Tan et al. 2015), interviewing and in-game records help to capture the players' behavior and the corresponding self-descriptions of players (**Q1.1**). To identify players' types in exploration, I use an inductive research method that extracts commonalities and patterns from the yielded rich data set. Instead of starting from pre-determined personality typologies (Goldberg 1993) or following up the methods of neurobiology research (Nacke, Bateman & Mandryk 2011), I investigate players' behavior directly. I extract patterns across the datasets collected during and after players' gameplay sessions (**Q1.2** and **Q1.3**). Thematic analysis provides a theoretically-flexible analysis method, which is suitable for tasks such as identifying themes from the users' experiences (Braun & Clarke 2006). Using thematic analysis, I analyze data gathered from twenty-five participants' exploration experiences when playing three different exploration games: the *pure exploration game*, the *killing* *game* and the *searching game*, built with StarCraft: Brood War (Entertainment & Entertainment 1998).

This research into the design of game environments can directly benefit two types of applications. The first type is the development of autonomous exploration agents. As Amigoni, Basilico & Quattrini Li (2014) has shown, several applications (ranging from classical map building to search and patrolling) fall within the scope of the broad exploration problem. Correspondingly, the *pure exploration game* simulates typical instances of classical map building applications; the *searching game* simulates the search applications; and the *killing game* simulates patrolling applications.

The second type is the design of spatial exploration mechanics in digital games. These three exploration scenarios represent a broad range of exploration mechanics in games, such as mapping game environments, collecting items and discovering bonus chances or items. Understanding players' behavior in the three different games promotes the development of human-like exploration agents and helps to identify the exploration mechanics in video games.

3.1 Experiment Design

Capturing and analyzing data from participants' playing spatial exploration is the way of answering the research questions. The experiment is based on three custom-designed, time-restricted games created on the StarCraft: Brood War platform. Participants were instructed to perform concurrent think-aloud activities, and verbalize what they were looking at, doing and thinking during the gameplay. The think-aloud data was combined with a video-cued retrospective interview post gameplay to obtain further insights into the participants' experiences and thought processes. I recorded all participants' think-aloud and interview videos, and then used NVivo (International 2017) to transcribe and analyze the transcripts. To help contextualize our results, I will briefly describe the StarCraft platform and the games I developed.

3.1.1 The StarCraft Game

I chose StarCraft: Brood War as our testbed due to its well-established API and malleability. StarCraft is also representative of the popular RTS game genre. The StarCraft AI Competition, first hosted by the AIIDE Conference in 2010 (Weber 2010), has become a notable testbed for evaluation of AI agents in academia (Buro & Churchill 2012).

The goal of a typical RTS game is to destroy the opponents' bases (structural real estate on the map) to conquer the entire play map. Players build and maneuver units to gather resources and go into combat with opposing units, in order to build more base structures and gain control of map regions. StarCraft's premise is based on fictional interstellar wars where players are required to select a race among three options (Protoss, Terrans, and Zerg) when starting a game. Each race provides the player with different units and strategic options.

The RTS game genre involves players making decisions for both high-level strategies and low-level tactical actions. It generally requires players to have good situational awareness in order to play well. The efficient uncovering of map information and effective use of this information is crucial to the success of players, which makes spatial exploration a core component of gameplay. Spatial exploration also enables the discovery and management of resources, which are used to either manufacture more units, including production units and combat units, or to acquire advanced techniques to enhance combat and general abilities. These resources are usually strategically placed on the maps, but are randomly generated for each new game instance.

The StarCraft provides a 2.5D top-down view as well as an interface that includes a mini-map (bottom-left of Figure 3.1) and terrain visuals (the main working window in Figure 3.1). This type of interface design can be seen in both early-generations of RTS games and it has been adopted by modern successors as well. It shows an overall view of the game state which allows players to maneuver units at a strategic level. This feature meets our requirement for investigating human-exploration strategies. Moreover, the RTS game genre is the primary application genre which this research attempts to expand upon.

Figure 3.1 The game environment of StarCraft: Brood War. The entire environment is covered by the fog of war (black shadows). The global map – left-down, the information window – middle - down, the control panel – right-down and the middle – the window of main view.

3.1.2 Test Game Environments

To collect detailed representative data about exploration activities, I developed three different game environments: the *pure exploration game*, the *killing game* and the *searching game*. In all the game environments, maps are covered by the fog of war – an artificial "fog" that blackens out territory that no units have travelled over yet (Figure 3.1).

Information about what the terrain looks like, and what items are under the fog is initially hidden from the players. Participants need to explore the environment by navigating a unit with a limited perception range through the unknown areas. These areas are then revealed to players when "perceived" by the game unit as it travels through them. Each game requires players to finish a specific task within a limited time frame.

- In the *pure exploration game*, players are required to explore the whole map as fast as possible within three minutes.
- In the *killing game*, there are 41 opponent space construction vehicles (SCVs) - a basic StarCraft unit - located on the map. Players are required to hunt 20 of the 41 SCVs within five minutes.
- In the *searching game*, participants are required to find the opponent's base within four minutes. In order to provide them with some guidance in terms of finding the opponent's base, participants are told that the opponent's base is located near a mineral site, and that the opponent's supply depots (basic StarCraft buildings) are distributed around the base area.

For the purposes of the experiment, only a small subset of the StarCraft game mechanics was used. There were no enemies fighting back, no resources had to be gathered by the player and the player did not have to build any units or factories. These simplifications were necessary to provide an exploration focus for the experiment. For the *searching* and *pure exploration* games, attacking actions were disabled. For the *killing game*, an on-screen counter showing the number of enemy units the player had to find and kill was added. For all three games, a timer was placed on the screen to indicate the remaining time left to complete the given task (Si, Pisan & Tan 2016).

The underlying feature of the three games is the common activity of exploring terrain. The *pure exploration game* was exclusively designed to evaluate the players' strategies and behavior in relation to revealing an unknown map. While the *killing game* and the *searching game* work based on exploration, players are encouraged to plan optimal routes to discover more items and to focus on where a specific item is located in the *killing* and *searching* game respectively. These two games allow us to investigate exploration behavior which is affected by the goals of searching and collecting.

3.1.3 Participants

Participants were recruited via undergraduate and postgraduate university mailing lists, public social networks and public areas in the university. The invitation of joining the experiment was broadcasted within the full range of the public network.

ID	Gender	Age	Hours	Game types usually played	Familiarity with RTS games	Experience of StarCraft	Recognition of StarCraft maps
P1	M	33	10 - 20	FPS, Strategy, RPG, Simulations, Puzzle, CB, Sports, RFS	5	3	4
P2	M	28	< 1	Sports	1	1	1
P3	M	27	1 - 5	Strategy, Puzzle	5	3	2
P4	M	29	< 1	FPS	5	1	2
P5	F	27	< 1	None	1	1	1
P6	M	21	5 - 10	FPS, Strategy, CB, PBG	5	5	5
P7	F	35	10 - 20	Strategy, RPG, Simulations	5	4	2
P8	M	35	1 - 5	Strategy, RPG	3	2	3
P9	M	22	10 - 20	FPS, Strategy, W&T	5	3	3
P10	M	26	< 1	CB, PBG, RLS	1	1	4
P11	M	20	1 - 5	FPS, Strategy, Simulations, Puzzle, PBG	4	2	2
P12	F	24	< 1	RPG, Puzzle	2	1	2
P13	M	23	10 - 20	FPS, RPG, Sports, RLS	5	1	1
P14	M	25	> 20	FPS, Strategy, RPG, PBG	5	5	5
P15	M	44	1 - 5	RPG	3	1	2
P16	M	30	< 1	FPS	1	1	1
P17	M	27	1 - 5	Sports	3	1	1
P18	F	22	< 1	Simulation, Puzzle, CB	1	1	1
P19	F	32	< 1	Strategy, CB, Social	1	1	1
P20	M	36	< 1	FPS, Puzzle, W&T, CB, Sports	2	1	1
P21	F	27	< 1	Puzzle	2	1	2
P22	F	28	< 1	Social, Sports	1	1	1
P23	M	33	< 1	Strategy	3	2	1
P24	M	39	1 - 5	FPS, Puzzle, Sports, RLS	2	1	1
P25	M	23	1 - 5	Strategy, Social	5	2	2

FPS	First – person Shooters	RPG	Role-playing Games	CB	Chance - based
PBG	Physical Board Games	RLS	Real-life Sports	W&T	Word & Trivia

Table 3.1 Demographic information and gameplay experience of participants

After posting the invitation for one week, I received intentions from twenty-five participants (7 females, 18 males), all of whom, then, signed up in this experiment. IRB approval was applied and granted before recruiting participants. A detailed description of experiment, including purposes, content, procedure, tasks, and video-recording configurations etcetera, was shown to each participant before each experiment session. After orally consenting to the study, participants filled an online pre-play survey to collect basic demographics like age, gender, gaming interests, gaming habits, and how familiar they were with RTS games and StarCraft in particular.

Participants were aged between 20 and 44 (M = 29, SD = 6.01). Except for two participants, most have rich video game experiences. Eleven participants usually play strategy games, ten participants play FPSgames, seven participants play sports games, seven participants play RPGs, four participants play simulation games, seven participants play puzzle games and three participants play social games. Of the twenty-five participants, ten indicated that they were familiar with RTS games, three claimed that they were experienced StarCraft players and four claimed that they could recognize some StarCraft maps. One participant indicated that he plays games for more than 20 hours per week, four participants between 10 to 20 hours, one participant between 5 to 10 hours, seven participants between 1 to 5 hours and twelve participants less than 1 hour per week. The demographic information and gameplay experiences of participants are shown in the Table 3.1.

3.1.4 Procedure

Participants were scheduled to attend the experiment individually at different times. After a participant completed the survey, the experimenter (the researcher who conducted the experiment) displayed a game demo to illustrate how to control and navigate game units. The participant was invited to practice control and navigation skills in the demo environment until he/she indicated that they were familiar with the gameplay. Then, the experimenter explained the targets that need to be achieved in each game. After that, participants started to play the games. Each participant was given the same time for playing a game (three minutes for the *pure exploration game*, five minutes for the *killing game*, and four minutes for the *searching game*). A game could be terminated in advance if the player completes the task and wins the game within the configured time. The order of the three games was randomized for each participant to avoid order effects and counter bias that might otherwise be introduced to the results with a fixed order.

During gameplay, participants were asked to perform the concurrent think-aloud. They were encouraged to describe what strategies they used to play the game and what their instant strategic thoughts and preferences were, and to explain their behavior to the experimenter. When a participant kept silent for a long time, and if the intent of his / her actions was not apparent to the experimenter, prompting was performed to encourage the participant to verbalize continuously. Short questions like “What are you doing now?”, “What is your strategy at the moment?” were used. After each game was completed, participants filled out a post-game questionnaire, in which they indicated their gameplay behavioral preferences and tendencies. After they filled out the post-game questionnaire, a post-game interview was conducted while watching a video replay of the game they had just completed. Here, participants had an additional opportunity to explain what they were thinking and feeling during gameplay, in case they missed out any important thoughts during the think-aloud. For both the think-aloud and interview, video data was recorded by two cameras: one facing the participant, and the other facing the screen where the actual gameplay or the video replay was running. The data collection of actual in-game behavior as well as verbal descriptions from the think-aloud and interview aims to answer the research question **Q1.1**. The entire experiment, ranging from the survey to the data analysis, was conducted in Games Studio (CB11.06.401, University of Technology, Sydney). The place was also employed to conduct all of the experiments in the rest of the thesis.

3.2 Thematic Analysis

Thematic analysis is an established tool for qualitative research (Guest, MacQueen & Namey 2011). Its common approaches are pinpointing, examining and recording themes (patterns) across data sets (Braun & Clarke 2006). Themes are defined as patterns within data, which highlight descriptions of common phenomenon that are normally associated with a specific research question (Daly, Kellehear & Gliksman 1997). For this experiment, thematic analysis was used to process both the verbalized think-aloud and interview data. Due to its flexibility in exploring data from a deep and structural perspective, thematic analysis helped us to extract strategic and preference patterns of exploration behavior as well as structural traits. The results of thematic analysis contributed to answer the **Q1.2**. Grounded in the typical thematic analysis process (Braun & Clarke 2006), I applied a four-phase inductive method as follows (Si, Pisan & Tan 2016).

3.2.1 Develop Proposal Codes and Themes

Data analysis began at the stage of collecting verbalized think-aloud and interview data, in which the data analyzer observed the entire process of data collection. In our experiment, the analyzer was the same person as the experimenter, participating as they did in the experimental design and conducting the data interpretation and thematic analysis. This arrangement allowed the analyzer to be fully immersed in the data by being involved in the data collection process as well. This, in turn, led to a better understanding of participants' experiences. It also helped to keep the verbal and transcribed data consistent. I nonetheless acknowledge the potential for greater experimental bias. To minimize the possibility of bias, the analyzer was required to meticulously record the data analyzing process, including detailed approaches for handling each part of the data as well as emergent issues and solutions worked out in the regular meetings with colleagues.

Similar responses were highlighted and noted by the analyzer while the experiments were conducted. After all the participants completed the experiments, the analyzer summarized his notes according to topics related to strategic preferences, reasoning processes and characteristics. These structured topics were used as initial draft themes for the data analysis.

3.2.2 Data Preparation and Familiarization with Data

For this phase, I collected verbal data within the think-aloud and interview, and the video records of game replay. The game replay and verbal data was recorded synchronously. This enabled the analyzer to review the audios of either the think-aloud or interview and the game replay videos synchronously, which provided a succinct way of recovering what happened during the experiments. Raw data from audio resources was transcribed into textual files to meet the requirements of marking and coding in the later stages of analysis. The verbal data was transcribed into textual form, along with game situation descriptions, participant behavior and comments in NVivo. The analyzer, who was present through all gameplay recording, was completely familiar with the data owing to repeated reading in an immersive way.

3.2.3 Code the Data and Extract Themes

In this phase, I extracted features from the data into codes. A code refers to "the most basic segment, or element, of the raw data or information that can be assessed in a meaningful way regarding the phenomenon" (Boyatzis 1998, p. 63). The coding process mainly focused on the textual data that described the act of exploration. The gameplay videos were used as supplementary content to better understand the transcripts.

The process of extracting themes began by constructing a hierarchical preliminary theme structure based on the initial theme drafts generated in the first phase. The analyzer encoded the data and categorized them into the relevant potential themes. If there was no corresponding theme, a new theme was created and inserted into the structure. The process continued until all the data was processed.

3.2.4 Reviewing and Re-constructing Themes

This phase started with the analyzer reviewing the themes from the previous phase. It involved the refinement, redefinition and reorganization of the themes. For example, some of the themes that lacked sufficient support from the data were pruned.

Following this, the themes were reorganized into common aspects of spatial exploration. This resulted in four main themes:

- *strategy*, which represents what strategies people make in playing the games;
- *reasoning*, or how they reason about situations and options;

- *conception*, which represents what spatial conceptions about the environments are mapped in their minds; and
- *hesitation*, referring to a reluctance to move when encountering certain instances of the game.

Each theme encapsulated common behavioral aspects that participants exhibited in the three exploration games. When reviewing the data sets grouped into these four themes, I further discovered that players had clearly distinguishable preferences. Within each theme, I then embarked on an iterative code-mapping process to re-organize the codes into different groups according to these preferences.

For example, within the theme reasoning, a code-map was generated, structured around sub-themes about what types of options: unexplored areas, paths, targets and other factors players appear to have considered in making choices (Figure 3.2). I merged similar themes and re-structured the code-maps by focusing on the objectives of the types of reasoning participants used, to give us the purpose of participants' reasoning. The resulting sub-themes of reasoning are: paths, terrain layouts, targets and unexplored areas. The themes that were subject to these sub-themes were more detailed objectives, specific goals and ways of reasoning (Figure 3.3).

Based on the map in Figure 3.3, I re-categorized the codes via the ways people do reasoning to distinguish behavior patterns among the themes. In this step, the preferences of methods (for example the theme "Special Items" means that people prefer to reason about the options by using their judgment about special items that they are tracking) were converted to be direct subtopics of reasoning, while other factors were grouped within different behavior preferences. I then generated a preference-centered code-map of reasoning (Figure 3.4).

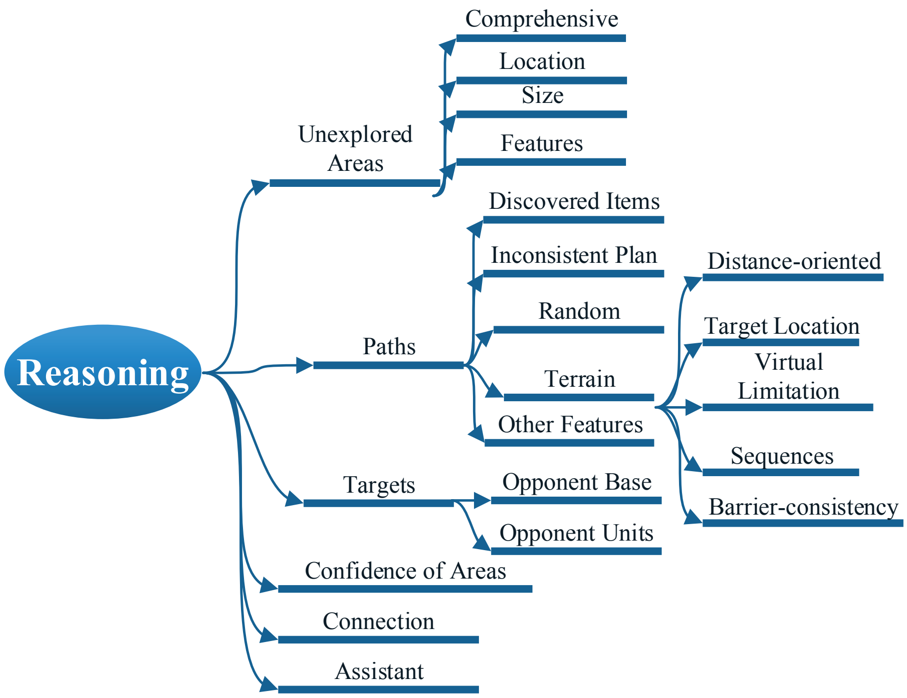


Figure 3.2 Initial codes map for the reasoning theme

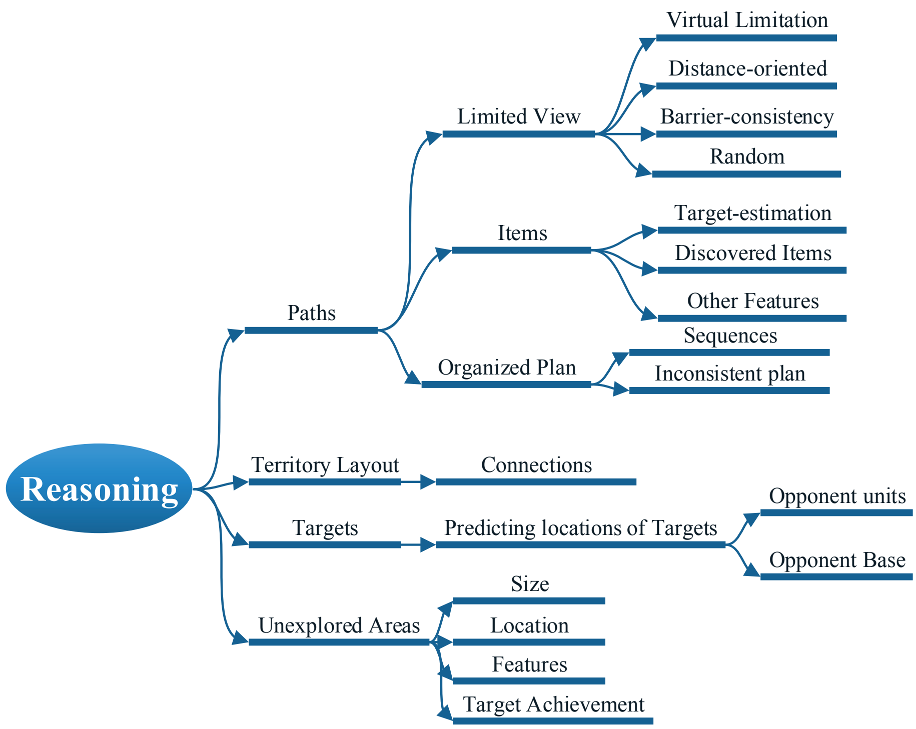


Figure 3.3 Objective-centered structure of the reasoning map

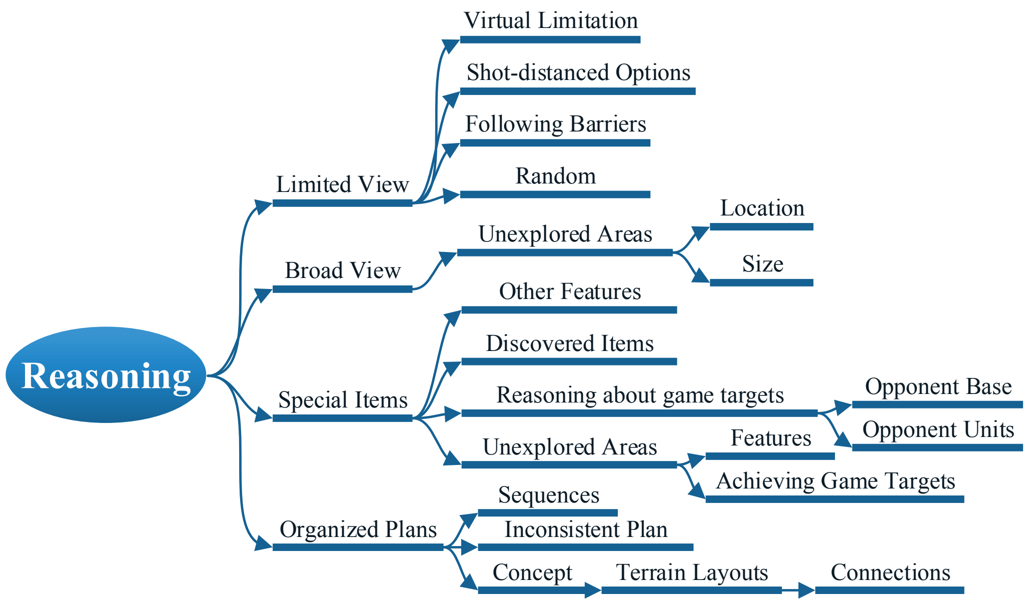


Figure 3.4. Preference-centered structure of the reasoning map

To get a better idea of our process, I can focus on the re-location of single atomic behavior, for example "Barrier-consistency". This behavior reflects players' reasoning that barriers exist along the direction from where these barriers are discovered, to the unknown areas they have not visited yet. Based on this, the corresponding behavior, "Following barriers", comes next, as players explore the barrier limits. This behavior refers to players' reasoning about terrain and the action of selecting a path for their next move. This behavior is, therefore, organized under the sub-branch "Terrain" of the main branch "Paths" (Figure 3.2).

In the Figure 3.3, the map was reorganized in an objective-centered fashion, where each sub-branch of "Paths" represented a group of decision factors when players make path-selection decisions. An example of an amendment in this step is the detachment of "Barrier-consistency" from "Terrain" and re-attachment to "Limited View", as the "Barrier-consistency" can be regarded as a kind of view limitation. At the end of the process, the map structure facilitates the articulation of player archetypes on the reasoning theme. The main branches are grouped with the consideration preferences (Figure 3.4). For example, “Barrier-consistency”, along with the branch “Limited view”, are re-structured. Then, “Barrier-consistency” is renamed as “Following Barriers”, because it represents the decision-making and situation-analyzing process better.

By using the same typological methodology, I re-organized the code-maps of the other three themes: strategy, conception and hesitation. Similar sub-themes are found across code-maps. For example, the sub-theme “limited view” exists in the strategy, reasoning and hesitation code-maps.

These sub-themes are identified as players’ preferences within the four aspects of behavior. By grouping these sub-themes across the four maps into four groups, I define four archetypes: *Wanderers*, *Seers*, *Pathers* and *Targeters*, which are comprehensive enough to encompass and identify participants’ common behavior patterns. Sub-themes and codes within these four aspects are then regrouped into these four archetype-themes. The characteristics of these archetypes and their performances on the aspects are discussed in the next section.

3.3 Classification of Gameplay Instances

The archetypes that emerged above depict behavioral traits in various exploration scenarios. The analysis in this phase aims to answer the **Q1.3**. I categorized all the gameplay instances into the four archetypes to investigate the distribution of the four behavioral types (Si et al. 2017). To reduce bias and embed the results of classification, I conducted the analysis with two independent coders and assessed the inter-coder reliability (ICR) in the process. The two coders were research assistants in the lab. Both of them have been trained to conduct thematic analysis, and had experiences of qualitative analysis.

The definitions and traits of the four archetypes were generated via the thematic analysis process described above. The archetypes were discussed and reviewed in group meetings that involved the two coders, in order to generate a set of classification criteria. Then, a set of instances were randomly selected from the entire instance data set as the sample. It contained the gameplay instances of 7 out of 25 participants. The two coders then classified the sample instances independently.

After independent classification was complete, the overall coding agreement and Kappa coefficient (Cohen 1960) were calculated to assess the ICR within the sample set. Consequently, the two coders collectively discussed the results with a third researcher to re-assess the classification criteria accordingly. In fact, since all three-people agreed on the initial rules, they were directly applied for classification. The overall agreement rating and the Kappa coefficient for this first wave of classification were 85.83% and 0.807 respectively, which provided enough confidence to continue the coding on the basis of existing rules (Landis & Koch 1977). In the next step, coders coded the rest of the 18 participants' data. Finally, the ICR was assessed over the entire data set by calculating the two coefficients.

3.4 Results

3.4.1 Player Exploration Archetypes

Our findings can basically be derived from the descriptions and characteristics of the four player exploration archetypes (PEAs) that were generated and evaluated by the procedure described in the prior section. I borrowed and recreated four English words: *Wanderers*, *Seers*, *Pathers* and *Targeters* to represent the four archetypes respectively.

Wanderers

Regardless of the game type, *Wanderers* move around without a definite destination or purpose. *Wanderers* do not have an explicit understanding of their location nor do they have specific plans on how to reach their next destination. They concentrate exclusively on getting around local map regions and discovering items that fall within the immediate cone of the exploration unit's vision. *Wanderers* prefer local landmarks and terrains, and they use them as references to navigate. For example, a typical *Wanderer*'s preference: "I think I just followed the edge [the terrain boundary that divides the map into regions]. But I didn't do it on purpose." (P21 – Interview – *pure exploration game*) This shows that he had no set targets and that he had minimal awareness of map features.

Seers

Seers aim to aggressively expand their visibility span when exploring unknown environments. Being able to see as much information as possible is the main priority for *Seers*. They seek to reveal as much of the unexplored map in the quickest time possible. For example, I observed a *Seer* (P11, which represents the participant number) employing a clockwise circular walking strategy to explore environments efficiently. His actions were supported by his interview statements (*pure exploration game*): "I referred to the map [overview map] at that point. I headed to the top of the screen. I was on top of this map. I used the clockwise to explore all the area. And I just followed the map down, to the major unexplored area." He had an explicit global view of the environment as well as eagerness to expand his visual field efficiently.

Pathers

The *Pather* archetype is characterized by elaborately structured cognitive maps of environments. Terrain features such as high land, low land, ramp, bridges etc., are highlighted, perceived, slotted and grouped by *Pathers*. *Pathers* will categorize a map into known-pattern classes by analyzing its appearance and reasoning about its functional features. Although in most cases the view of the entire environment is not available for players, *Pathers* consistently attempt to keep track of highlighted map features in order to cumulatively construct patterns which are then classified based on their prior map knowledge. An example of a *Pather*'s response is: "At this point, I was confused by the map, because I realized there was a layer. But, I forgot. I completely forgot where the way was." (P21 – Interview – *Killing game*) When asked by the experimenter on what the 'layer' referred to, the participant answered, "The high land. At the point, I realized that this high land was somehow kind of a bridge [linking] to different areas. So, I needed to climb, maybe, up and down to find a way out [from areas to the bridge]." This shows that she was trying hard to construct a structured-map representation in her mind.

Targeters

The *Targeter* archetype is objective-oriented towards terrain features. Their behavior appears to have specific targets underpinned by clear tactical plans. *Targeters* seek landmarks, items and any other identified objects that can serve as hints of target locations, such as resources and opponent locations. They keep predicting the locations of these targets, and verifying their predictions. They then adjust their plans with each new discovery. For example, a *Targeter* (P20 – Interview – *Searching game*) said: “I just realized that I was getting close to [the base]. Then I thought it was in the corner, to be honest. Then I thought [that I have] to go and check that corner. I thought [it] may be there, maybe in the small corner that I can’t see. That’s why I explored it and, OH NO, it was not there. Then I went back. Here, I couldn’t believe that I was wrong.” The participant’s disappointment shows her level of confidence about her prediction. When asked by the experimenter to elaborate, she also mentioned: “[The base should be] exactly between these two [mineral sites]. Now, yeah, I began to find [it]. Then I saw this [supply depot]. I thought, OK, it could be something around this area [pointing to the middle black area of the map]. And then I saw a path there.” It appeared that she was keeping track of hints, as well as analyzing them continuously, in order to locate the opponent’s base.

3.4.2 Behavioral Aspects of Archetypes

Within this section, I describe how the behavior of the four archetypes differ in terms of the four behavioral aspects: *strategy*, *reasoning*, *conception* and *hesitation*. For each aspect, the behavior of each archetype is described. It should be noted that not all the archetypes have corresponding behavior for all the aspects, which means that for some of the aspects below, not every archetype is described underneath. For example, there is no description of *Targeters* on the strategy aspect, because *Targeters’* strategy behavior is not explicitly identified according to the data set.

Strategy

"A plan of action designed to achieve a long-term or overall aim."(Dictionary 2007b) The term "strategy" is employed, here, to represent the "plan of action" players make to "achieve" their "overall aims". Different archetypes express their strategies differently based on their preferences.

Wanderers do not possess any systematic strategies. At the early stages of exploration, a *Wanderer* is more likely to choose a random direction to move forward. Their typical thought processes are "I have no idea" (P5 – Think aloud – *Pure exploration game*) and "I was just exploring. I had no preferences" (P18 – Interview – *Killing game*). Subsequently, tracking terrain features, for example, boundaries, is a common type of behavior. A *Wanderer* (P2 – Interview – *Killing game*) described his exploration strategy as: "I don't know where to go, because I don't know how to find a path. And there is no way."

Seers keep a global view of the environment. Their general strategies are normally direction-oriented, which include an explicit sequence of exploration to cover different sections of the map. A *Seer* (P4 – Interview – *Killing game*) described his strategy as, "I found [realized] the overview map. I found I was on the top [side of the map]. So, I wanted to go down [side of the map] to search another place." Additionally, this sole focus on map uncovering is also a strategic priority for *Seers* when considering strategies in the *killing game* and the *searching game*, where uncovering unknown terrain is not the main task. For instance, a *Seer* (P11 – Interview – *Searching game*) said, "I continued [using] my clockwise pattern to cover the most areas."

Pathers take advantage of the structure in maps. They normally define enclosing areas where they have already explored, and prefer to uncover a region completely before they move to explore another area. For example, when a *Pather* was asked why he went a certain direction, he replied “Because I thought if I go down [side to the area], I don’t have to like go back.” (P19 – Interview – *Pure exploration game*). Another behavior identified was that they are actively looking for terrain connections among different parts of maps, for example, “I just want to search a connection between this part and another part.” (P2 – Think aloud – *Pure exploration game*)

Reasoning

In this thesis, the concept *reasoning* refers to *practical reasoning* which is defined as “a kind of goal-directed reasoning that seeks out a prudential line of conduct for an agent in a particular situation.”(Walton 1990, p. 405) During the process of exploration, players reasoned about unexplored areas, paths and targets based on what they have already discovered. Different archetypes approach this differently.

Wanderers normally choose where to go within the limited local view of the map based on random guesses. For example, I observed a participant who navigated his unit towards the path to the right side of the map. When asked why he didn’t go to the path that leads downwards, he said, “I didn’t see the overview [map] clearly. So, I turned right.” (P17 – Interview – *Searching game*)

Seers prefer navigational options that can result in larger visible regions. For example, a *Seer* participant explained his choices as, “There is also much area to explore. So, I move down [side of the map] for efficiency. So, I start going south [down side of the map]. There is no more area to the east [right side of the map].” (P11 – Interview – *Killing game*)

Pathers keep a structured representation of the map and a clear prioritized sequence of where to go in strategic order. For example, I observed a *Pather* participant choosing a certain path, as opposed to an alternative path, to an area which she had partially uncovered. When asked about her reasoning, she said, “Because I saw it [the area] from the other side. I couldn’t access it. So, I go to that [area] first, clean that area.” (P19 – Interview – *Pure exploration game*)

Targeters reason in a way that is consistent with their objective-oriented preferences, i.e. finding key objects of interest such as the opponent’s base. Their reasoning process is anchored on the accumulation of hints from map features in order to predict locations of targets within unexplored areas. For example, when asked about the reasoning on why a *Targeter* participant chose to search in the high platform (which led him to find the opponent base eventually), he replied, “Because, at that point, I think that base is really close. The first time I saw that one ... At the first time, I saw this building [supply depot], and after a few seconds I saw another one, I think it’s because these buildings are around the enemy [opponent] base, so I think maybe it’s in the middle. So, I go up.” (P13 - Interview – *Searching game*)

Conception

The *conception* specifically refers to the concept of space, which is considered as a fundamental way to understand the physical world (Ekholm & Fridqvist 2000). I use the word “conception” here to represent the way of how a player constructs a cognitive representation of the game map, which also varies among different archetypes.

Seers apply a direction-based approach in structuring the cognitive map, for example, segregating a map into the top-left, top-right, bottom-left and bottom-right parts. An example of this type of segregation can be seen in a *Seer* participant's thought process: "My strategy is just to walk from left [side of the map], and to the right [side of the map]. And up [side of the map] and from right [side of the map] to left [side of the map]." (P25 – Interview – *Pure exploration game*)

Pathers cumulatively maintain a structured cognitive map based on each new acquired knowledge of the environment. They normally have a pre-conceived notion of the layout of the environment, and cumulatively construct the cognitive map by incorporating the gradually acquired spatial knowledge. Topological-map-like structures normally exist in *Pathers*' minds. For instance, a participant (P3) who preferred to use computer science terminologies (depth-first search and breadth-first search) to describe his exploration behavior, described his initial strategy in the *killing game* as such (Interview): "I need to search in detail, which means I can't leave any black patches. So, I just go depth-first search. And then, I followed the left edge [the terrain boundary that divides the map into regions] and keep going". In the *searching game*, he employed both the depth-first search and breath-first search techniques to position the enemy base. He explained (Interview), "I saw a bridge first, so I just go through it, and follow the edge … Actually, this was kind of depth-first search." When he discovered an enemy cue, he said: "I could see the landmark, which was the oxygen supply [supply depot]. So, I thought I should start the breadth-first search now."

Hesitation

The word "hesitation" normally means "The action of pausing before saying or doing something." (Dictionary 2007a) Sometimes, the "pausing" is expressed as recycling, where "a normal pattern is to recycle to the beginning of the utterance (perhaps more than once)." (Hymes 2008, p. 14) I use the word "hesitation" to represent a common behavior observed is travelling back and forth in explored areas. The reasons, however, are highly varied and situation-specific. I define and classify these kind of behavior as hesitation. Different archetypes are driven by different motivations to perform hesitations.

Wanderers hesitate for two reasons: a lack of specific strategies and unfamiliarity with environments. The combination of these two reasons is especially apparent in the *killing game*. "Why did you keep on moving forward and backward within the areas you have explored?" asked the experimenter. "Because I am sure that I have been here at the first time, and I regarded the fly thing as an enemy [opponent unit]. But I was wrong. I think I didn't have a CLEAR VISION of the map. I didn't have some theories about how to explore the new enemies [opponent units]. So, I just moved back and forward." (P2 – Interview – *Killing game*) said.

Pathers' hesitation behavior stems from their hesitations in ordering the sequence of visiting points. For instance, one participant (P16 – Interview – *Pure exploration game*) explained his hesitant movements as follows: "I didn't take the other view - the right-side view. I missed one connecting path, so I return there. So, I thought maybe if I come back to the same place. Then I would find a way to go to the right [side of the map]. Then I went to up [side of the map] again, I can't find way to right. I spent some time near here." When I looked at the game replay, I found that he had explored the left part of the map, and was attempting to find a connection to explore the right side.

The *Targeters*' hesitation in exploring environments with behavior of walking back and forth is caused by their goal of tracking objects. A typical example is a participant (P20 – Interview – *Searching game*) who gave up moving on his current path and returned to explore repeatedly. The experimenter asked, "Why did you go back?" and the answer was, "Because previously there wasn't a mineral site nor a lot of places, but, when I saw this one [supply depot], I changed my mind. Because there were more buildings."

3.4.3 Archetypes in Different Instances

	Pure Exploration Game	**Killing Game**	**Searching Game**
Wanderer	P5, P18, P21, P22	P2, P18	P10, P17, P18, P22, P23
Pather	P1, P2, P3, P7, P9, P13, P15, P16, P19, P20, P23	P3, P21	P8
Targeter		P1, P7, P9, P10, P14, P15, P17, P20, P22, P24	P1, P5, P6, P7, P9, P13, P14, P15, P19, P20, P21, P24, P25
Seer	P4, P6, P8, P11, P12, P14, P17, P24, P25	P4, P6, P8, P11, P12, P13, P16, P23, P25	P4, P11, P12

a. Archetype distributions in each game type

	Pure exploration game	Killing game	Searching game
P1	P	T	T
P2	P	W	N
P3	P	P	N
P4	S	S	S
P5	W	N	T
P6	S	S	T
P7	P	T	T
P8	S	S	P
P9	P	T	T
P10	N	T	W
P11	S	S	S
P12	S	S	S
P13	P	S	T
P14	S	T	T
P15	P	T	T
P16	P	S	N
P17	S	T	W
P18	W	W	W
P19	P	N	T
P20	P	T	T
P21	W	P	T
P22	W	T	W
P23	P	S	W
P24	S	T	T
P25	S	S	T

W	Wanderer	S	Seer	P	Pather	T	Targeter	N	None

b. Categorization of each participant in different games

Table 3.2 Archetype classification of participants for each game type

The consensus classification between the two coders is shown in Table 3.2. With 25 participants, there were 75 gameplay instances in total. The two coders attained consensus categorization in 69 out of the 75 instances. In the *searching game,* most players (59% of instances) tend to exhibit the traits of the *Targeter*. In the *killing game*, players were roughly evenly distributed in the *Targeter* (43%) and

Seer (39%) archetypes respectively. In the *pure exploration game*, it was interesting that no players exhibited the *Targeter* archetype. In the *searching game*, most players exhibited the *Targeter* (79%), with a few exhibiting the *Seer* (14%) archetype.

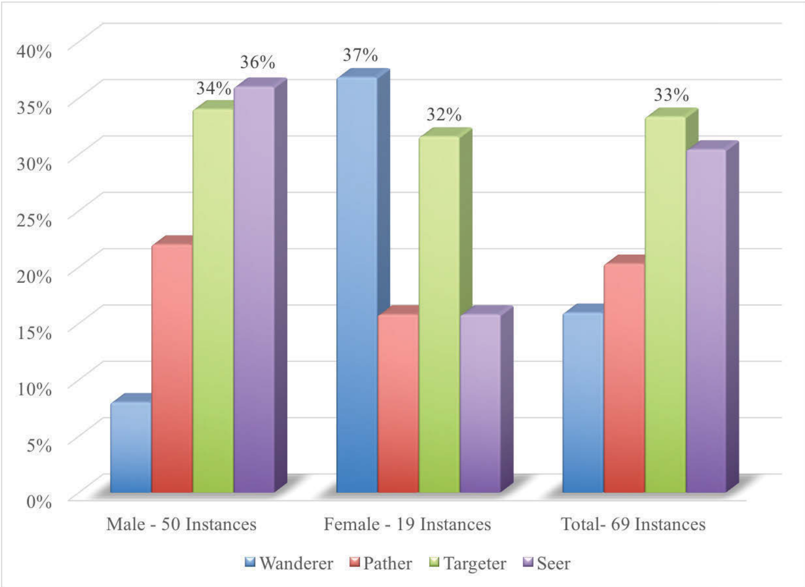
The classification results in Table 3.2 produced satisfactory reliability. The reliability measurement consists of an overall agreement rating of 90.82% and a Kappa coefficient of 0.892, based on our inter-coder assessment across the entire data set.

3.4.4 Exploration Types & Demographic Types

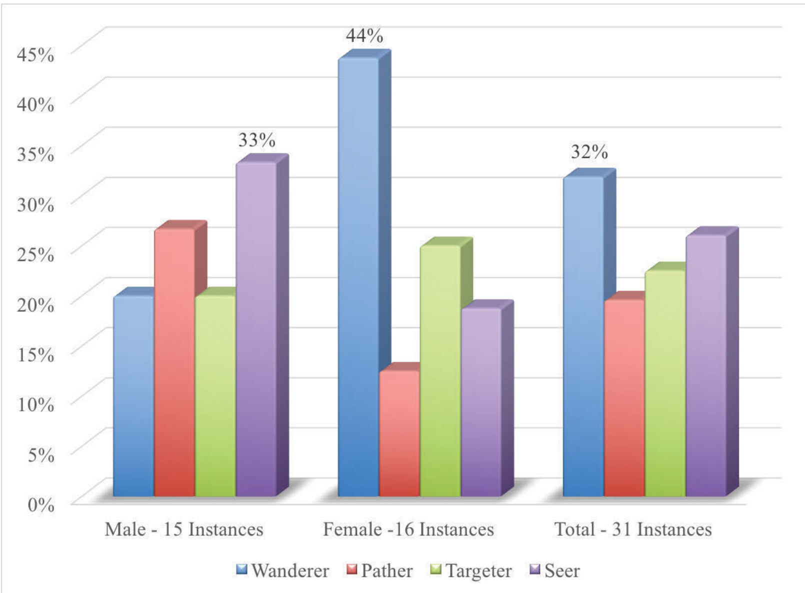
Gender

Different genders of players express rather different archetypes across the three games, except for the *Targeter* archetype, which I classified a significant portion of both male (34%, n = 17) and female (32%, n = 6) participants as *Targeters*. It is consistent with the prior observation that the *Targeter* archetype represents the majority of overall players across the games. Meanwhile, the *Seer* (36% of male instances, n = 18) and *Wanderer* (37% of the female instances, n = 7) archetypes were the dominant archetypes for males and females respectively (Figure 3.5.a).

In Table 3.1, we can see that six of the seven female participants played games for less than one hour per week, and one of them played games for ten to twenty hours per week. This presents a possibility that low gameplay proficiency may have an effect on the results for analyzing the gender factor. The population of female players (one person P7) who comparatively played lots of hours per week is too small to analyze. In Figure 3.5.b, the archetype distribution is compared across genders with same level of gameplay time by eliminating instances where the gameplay hours are more than one. Interestingly, the *Seer* (33% of male instances, n = 5) and *Wanderer* (44% of the female instances, n = 7) archetypes still dominate for male and female groups respectively (Figure 3.5.b).



a. Original data



b. Novices' data whose gameplay hours are less than one

Figure 3.5 Relation between gender groups and the archetypes

Gameplay Hours

I compared the proportion of participants for each archetype based on the number of hours played per week (Figure 3.6). The most glaring observation is that 91% of participants who play games for less than one hour per week are *Wanderers*, which shows that being unfamiliar with gameplay forges *Wanderers* (Figure 3.6). This is consistent with the notion that *Wanderers* possess the least "gamer-savvy" attributes, i.e. they are the least strategic and do not give deep thought to the exploration task, a game feature which is central to many modern video games.

I also compared the proportion of participants across archetypes for each category of weekly gameplay hours. Here I observe that 50% of participants who spend 1-5 hours per week on playing games are *Seers*, while 63% of those who spend more than 5 hours are *Targeters* (Figure 3.7). This, again, is consistent with the fact that more avid gamers (who spend more time each week) tend to exhibit more elaborate behavior (i.e. those characterized by *Seers* and *Targeters*) that involve deeper analysis for their resulting actions. It is also interesting to note that the *Pather* archetype lends itself well to more avid gamers, but it is exhibited to a lesser extent in our study.

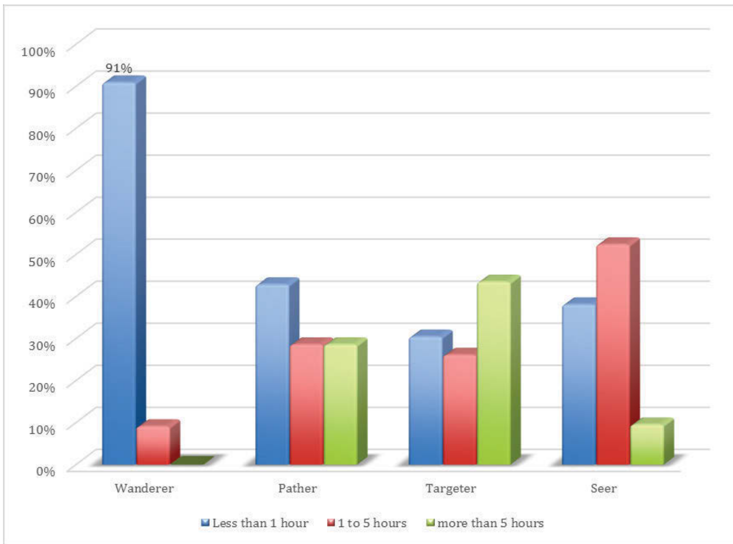


Figure 3.6. Relation between weekly gameplay hours and the archetypes – grouped by types

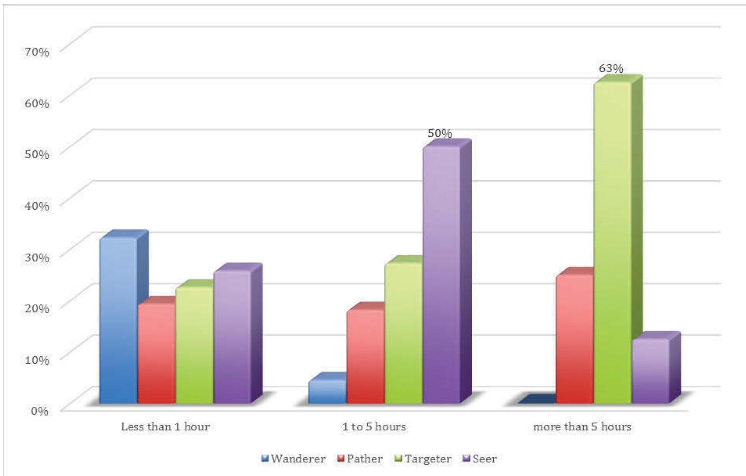


Figure 3.7. Relation between weekly gameplay hours and the archetypes – grouped by playing time

Real-life Navigation Abilities

Within the pre-game questionnaires, I employed three five-point Likert scale (Likert 1932) questions to evaluate people's navigation experience in real-life. They are:

1. I keep a clear egocentric distance and direction of my home in my mind, every time I leave home;

2. I am easily disoriented in an unfamiliar environment; and

3. I have a good spatial memory of places, where I have been to.

These questions serve to evaluate the three key aspects of spatial navigation abilities: distance estimation (Jeffery 2007; Moser & Moser 1998; Wilson et al. 2003), spatial orientation (Hegarty et al. 2002; Iaria et al. 2009) and spatial memory (Montello et al. 1999). Previous research has focused on developing evaluation scales to test these abilities respectively. Instead of combining them into a comprehensive version, I evaluated participants' navigation abilities via the three questions in the pre-play questionnaire, which helps participants to concentrate on game playing sessions without too many distractions. The summarized scores of the three questions are shown in Table 3.3:

	Wanderer	Pather	Targeter	Seer
Means	**9.91**	10.93	**11.17**	10.38
Standard Deviation	**1.76**	2.09	**2.55**	2.27

Table 3.3 Real-life navigation abilities. Means and standard deviations of the total scores representing participants' real-life navigation abilities. The total scores are a sum of 3 Likert scale (1-5) items (max score of 15).

The participants who exhibit the *Wanderer* archetype have the poorest real-life navigation abilities (M = 9.91, SD = 1.76), while participants who exhibit the *Targeter* archetype have the best real-life navigation abilities (M = 11.17, SD = 2.55). This might imply that, other than gameplay experience affecting their behavior in exploration, real-life navigation abilities might also play a part in explaining the behavior participants exhibit, for example, poorer real-life navigation relates well to more non-systematic exploration behavior typical of the *Wanderer* archetype. In one example, a *Wanderer* (P22 – Interview – *Pure exploration game*), who marked 10 in the real-life navigation ability testing, ignored a bridge, which was explicitly shown in her main view. She explained the reason why she ignored it as: "Maybe I thought that's the same bridge, the one that I found in the beginning."

3.4.5 Preferences for Different Terrain Features

In the post-game questionnaire, participants were also evaluated on their preferences to seek and follow the four types of environmental features present in the game: (1) open space; (2) edges such as walls, obstacles, cliffs and riversides; (3) connections such as connecting paths, bridges and narrow ramps; and (4) landmarks, such as buildings, creatures and other special items. Their responses are summarized. The means and standard deviations are calculated and listed in the Table 3.4:

	Open Spaces		Edges		Connections		Landmarks	
	M	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**
Wanderer	3.09	1.22	2.68	1.12	**3.73**	**0.72**	3.18	1.06
Pather	3.36	1.22	**4.04**	**0.82**	3.79	0.80	2.50	1.21
Targeter	**3.65**	**0.88**	3.07	0.95	3.46	0.80	**3.54**	**1.09**
Seer	**3.67**	**1.15**	3.60	1.00	**3.76**	**0.78**	2.88	1.08

Table 3.4 Preferences to terrain features. Means (M) and standard deviations (SD) of the evaluations of participants' preferences to different terrain features.

From Table 3.4, it can be seen that *Wanderers* have the strongest preference for connections (M =3.73, SD = 0.72). *Pathers* have the strongest preference for edges (M = 4.04, SD = 0.82). *Targeters* have strong preferences for both open spaces (M = 3.65, SD = 0.88) and landmarks (M = 3.54, SD = 1.09). *Seers* have strong preferences for both open spaces (M = 3.67, SD = 1.15) and connections (M = 3.76, SD = 0.78).

The strongest preferences of each archetype were all consistent with the think-aloud responses of participants classified into that archetype, for example, for the *Pather* archetype, P1(Think aloud – *Pure exploration game*), whose preference value to edges is 5, said "I suspect that there was a big ocean there. I am goanna check this. Try to find way to here. There might be a lake here. I suggest it's a lake." This provides additional confidence that these are the behavioral tendencies distinguishable between the different archetypes I have uncovered in this chapter.

3.5 Discussion

3.5.1 Mapping with General Gamer Types

Even though the four archetypes I discovered were based on our unique study environments aimed at investigating exploration behavior, it is interesting to note that they are relevant to other more general gamer types devised in prior research (Nacke, Bateman & Mandryk 2011). The connections between our four archetypes and Nacke's types are described below:

- The *Wanderer* can be connected to Nacke's *Seeker* and *Survivor* types. The *Seekers*' preference of seeking instant and easy enjoyment from the environment could map to the *Wanderers*' characteristics of exploring local items. In relation to Nacke's *Survivor* type, *Wanderers*' fear emotions as what *Survivors* have may motivate players to focus exclusively on their immediate localities and not see or plan for the broader exploration task.

- The *Seer* can be connected to Nacke's *Seeker* and *Daredevil* types. The *Seer* is similar to the *Seeker* as both of them have interests in the environments themselves. Unlike the *Wanderer* archetype, in which players' behavior can be associated with a sense of being lost, the *Seer* archetype tends to be more aggressive and risk-taking. This element coincides with the characteristics of the *Daredevil* type.

- The *Pather* can be connected to Nacke's *Seeker* and *Mastermind* types. The *Pather* has similar characteristics as the *Seeker* but with the addition of maintaining a structured mental map. On the other hand, the *Pather*'s preferences for making elaborate strategies to reveal the structure of virtual environments could be mapped to the *Mastermind* type.

- The *Targeter* can be connected to Nacke's *Achiever* and *Mastermind* types. The *Targeter* is similar to the *Achiever* as the objects that *Targeters* hunt for are similar to the goals that *Achievers* attempt to complete. The *Targeter* also prefers to reason about acquiring information for discovering the target items, which maps to the characteristics of enjoying solving puzzles in the *Mastermind* type.

A player may exhibit several types of exploration behavior depending on game environments and tasks. The summarized connections help to better understand the four behavioral types discovered in map exploration, and provide a lens to predict possible exploration behavior that specific Nacke's player traits may lead to. Factors that determine a specific type of exploration behavior are discussed below.

3.5.2 Different Archetypes for Different Games

I found that the archetypes exhibited by a participant might not be consistent across all three exploration games. In further analysis of these instances, it was apparent that participants who didn't exhibit consistent archetypes in all three types of games possessed multiple archetypes themselves. They expressed one dominant archetype, alongside other minor archetypes in different games.

Game mechanics could be one vital element that led to this common variation. For example, when observing P6's (Interview - *Seer*) gameplay, whenever he avoided narrow paths he aggressively expanded his map viewing area in the *killing game*, saying, "My main attention at this point was to EXPLORE ALL [emphasis added] the high ground. So, I just continue walk on the high ground." Interestingly, he also exhibited the *Targeter* archetype along with the *Seer* archetype in playing the *killing game*. He said, "I think, at the point, I realized that SCVs are near minerals," when he reviewed the early stages of playing, which potentially indicates that he extracted the knowledge of positioning targets very quickly. Later, instead of continuing to explore the remaining parts of a region, where he had already revealed part of it, he gave that up and moved on to other regions, in which he explained: "I realized it was too narrow for minerals."

In contrast, whilst in the *searching game*, his *Targeter* archetype dominated behavior (Interview): "At this point, I was around here, and I saw a supply depot. I was not sure whether it [the target enemy base] was going to this part [the highland at the top of the map] or that one [the high land in the middle part of the map]. Before going further down, I thought I'd have to check." His explanation of his behavior indicates that he was sensitive to the cues, and made substantial reasoning of the target location. This is typical behavior of a *Targeter*.

In this example, I discovered that P6 possessed two archetypes - the *Seer* and the *Targeter*, which emerge in varying intensities in the participant's behavior in different games (the *killing game – Seer*, the *pure exploration game – Seer*, and the *searching game* - *Targeter*). The differing game goals in the three game types (for example, seeking targets was the primary goal in the *searching game*) led to different dominant archetypes observed in the players across the games. It should be noted that some of these game goals might occur in more than one game type; nonetheless, the primary goal for each game remains explicitly different, which facilitated the differing behavior observed across the games. For example, seeking targets was an explicit primary goal of the *searching game*; players in the *killing game* had to hunt for targets as well; however, in this case it was an implicit goal compared to the primary goal of destroying these targets. Moreover, different game mechanics (for example, sparse distribution of enemy units in the *killing game*) also contributed to the variation in gameplay across the three game types.

3.5.3 Different Archetypes in One Game

As mentioned in section 3.5.2, I noticed that a participant might significantly exhibit more than one archetype in a single gameplay instance. For instance, when P8 was playing the *killing game*, he, sometimes showed obvious effort in recognizing the map structure: "Because mostly the parts of the map are downside, so I tried to go to…", and manifested explicit attempts at finding opponent units, "I thought, when I was playing some games, I saw enemies are always hiding in some corners." (Interview). This shows some traits of a *Pather*. However, his dominant behavior was classified as a *Seer*, as they employed a general mapping strategy, "Maybe go upside. Cross the whole upstairs, upside and downside. And explore the whole area", and prefers to explore open spaces, "Just go explore the open space … To explore [the dark area]." This might be attributed to studies that have shown that players' mostly exhibit multiple personal characteristics in games, such as emotions, play skills, social preference and obsessive tendencies (Bateman, Lowenhaupt & Nacke 2011). It was even rare that a player exclusively possesses one single trait in playing one type of game. This phenomenon appears to surface in our findings as well, although through our analysis, I do find that we are able to confidently identify a dominant archetype in most cases. The archetype table (Table 3.2) lists the eventual dominant archetypes derived from our coding process.

3.5.4 Impact of Player Demographic on Archetype

As shown in the Results section, player demographics like gender, weekly gameplay hours and real-life navigational abilities appear to have an effect on the exploration behavior, i.e. the player's archetype. Many of these findings appear to conform logically to the archetype behavior. For example, participants who play less hours and are less familiar with games, as well as those with lesser real-life navigational abilities, tend to be *Wanderers*. However, these relationships are not conclusive as they were not the primary focus of this research, and further research needs to be done to establish these relationships. I suggest this as possible future work.

3.5.5 Preferences for Terrain Features

In the results, I found that strategic preferences on environmental features support the exploration behavior characteristics of each archetype. For example, *Wanderers* prefer connections, which provides them with an easy way to find visiting spots, as they do not have a systematic strategy for exploration. In contrast, I found that *Pathers* prefer edges the most, which fits their typical behavior of paying more attention to the structural definition of terrain features.

3.6 Conclusion

In this chapter, I answer the research question **Q1** by presenting a study that examined the game exploration traits of 25 players playing three types of custom-designed exploration games on the StarCraft: Brood War platform. By using thematic analysis on both concurrent think-aloud and video-cued retrospective interviews, I uncovered four behavioral aspects - *strategy*, *reasoning*, *conception* and *hesitation* - that provided several angles from which to understand exploration activities in a virtual game world (**Q1.1**).

By distinguishing behavior according to the four behavioral aspects, I further showed that players can exhibit one or more of four player exploration archetypes, or PEAs, that represent different explorative archetypes: *Wanderers*, *Seers, Pathers* and *Targeters*. Inter-coder classification analysis was conducted to identify each gameplay instance into a certain archetype. The results also show that the dominant archetypes for participants vary in different game types (**Q1.2**).

Analyzing the relationships between the behavior in the derived archetypes and the behavior inferred from the survey responses, I found that *gender*, *weekly gameplay time* and *real-life navigation ability* had significant effects on the eventual archetypes into which I classified players. Additionally, participants' preferences for different terrain features, which I collected from the survey responses, match the traits of the archetypes corresponding to each player (**Q1.3**).

The findings about how human doing spatial exploration are implemented to design a believable exploration agent in Chapter 5, where I employ a heuristic method. The experiment environment designed in this chapter is also consistently utilized in the following chapters. In next chapter, I investigate the differences of behavior patterns between human players and computer agents in exploring virtual environments.

Chapter 4. Understanding Believability of Spatial Exploration Agents in Digital Games

This chapter aims to answer the research question **Q2**: "What behavioral differences exist between normal players and automated exploration agent?" It is divided into three sub-questions.

Q2.1 Can an external observer distinguish between human players and computer agents in spatial exploration scenarios?

Q2.2 What behaviors are identified as distinctly belonging to computer agents?

Q2.3 What behaviors are identified as distinctly belonging to human players?

To answer these three questions, I developed a third-person assessment system to evaluate the believability of human players as well as several state-of-the-art automated exploration agents. Independent judges rated the believability of gameplay subjects on a Likert scale-based questionnaire. Semi-structured interviews were also used to obtain more elaborate descriptions of believable versus unbelievable behavior. I used a thematic analysis method to extract behavioral patterns in the lens of believability.

4.1 Game environment

The game environments are same as those developed in Chapter 3 (see 3.1.2 Test Game Environments). In the following chapters, the game environments are all the same as those in Chapter 3.

4.2 Computer-agent Objects

Computer agents are implemented according to several state-of-the-art autonomous exploration algorithms, which reflect the three major approaches in this area: (1) artificial potential field (APF) (Holz et al. 2010), (2) multiple criterion decision-making (MCDM) (Basilico & Amigoni 2009) and (3) topological (Akdeniz & Bozma 2015). As a baseline, I also create a computer agent that explores and plays in a random way.

Frontier-based (Li, Amigoni & Basilico 2012) and information entropy (Amigoni & Caglioti 2010; Charrow et al. 2015; Holz et al. 2010) are two major methodologies in developing autonomous exploration agents within one single agent systems (Juliá, Gil & Reinoso 2012). Many studies illustrated that frontier-base algorithms were simple but efficient strategies (Holz et al. 2010). Algorithm random, APF and MCDM are all frontier-based, meanwhile MCDM also integrates information entropy. Topological method is a representation of classical structured searching methods, which constructs topological structure in searching space, and determine visiting operations on it.

The typical process of automated exploration by a unit with a limited visual range in an unknown environment is summarized by (Amigoni & Caglioti 2010; Si, Pisan & Tan 2014b) as:

a) The computer agent perceives the surrounding environment.

b) The map patches perceived are integrated into the explorer's map-representation system.

c) Candidate next-best positions are identified from its map representation system, according to a specific identification strategy.

d) The identified positions are evaluated via an evaluation approach.

e) An optimal position is chosen as the goal of next movement after the evaluation.

f) The explorer goes to the selected optimal position and continues from step a).

The basic map representation system used in the following four algorithms is a grid-based approach, where the environment map is divided into equal-size squares. Each square is labelled as known or unknown, referring to whether the exploration unit has been perceived it or not.

4.2.1 Random

This strategy acts as the baseline of the performance of computer agents' exploration strategies. A computer agent employing the random strategy selects the target from candidate positions to explore in a random manner. Candidate positions are selected from frontiers by doing exploration. Frontiers are defined as edges located between explored areas and unknown areas. The pre-condition is that the strategy cares about the areas and targets which are unknown and undiscovered. Therefore, each movement decision is to expand to move towards a discovered enemy item.

4.2.2 Artificial Potential Field

In this algorithm (Holz et al. 2010), the points that are located on the frontiers are considered as the candidate points in each step, where the agent decides where to go. Distance is the sole factor used to evaluate potential points. The candidate position with the nearest distance from the current explorer's location is selected as the next optimal location.

4.2.3 Multi-criterion Decision-making

Candidate positions of MCDM are selected from frontiers as well. This algorithm combines the potential values from different criteria: travelling distance, potential revealing areas, and potential revealing segments, in order to evaluate and select the next-best position at each step. Our implementation is based on (Basilico & Amigoni 2009), where the Choquet fuzzy integral (Grabisch & Labreuche 2008) technique is employed to eliminate the overlaps when accumulating the potential values.

4.2.4 Topological

This algorithm procedurally generates and maintains a topology map, in which the visited key points or candidate positions are the nodes of this map (Akdeniz & Bozma 2015). In the beginning of gameplay, an empty topology map is created. New nodes are inserted in the map as places are perceived. Nodes, where the places surrounded are revealed, are labelled as visited. Others are labelled as unvisited. The labels are updated in each step when new areas are perceived. Unvisited nodes are selected as candidate positions in each step. I use multi-criteria from MCDM to evaluate candidate positions, and select the best one as the optimal position.

4.3. Experiment Design

Our experimental approach employed a third-person observation assessment to evaluate the believability of computer agents. Gameplay videos of the three game scenarios from both human and computer agents were recorded. Seven judges then viewed the two-minute clip of each video, attempting to distinguish human players from computer agents' based on the gameplay video. Both online questionnaires and semi-structured interviews were used to obtain responses from the judges. The questionnaires evaluated believability ratings, and the interviews probed further into why the judges made their judgements (for example, explained their scores using appropriate video segments).

4.3.1 Judge Selection

Believability relies on the judgments of observers, who watch the behavior of characters or playing bots in video games. It is difficult to claim one computer agent is absolute believability or not, due to varieties in the judges' personalities, preferences, and life experiences. The degree of the judges' expertise is an important subjective factor in identifying the believability of a character, as in Hingston's choice in the BotPrize (Hingston 2009), where he believes the professional knowledge of judges guarantees high accuracy in terms of judgments. The judges' domain knowledge of game playing, however, takes a more pivotal role. This is because human behavior varies from situation to situation. In-game actions are, sometimes, entirely different from what people will do in real life, and this is due to the different settings. Therefore, I invited players who regularly play video games and have substantial knowledge in the domain of RTS games as the judges. I chose judges who are neither novice players nor game gurus, but mid-level players. As Warwick and Shah's research suggests (Warwick & Shah 2015), keeping both human players and computer agents attempting to be a human that judges expect could reduce recognition errors and increase the accuracy of the Turing test. Another advantage of having mid-level players as judges is that they will be the major potential consumers of the games with believable characters and bots. Seven judges were involved in this research. Their demographic information and gaming experience are shown in Table 4.1. All of the judges have years of gameplay experiences in the RTS genre and relevant others. They are also playing video games for several hours every week. Their experiences in gameplay satisfy our requirements to judges. Their demographic information listed is only used to demonstrate their characteristics instead of comparing the variances.

ID	Gender	Age	Years of gameplay	Gameplay hours per week	Game types usually played
J1	M	28	> 10	10 - 20	RTS, RPG
J2	M	24	> 10	1 - 5	FPS, RTS, RPG, Simulations, W&T, CBG, Sports, PBG, RLS
J3	M	26	> 10	1 - 5	FPS, RTS, RPG, Simulations, CBG, Sports, PBG, RLS
J4	M	25	5 - 10	1 - 5	FPS, RTS, RPG, Simulations, CBG, Sports, PBG, RLS
J5	M	23	< 2	1 - 5	FPS, RTS, RPG, Simulations, Puzzle, Sports
J6	M	24	2 - 5	10 - 20	RTS, Social, Sports, RLS
J7	M	23	5 - 10	5 - 10	FPS, RTS, Sports

RTS	First – person Shooters	RTS	Role-playing Games	CB	Chance - based
PBG	Physical Board Games	RPG	Role-playing Games	RLS	Real-life Sports
W&T	Word & Trivia				

Table 4.1 Demographic information and gameplay experience of judges

4.3.2 Procedure

The experiment was conducted as follows:

1. The researcher introduced the background of the experiment (for example the platform, purpose, procedure, and tasks needed to be completed) to the judges.

2. Judges filled in the pre-game survey which consisted of general demographic questions and gameplay background questions.

3. Judges played the three different games to familiarize themselves with the context.

4. Gameplay videos for the same game were displayed to each judge in a pairwise manner. The permutation of video pairs as well as the sequence of displaying was randomized to minimize biases. After watching each couple of gameplay videos, each judge was required to answer the Likert scale questions with five scales (i.e. *definitely a computer agent*, *most likely a computer agent*, *unsure if it is a computer agent or human*, *most likely human* and *definitely human*) to evaluate the human-likeness of each video. The next question asks judges to elaborate and provide support for their evaluation. They were encouraged to identify segments of playing videos that supported their reasoning.

5. After judges had evaluated all the gameplay videos, the researcher conducted a semi-structured interview with each judge to discuss in detail their expectations of what believable gameplay agents would be like.

Each judge completed the experiment together with the researcher respectively. All of the judges played the games, watched videos and filled out the questionnaires without interruption or any interaction with the researcher. Interview sessions were recorded via webcam, transcribed and then analyzed.

4.3.3 Semi-structured Interviews

	Main Questions	Additional Questions	Clarifying Questions
1.	Is it easy to distinguish human gameplay from the set of clips? OR Are there any difficulties you confronted in distinguishing human and computer agents' gameplay?	How did you distinguish human gameplays? What difficulties did you confront with? How did you cater for these problems? What strategies did you use to make the judgment?	Can you expand a little on this? Can you tell me anything else? Can you give me some examples?
2.	Can you please summarize several key behaviors which you believe were exhibited by human players within the clips?	Why did you choose them?	
3.	Can you please summarize several key behaviors which you believe were exhibited by computer agents from the clips?	Why did you choose them?	

Table 4.2 Semi-structured interview questions

Semi-structured interviews were organized to collect qualitative data in-depth. They were used to investigate the judges' expectations of believable agents as well as their perceptions of believable and unbelievable behavior referring back to their personal experiences. An interview session was organized after completing the online questionnaire for each participant. The main theme of the interview was how they distinguished human gameplay from computer agent gameplay, which includes investigating their strategies, and the concepts as well as patterns of behavioral difference that they discovered. The initial set of planned questions as well as the additional and clarifying questions asked during the interviews are outlined in Table 4.2.

4.4 Thematic analysis

Thematic analysis was employed to analyze the post-game interview data as well as judgment comments within the questionnaire responses. As a primary aim of this study is to identify behavioral patterns that impact the believability of spatial exploration agents (see **Q2.2** and **Q2.3**), thematic analysis was chosen to categorize the judges' comments about gameplay performance. A four-phase inductive method (Si et al. 2017) developed in Chapter 3 (see 3.2 Thematic Analysis) is used here. I used NVivo to help us transcribe interview records, process textual data and conduct thematic analysis.

Initially, textual data was coded via the common topics judges spoke about (Figure 4.1). The code tree is centered around the major theme - *behavioral patterns* - which is the main aim of this research. The first level of nodes, such as *mapping strategies*, *forward and backward*, *corners*, *bridges,* and *search patterns*, represent the aspects where human players and computer agents show distinct actions. For example, *mapping strategies* coded descriptions about how players (human and computer agents) map the environments. *Bridges* refer to the manners in which players interact with bridges. The leaf nodes appear in pairs, where *H* means the identified features of a human while *C* represents those of computer agents.

Next, let's move on to the phase of reviewing and re-constructing themes (3.2.4 Reviewing and Re-constructing Themes), where the refinement, redefinition and reorganization of themes are involved. Themes that lacked sufficient support from the data were pruned. New themes which were supported with sufficient data were created. The first level sub-nodes were evaluated, re-coded, deleted and merged in the code tree (Figure 4.1). For example, the node of *neutral units* was merged into the *obstacles* node, since neutral units can be regarded as a kind of special obstacle. The *direction changes* node was eliminated because a conflict arose from the judges' comments about this aspect. The *mapping strategies* node and *enemy* node were re-named and re-coded into *exploration*, *killing* and *searching* (Figure 4.2), because these aspects of behavior were highly associated with the goal of each game.

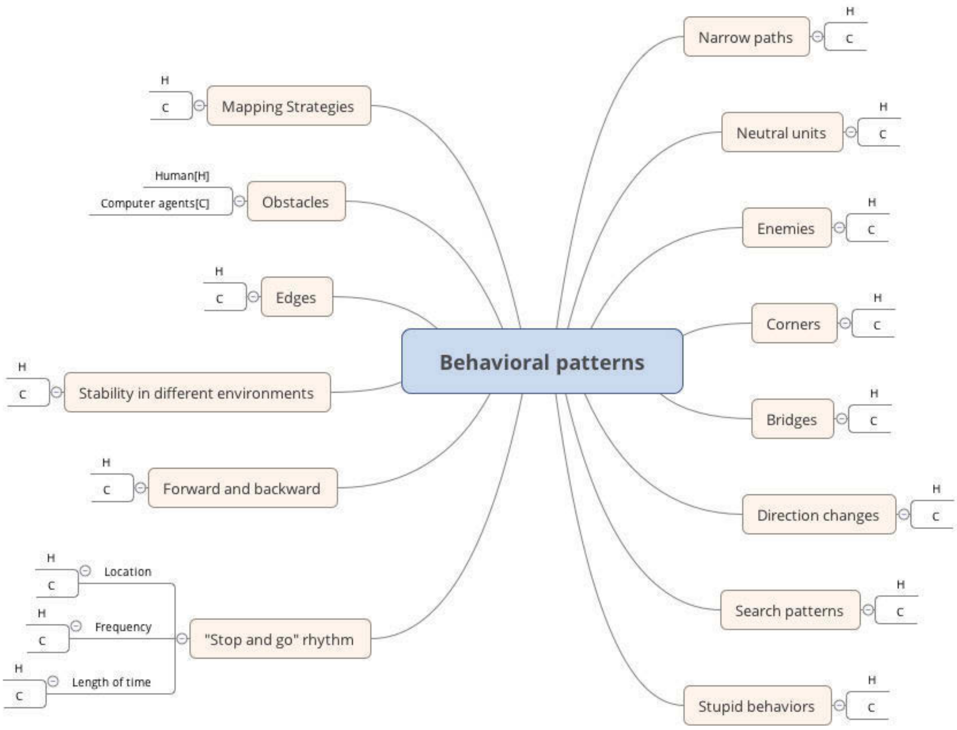


Figure 4.1 Code tree of textual data

Investigating inner relationships among nodes in Figure 4.1, I discovered that they could be grouped into four categories: *interaction with environments*, *game-goal orientation*, *navigation* and *sense of mechanical* (Figure 4.2). A description of these four categories and details about patterns of the behavioral differences between human and computer agents are introduced in the section examining the behavioral differences defined by judges.

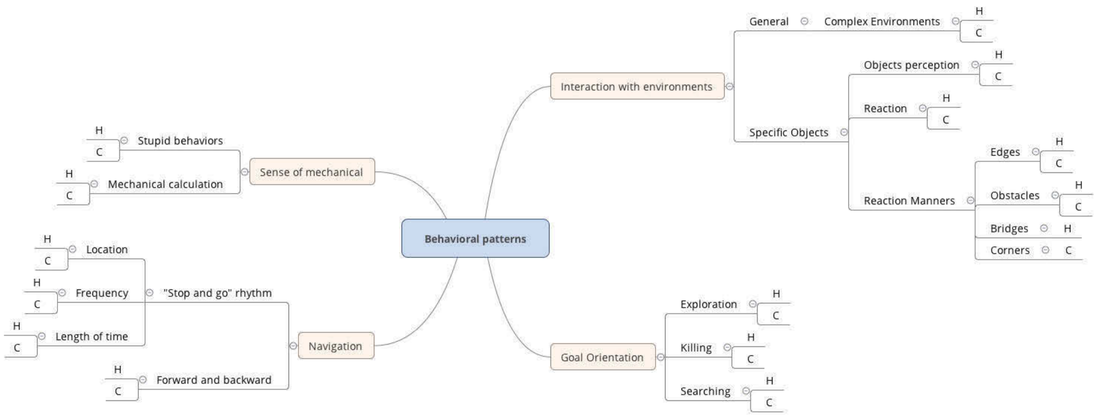


Figure 4.2 Themed code tree of textual data

4.5 Results

4.5.1 Believability Ranking Results

Figure 4.3 and Figure 4.4 illustrate the ranking results that are cumulated from questionnaire responses. All seven judges observed gameplay videos and scored each of them. The five response choices I used in this experiment are "balance", where the Likert item has an equal number of counterparts to the "*unsure if it is a computer agent or human*" on both sides. Carifio and Perla (Carifio & Perla 2008; Carifio & Perla 2007) suggested that responses to Likert scale can be treated as *numeric* data. Norman's (Norman 2010) study proved that "Parametric statistics can be used with Likert data, with small sample size, with unequal variances, and with non-normal distributions, with no fear of 'coming to the wrong conclusion'." We, hence, mapped the responses to the choices into numbers from 1 – 5, and calculate the means and standard errors of them to compare the believability across the objects in this and following chapters.

In Figure 4.3, the value represents the average score for each player. It is calculated via the Formula (4.1).

$$V_p = \frac{\sum_{i=1}^{N_J} \sum_{j=1}^{N_G} v_{ij}}{N_J * N_G} \qquad (4.1)$$

where, V_p represents the ranking value for each player, N_J means the number of judges, N_G means the number of games and v_{ij} is the ranking score given by the judge i for the gameplay in game j. The value in Figure 4.4 demonstrates the average score for each player in playing each game. It is computed via Formula (4.2).

$$V_g = \frac{\sum_{i=1}^{N_J} v_i}{N_J} \qquad (4.2)$$

where, V_g represents the ranking value for each player in playing one game and v_i is the ranking score given by the judge i. The human 2 has the highest score, while the Random agent has the lowest. MCDM performs the best among computer agents. Investigated by game types, the *killing* gameplay of the human 2 reached the full score - 5, while the Topological agent's playing of the *killing game* was ranked as the least believable. The difference in believability between humans and computer agents was most pronounced in the *killing game*.

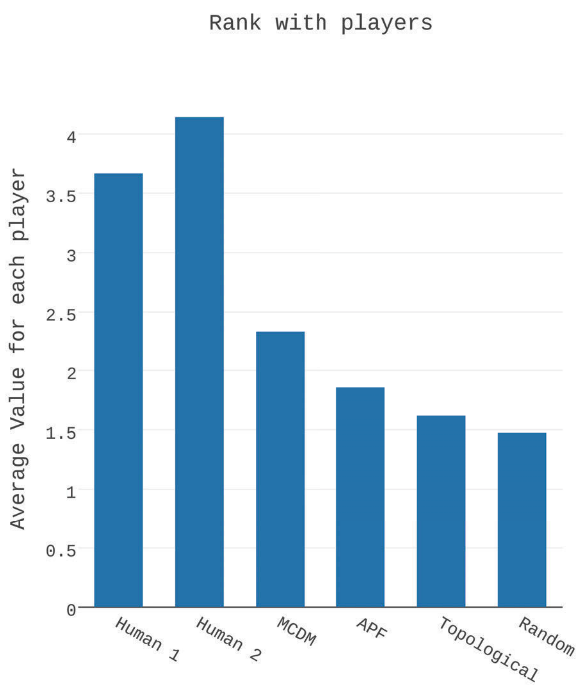


Figure 4.3 Believability ranking for each player

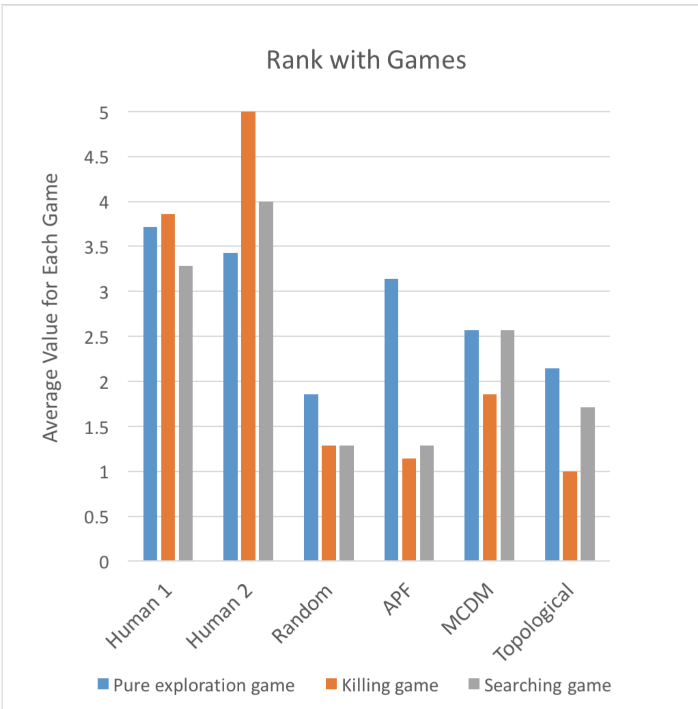


Figure 4.4 Believability ranking for each player in each game

Figure 4.5 illustrates the average score of believability that each player achieved in each game, where human players' score is higher than that of computer agents' in all the games. Scores in the *pure-exploration* game show that the APF agent's behavior of environment mapping significantly approach human players in believability, where the APF has a score of 3.14 while the human has a score of 3.71. By contrast, the APF's scores are far lower than the human players' in the *killing game* and the *searching game*.

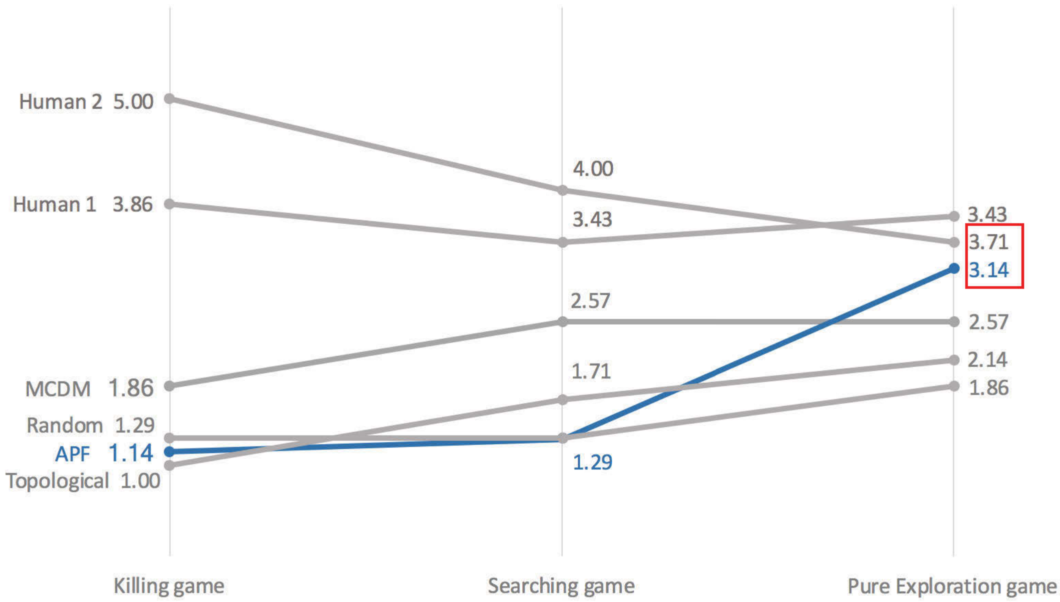


Figure 4.5 APF's gameplay is approaching human's performance in the *pure exploration game*

Even though the players' performance of believability varies considerably in the different games, the human players' performances are significantly better than the computer agents. In Figure 4.6, the lines of human players' scores stay higher than those of the computer agents in all three games.

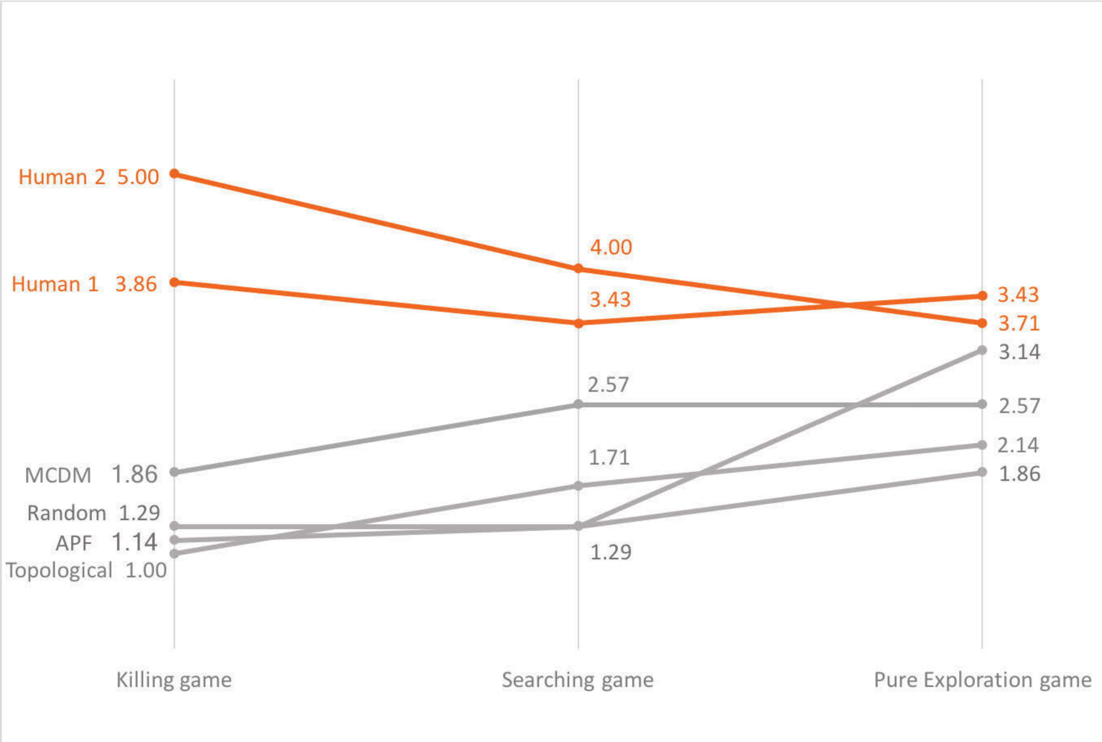
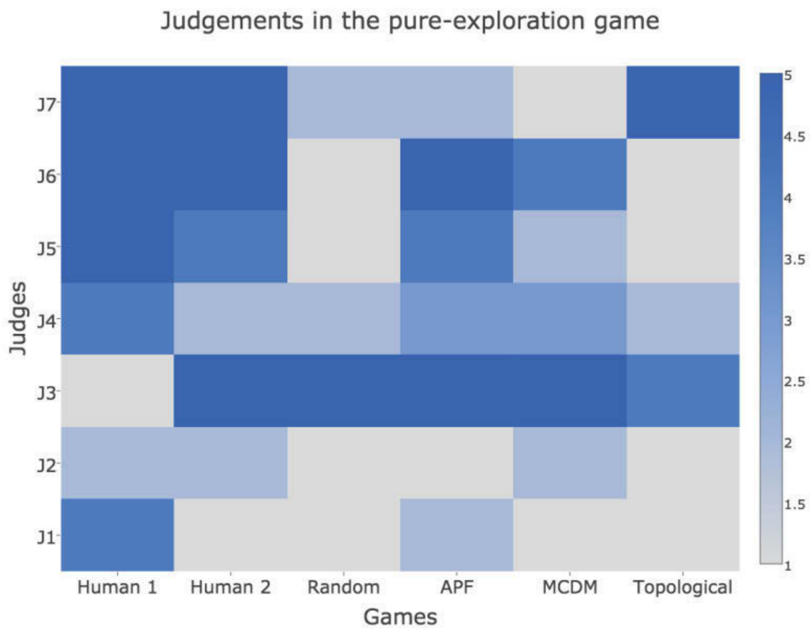
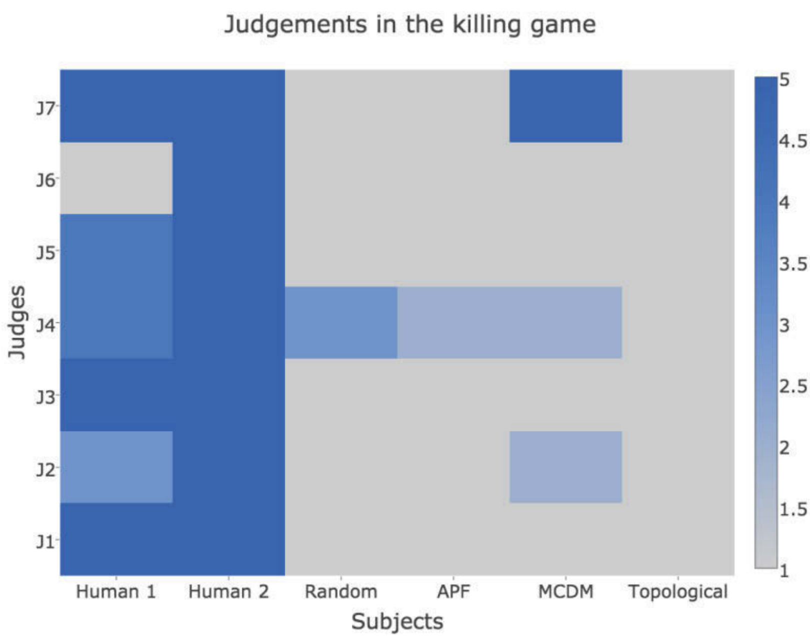


Figure 4.6 Human's performances are significantly better than the computer agents' performance

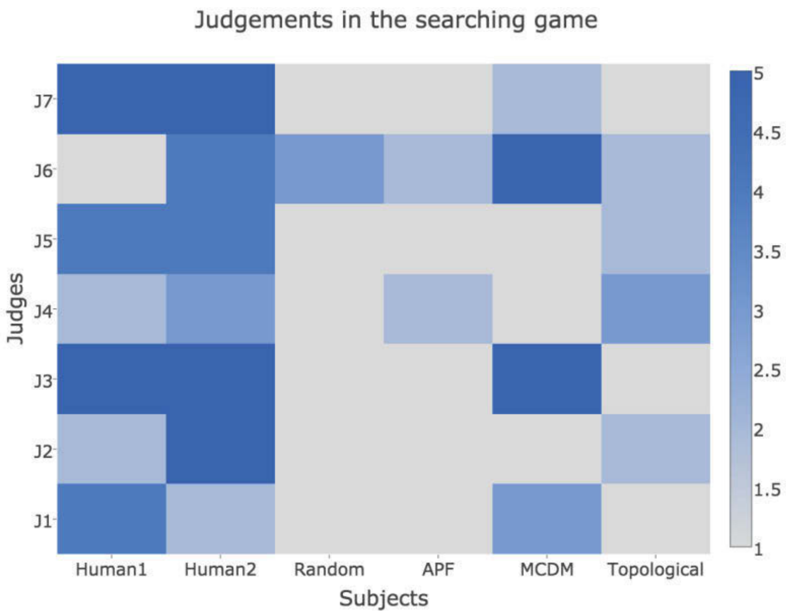
Judgments of the seven participants are shown in Figure 4.7, where the blue color represents the higher score while the grey color means the lower score. Heat maps in Figure 4.7 highlight two points: 1) In the *killing game*, higher scores of believability are concentrated in the columns of human subjects, and lower scores are mostly distributed in the columns of the computer agent subjects (Figure 4.7.b). Comparably, the distributions of the higher and lower scores are sparse in the *searching game* and the *pure exploration game*. 2) Some judges prefer to give higher scores, such as J3 in the *pure exploration game* (Figure 4.7.a). Some prefer to give lower scores, such as J1 and J2 in the *pure exploration game* and the *searching game* (Figure 4.7.b and Figure 4.7.c).



a. Distribution of scores in the *pure exploration game*



b. Distribution of scores in the *killing game*



c. Distribution of scores in the *searching game*

Figure 4.7 Score distributions in the three games

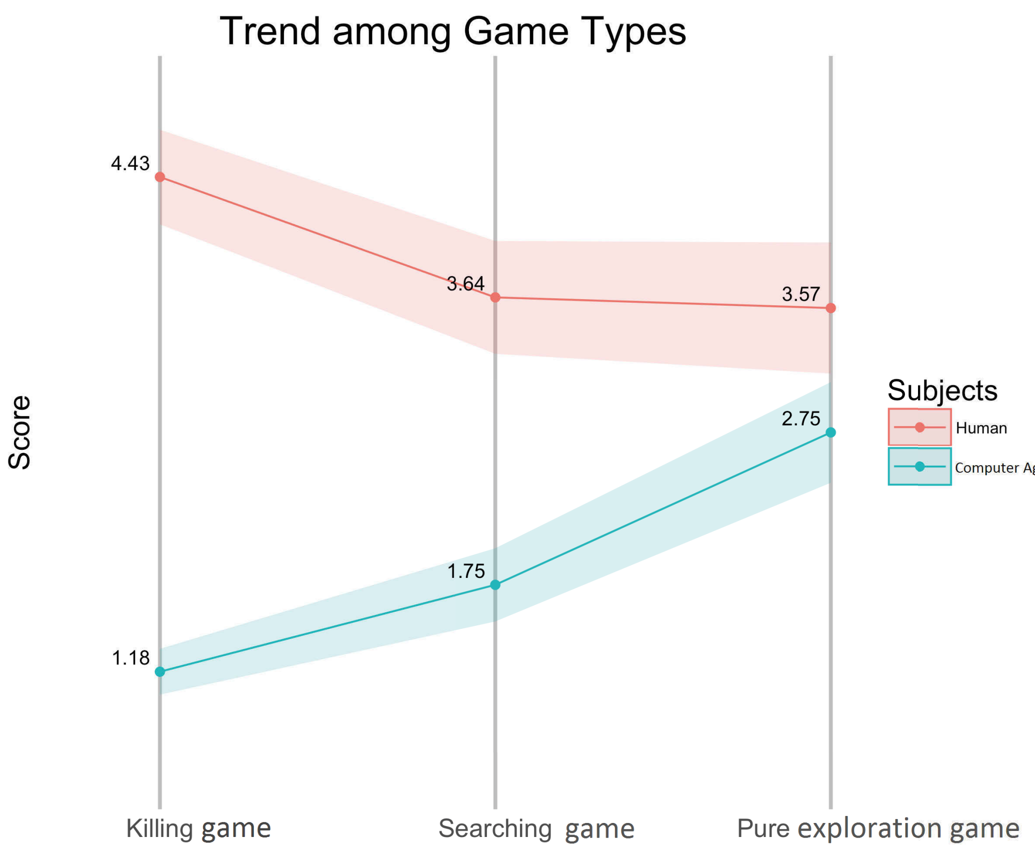


Figure 4.8 The trend of performances among the three games

The average score for players in each game reveals the trend of performance among the three games (Figure 4.8), where the lines represent the average value of the scores given to human and computer agents respectively, and the corresponding fitting areas illustrate the ranges of the standard errors. This figure shows the trend of scores among the three games. The human players' ranking scores decreased from the *killing game* to the *pure exploration game* via the *searching game*, while the computer agents' scores increased.

4.5.2 Misjudgment

Misjudgment is defined as a human player is judged as a computer agent and vice versa. Figure 4.9 shows the percentages of misjudgments among three types of games for each player. Misjudgments in the *pure-exploration* gameplay are high in both the human and computer agent sides. The APF agent has the highest number of misjudgments in playing *exploration* among computer agents. In many cases, there is no misjudgment in the *killing game* (for players of Topological, APF, Random and human 2) and the *searching game* (for players of Topological, APF, and Random). The *killing* gameplays have the least number of misjudgments. In both the *killing game* and the *searching game*, among computer agents, only the MCDM agent puzzled judges as it was regarded as a human player, while the other three strategies were not even misjudged once in the two games. The misjudging percentages are therefore reported as zero in Figure 4.9.

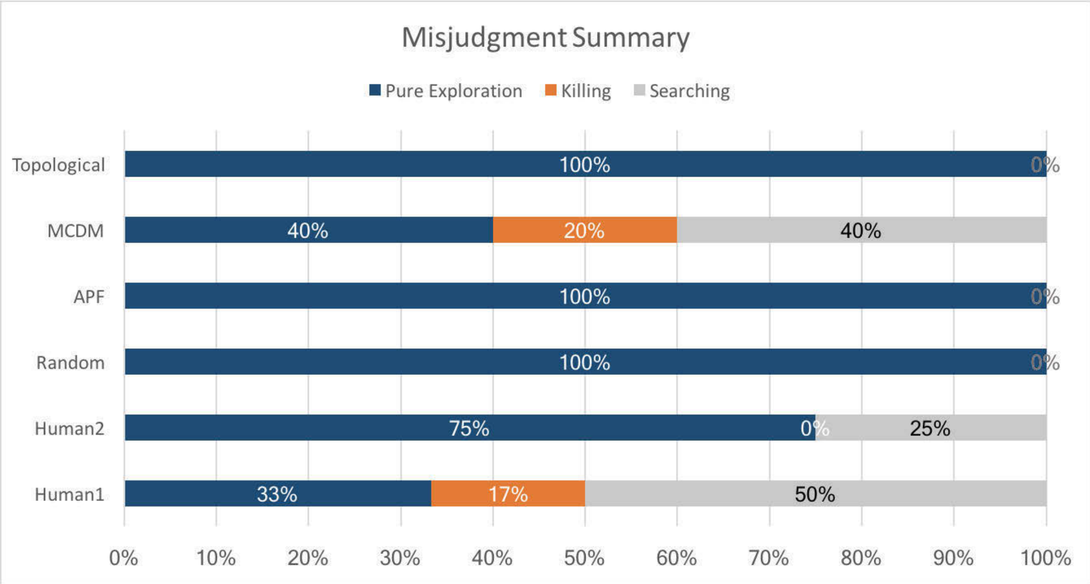


Figure 4.9. Misjudgment summary

4.5.3 Behavioral Differences Defined by Judges

From the questionnaire and interview data, four aspects of behavioral differences were extracted using thematic analysis: *interaction with environments*, *game-goal orientation*, *navigation* and *sense of mechanical*.

Interaction with Environments

It was commonly observed that players interact with environments in three types of games. The behavior was exhibited in relation to the global scene, with multiple factors, such as the outline of terrains and involvement, and interaction with particular items, such as edges, obstacles, bridges, corners, and enemies. The differences were presented in terms of environment perception, cognition and reactions. The humans had advantages in perceiving the outline of environments quickly and reacting in a reasonable way while agents could compute accurately, but sometimes their behavior didn't make sense to people.

Computer agents perform well in simple and small-scale local areas, but poorly in large and complex environments due to the complexity of computations. By contrast, human players conquer the complexity well because they are capable of recognizing surroundings quickly. As judge 4 put it during the interview, “Like what I observed, human and machines performed in an approximately same way in a simple and flat area. However, in areas, where there are a bunch of corners, highlands, lowlands and possible paths, machines’ behavior was not stable. They stopped and were confused where to go next. This would not happen to human players because they would know the situation by just having a look.” The agents’ weakness in perceiving global environments was illustrated in an example from the questionnaire response (J2 – Topological–*Searching game –most likely a computer agent*). “It seems that this agent did not know how to use the mini-map since it went right at first but it was evident that the agent was located in the top-left corner of the map.”

When interacting with special objects, such as edges, obstacles and bridges, human players are capable of perceiving them efficiently, conducting proper reasoning, and performing appropriate reactions. Computer agents are not sensitive to these items. They respond slowly or even totally ignore them. For example, judge 5 said “AIs did not play well at the beginning of the games. They were not sensitive to some special objectives, such as bridges. They did not behave well at corners of maps as well.” Human players could perceive environments and make decisions quickly. This is apparent from questionnaire comments, “It could quickly find the path by using the mini-map at 44 seconds [The Explorer made a decision among two choices, a ramp, and a bridge to the bottom side of the map].” (J2 – Human 2 –

Killing game –definitely human) And “This is a human agent since he chose the path by what he saw. When he found the obstacles, he stopped immediately and selected another way [at time frames, 14”, 29,” 30,” 33,” 34,” 38” and 40”].” (J2 – Human 2 – *Searching game – definitely human*). Computer agents were identified by their ignorance of special objectives. For example, as judge 2 commented in the questionnaire: “This should be a computer agent since when the SCV first moved down on the map, however, there was a bright new path [bridge] on the right but it chose to turn left at 15 seconds.” (APF – *Searching game – definitely a computer agent*). Human players react efficiently, as the questionnaire response makes evident: “The reactions were quick and correct. There were few redundant movements in the videos.” (J4 – Human 1 – *Killing game – most likely a human player*). Judges sometimes were confused by computer agents, when they observed the special items but did not react. In the *killing game*, judge 7 (APF – *definitely a computer agent*) commented “When it found the target, it spent too much time to think what to do. For example, it spent much time on walking around and attacking the last enemy in the first enemy campsite from 15 seconds to 20 seconds. It also missed the target that located in the top-right corner at 50 seconds and 1 min 59 seconds.” Different manners of reacting to various types of particular items are summarized in Table 4.3.

Edges	H	Follows edges but does not attach to them	J6 – Human 1 – *Pure exploration game – mostly likely human* "The robot went alongside boundary but sometimes ignored the corner. [It walked a big circle in regions, but didn't go further into corners, such as top-left corner at 53" and top-right mineral corner at 1'48"]."
	C	Attaches to edges	J7 – Topological – *Searching game – definitely a computer agent* "It always moved near the edge, for getting more view. human should not do this. When it found a mineral site [top-left corner behind mineral site from 13" to 22"], it stopped and searched in tiny and narrow channels."
Obstacles	H	Alters movement paths in time when confronting with obstacles	J2 – Human 2 – *Searching game – definitely human* "This is a human agent since he chose the path by what he sees. When he found the obstacles, he stopped immediately and chose another way [The behavior could be observed at 14", 29," 30," 33," 34," 38,"40"]."
	C	Could not identify obstacles or be disturbed by obstacles	J2 – APF – *Pure exploration game – definitely a computer agent* "It always hit the obstacles [It hit river banks and stopped at 26," 31," 43," 56," 1'18," 1'22," 1'32", and hit a monster at 35"] which seems not a human behavior." J2 – MCDM – *Killing game – most likely a computer agent* "The unit spent a little bit longer time to find enemies when there were obstacles between it and the enemies."
Bridges	H	Behaved reasonably around bridges	J5 – Human 1 – *Pure exploration game – definitely human* "This should be human since the SCV took a look around the bridge to clean the starting area with a smart movement before it went through."
	C	Was stuck or hesitated on bridges	J2 – APF – *Searching game – definitely a computer agent* "This should be a computer agent since when the SCV first moved down on the map, there was clearly a new path [bridge] on the right but it chose to turn left at 15." It had hesitation to go through the bridge."
Corners	H	Captured corners and moved away efficiently	J3 – Human 2 – *Pure exploration game – definitely human* "The searching path was always in the middle of roads. It did not search unnecessary edge or corner [It moved away from the top corner at 25", the top-right corner at 1'18", and the right bottom corner at 1'54"]."
	C	Wasted time or was stuck around corners	J1 – APF – *Pure exploration game – definitely a computer agent* "The player tried to walk across an uninformative corner twice at 4" and 48." It is definitely not a human being."

Table 4.3 Reaction to subjects (H – Human player, C – Computer agent)

Game-goal Orientation

Global goal-awareness of human players' behavior is another aspect of the differences revealed by the judges. Since each game has an explicit goal with a time limitation, the judges assumed that reasonable human gameplay should exhibit fulfilment of complete goals rather than wasting time or going idle. Computer agent subjects were also identified according to this assumption.

As explained in the section 3.1.1 Test Game Environments, mapping the entire game environment within a time limitation is the task of the *pure exploration game*. Having well-planned strategies, keeping a global view and spending less time around uninformative areas indicated human behavior. This is because this behavior displayed positive actions to complete the mission. This is illustrated by a quote from the questionnaire response: "It had planned when it moved to the unknown map. It chose a route with more horizon. When it needed to be back, it selected [a] short route." (J7 - Human2 - *Pure exploration game – definitely human*). Judge 5's observation indicated that human 2 had a global view: "This seems to be human since the movement of the SCV was reasonable and it had a global view of the exploration." (J5 – Human 2 – *Pure exploration game – most likely human*). The computer agents' behavior of exploring without plans, being stuck and wasting time, and re-visiting uninformative places (especially the starting area) were also highlighted by judges. For example, "In a *pure exploration game* with a time limitation, I don't think a human player will return to the path that he/she has already explored. At 1'40", if I was that player, I would definitely go to the north direction instead of the starting point." (J1 – MCDM – *Pure exploration game – definitely a computer agent*) and "It wasted too much time on the throat [at 19" and 22"]. Its movement looks like [it is] without [a] plan" (J7 – MCDM – *Pure exploration game – definitely a computer agent*).

In the *killing game*, units should be attacking enemies immediately and efficiently as the game goal requires players to kill as many enemies as possible in a limited time. For example, "The soldier killed SCVs immediately when it saw them [from 10" to 16", and from 44" to 54" at the top-right corner]." (J3 – Human 1 –

Killing game – definitely human) and “It had planned, did not miss targets and kept discovering the map” (J7 – Human 2 – *Killing game – most likely human*). Computer agents were recognized since they didn’t hunt enemies that immediately appeared within their visual range. Judge 1 commented “If the player was a man, the player would kill the SCV immediately at 46” in the video. However, the player did not.” (J7 – Topological – *Killing game – definitely a computer agent*). Sometimes they even ignored enemy units and passed by. As judge 5 said, “This should be a computer since the gunner missed the two SCVs at the top-right corner of the map twice [at 41” and 1’18” in separate].”

The *searching game* requires players to search the enemy base by reasoning in relation to the environment and the clues discovered. Exhibiting reasoning behavior convinced judges to classify the certain subject as a human player. For example, “It kept moving. Meanwhile, it continuously analyzed situations, and they were human actions. The operation was fluent. When it found out the target building, it discovered more places. That looks like what [a] human would do [discovering a clue building and moving back to have a look at 41”].” (J7 – Human 2 – *Searching game – most likely human*). Judges distinguished computer agents when observing the exploring unit travelling into unreasonable areas. For instance, “Since the player should know the target base could not be located at such [a] narrow corner of the map, a normal human player would never do that like what the SCV did [visited the top-left corner] at 14 seconds of the video.” (J1 – Topological – *Searching game – definitely a computer agent*).

Navigation

Navigation is a very typical behavior in video games. It also takes a big proportion of the gameplay, since exploration itself can be regarded as a particular type of navigation. In the experiment, two themes of navigation: the “stop and go” rhythm and walking back and forth, are extracted to distinguish humans from computer agents.

The “stop and go” rhythm refers to the navigation phenomenon where the game unit is controlled to walk and stop in pace. The frequency, length of the stopping time and stopping locations are three key factors. Human players tend to have low frequency and acceptable time when stopping. For instance, “The operation was fluent. But it had a clearly thinking time [Stopping at the right edge of the map at 57”].” (J7 – Human 1 – *Searching game – most likely human*). Computer agents, however, have a high frequency of stopping. Stopping locations are normally random points of open spaces. For example, “This SCV had visible stops when it moved [at time frames of 3”, 7”, 11”, 15”, 19”, 28”, 38”, 1’3”, 1’12”, 1’20”]. However, there were no obstacles in front or next to it.” (J2 – MCDM – *Pure exploration game – most likely a computer agent*). Sometimes, their stopping time was quite long. Judge 4 commented: “The agent was like a computer due to the facts that it sometimes goes to the 'dead corner' [from 1’56” to 2’02”] and that its decision-making period was quite long. But I think this might also happen for a 'newbie' player. I am not quite sure it was controlled by a computer.” (J4 – APF – *Pure exploration game* – unsure if it is a computer agent or human).

During gameplay, players navigate the game unit to walk back and forth in some cases. The difference between humans and computer agents is that human players normally have a clear purpose while computer agents’ purposes are obscure. For example, “SCV went back the path it just passed within a purpose [It discovered a clue building and moved back to have a look at 41", and captured the frame of the top-right region, and turned back to the main path soon at 57"]." (J3 – Human 2 – *Searching game – most likely human*) and "This should be a computer agent since the SCV repeated the moving loop [Moved back to visited areas at 1'11"] and it had hesitation to go through the bridge." (J5 – APF – *Searching game – definitely a computer agent*).

Sense of the Mechanical

Perceiving a sense of the mechanical from the gameplay gives judges an insight to distinguish the controller of the gameplay. Computer agents sometimes release a sense of the mechanical by making obvious mistakes. Judge 6 commented: "The design of process has some errors, so the robot kept the same action nearly four times. If this were a human player, there would not be [these] kind of mistakes." (J6 – APF – *Killing game – definitely a computer agent*). They sometimes exhibited programmed behavior patterns. For example, "We can tell that the searching path followed some patterns, for example explore each direction in the same distance." (J3 – APF – *Searching game – definitely a computer agent*). Ultra-fast movements also produced *senses of the mechanical*. Judge 3 said, "The searching path followed some patterns. The operation was too smooth." (J3 – MCDM – *Killing game – definitely a computer agent*). To be identified as human, players present *senses of the anti-mechanical*. Highlighted tricks could be displaying random behavior, hiding behavioral patterns and altering strategies. Examples are exhibited if we consider several questionnaire comments by judges. "The searching path is more [random] than AI." (J3 – Human 2 – *Killing game – definitely human*). "SCV went back the road it just passed within a purpose. I cannot tell any operations following a pre-set pattern.” (J3 – Human 2 – *Searching game – definitely human*). “The searching pattern changed from the beginning to the middle period of the game. It sometimes followed the edge of the road, but sometimes not. The operations were not always kept at the same speed.” (J3 – Topological – *Pure exploration game – most likely human*).

4.6 Discussion

4.6.1 Human Players Are Distinguishable from Computer Agents

The results of the experiment illustrate that spatial exploration behavior of computer agents and human players were easily distinguishable by mid-level RTS players. Even though some cases show that a computer agent’s (APF) performance is approaching the human players’ in the *pure exploration game*, a human’s performance is still significantly better than the computer agents in all cases. The behavioral gaps among human players and computer agents demonstrate that the game environment is an important factor that impacts the results of judgments.

Human players were consistently ranked higher than computer agents (**Q2.1**). During the interview sessions, most of the judges indicated that it was not difficult to distinguish human players from computer agents in the videos. Human performances exhibited a higher level of believability in all three games (Figure 4.6). This fact indicates that 1) the performances of human players and state-of-the-art computer agents are significantly distinguishable in spatial exploration games; and 2) a third-person observation approach is suited to identify believability in this context.

Even though the overall scores of human players are much better than the computer agents, APF’s human likeness score is closer to that of human players in the *pure exploration game* (Figure 4.5). APFs also have a high rate of being perceived as human players in the *pure exploration game* (Figure 4.9). A possible reason is that the algorithm drives the exploration unit to reveal frontier areas which are close to the unit. This kind of behavior is similar to the manner in which human players explore when extra information (for example layout of terrain and special items) is given.

4.6.2 Complexity of Environments Affect the Results of Testing

The game environment is an important factor in assessing the believability of spatial exploration. Gameplay records of computer agents in the *pure exploration game* achieved higher scores than those in the *searching game* and the *killing game*. In contrast, gameplay cases in the pure exploration achieved lower scores than those in the *searching* and *killing* games (see heat maps in Figure 4.7). In addition, Figure 4.8 shows that believability scores for human players decrease from the *killing game* to the *pure exploration game*, while the scores of computer agents' increase. It reveals the fact that the gap between the believability scores of humans and computer agents is decreasing from the *killing game* to the *pure exploration game*.

Investigating the size of maps and the complexity of terrains and tasks in each game, we can see that the *killing game* (which has the largest map, multiple highlands, lowlands and regions, and multiple tasks) is the most complex game. The *pure exploration game* (which has a flat terrain with a single task) has the least complexity (Figure 4.10 and Table 4.4). Corroborating this with the results which show the biggest distinction is in the *killing game* while the smallest distinction is in the *pure exploration game*, I conclude that believability of subjects can be more distinctly identified in complex environments than in simple environments. For example, gameplays in complex games have a lower rate of misjudgment that in simple games (Figure 4.9). Some judges also proposed similar conclusions in their interview comments, for example "Generally, I think the computer behaves poorly in complex environments … It depends on how much information can be provided from the video. In simple environments [say] a flat area, the performances of human and computers are similar." (Interview - judge 4).

Games	Environments				Tasks
	Size(pixel)	Regions*	Regions on high lands	Regions on low lands	
Pure exploration game	64 * 64	5	0	0	Map environment
Killing game	64 * 96	13	5	2	Map environment and kill enemies
Searching game	96 * 64	8	4	0	Map environment and search the enemy base

* Regions refer to enclosure areas which connect with other areas via narrow paths (Forbus, Mahoney & Dill 2002)

Table 4.4 The complexity of game environments and playing

4.6.3 A Framework of Believability Criteria

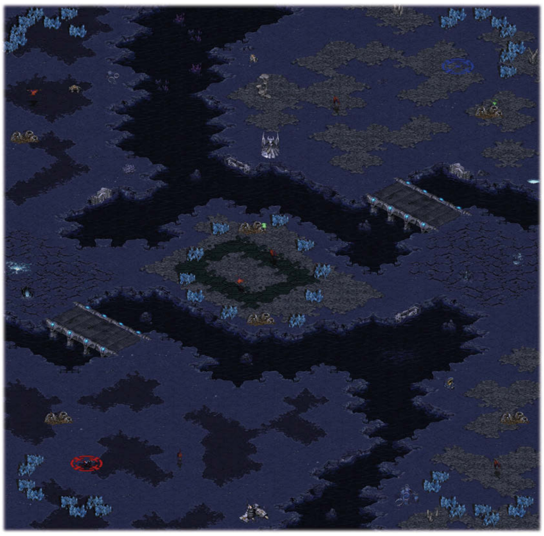
Based-on participants' comments and interview responses, I extracted a structured framework of believability criteria in spatial-exploration, which reflects on four aspects:

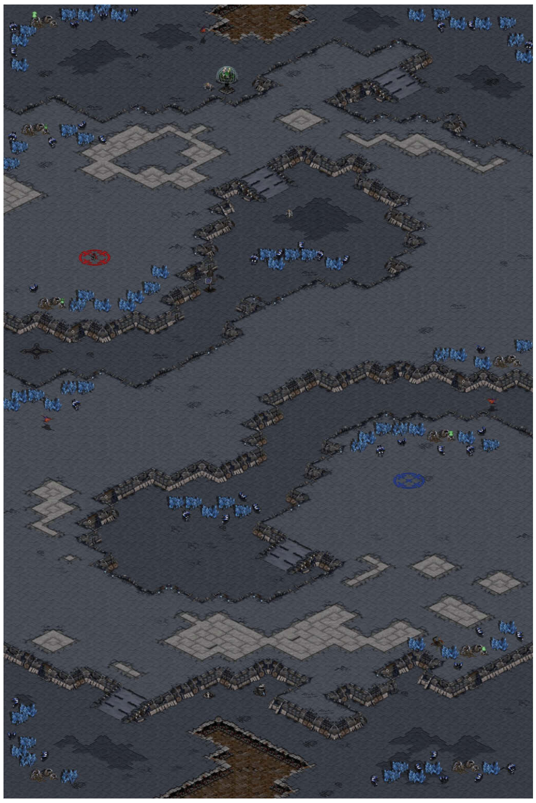
1) interaction with environments

2) game-goal orientation

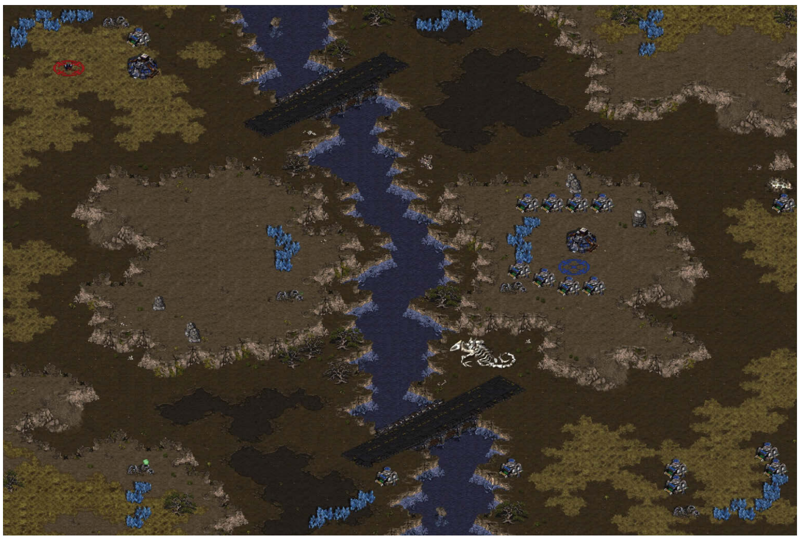
3) navigation

4) sense of the mechanical.





a. pure exploration game *b. killing game*



c. searching game

Figure 4.10 Game environments

It reveals the behavioral differences between humans and computer agents in performing exploration in video games. *Interaction with environments* reflects the way in which players react to the environmental elements discovered (for example layout of terrains, obstacles, and bridges). Judges highlight their attention on the reactions of players when observing special items. As the results indicate, the human players' reaction times and manners are different to those of computer agents. Laird and Duchi's (Laird & Duchi 2000) discovery that decision time is a factor to distinguish humans and computer agents has a linkage to our findings. Reaction time to terrain items is a factor in exhibit human-likeness on this aspect. Illustration of abilities which have a human-like cognition of terrain patterns (for example corners, bridges and layout of terrains), and apply corresponding reaction manners, however, is what a human-like computer agent needs to deeply exhibit.

Oriented by game goals, human players attempt to have corresponding strategies to achieve goals efficiently. Computer agents, however, sometimes, do not exhibit that their behavior is game-goal oriented. Hingston (Hingston 2009) reported that judges expected believable bots would exhibit sound tactical play, and Reynaud, Donnart & Corruble (2014) suggested efficiency is another factor to distinguish humans and computer agents. Those findings are relevant to the patterns on the *game-goal orientation*. Additionally, the *game-goal orientation* emphases much on the exhibition of tracking goals, instead of the completion of game goals.

Navigation highlights two notable patterns: "stop-and-go" rhythm and hesitations. "Stop-and-go" rhythm represents a pattern of movement pace. A "stop-and-go" action at a right position (for example connection points) with a proper time exhibits a sense of thinking. While flush and uncontrolled "stop-and-go" actions ruin the sense of human-likeness. It is interesting that ultra-fast behavior, instead of having proper "stop-and-go" actions, was regarded a kind of *sense of the mechanical*. This finding extends Reynaud's (Reynaud, Donnart & Corruble 2014) criterion of efficiency. Having hesitations with clear purposes is a criterion of believability. It is also an evidence, and a special instance of exhibiting *game-goal orientation*.

The aspect of the *sense of the mechanical* covers machinery behavior that computer agents perform in applications of spatial exploration. The behavior of obvious mistakes has a linkage to the finding of "obvious stupid behaviors" in Hingston's experiment (Hingston 2009). Programmed behavioral patterns and ultra-fast movements are another two highlighted criteria to distinguish computer agents from human players. I also summarized *sense of the anti-mechanical* from humans' behavior which provides a potential way to eliminate the exhibition of programmed behavioral patterns by displaying random behavior, hiding behavioral patterns and altering strategies. Combining proper "stop-and-go" actions is a potential way to reduce the *sense of the mechanical* that ultra-fast movements generate.

The four aspects of behavior patterns construct a framework of believable criteria which could be extended and applied to evaluate and create believable computer agents in virtual environment. Because the four aspects are commonly appearing, and constitute a major frame of gameplay in other genres. For example, a computer agent that plays FPS games has a clear game-goal (for example eliminating opponent units in Counter-Strike (L.L.C. 2000)) needs to *interact with environments* (for example following walls to approach enemies), and navigate itself to search enemies or achieving other goals. The frame of *sense of the mechanical* is also presented to this computer agent. Our framework is applicable to computer agents in FPS games. Some more criteria, such as collaboration with teammates, need to be integrated into the framework as extensions.

Behavioral differences summarized in *interaction with environment* and *navigation* reflects general patterns of differences between computer agents and human when navigating in virtual environments. *Interaction with environments* reveals the believable criteria of behaving within terrain patterns as well as interacting with common terrain objects (such as walls, obstacles and bridges etc.). Patterns in *navigation* provide a way to evaluate the pace of movements and hesitations – a noted behavior. Those findings present a basic idea of evaluating the believability of movements and navigation behavior in general virtual environments.

4.6.4 Guideline of Developing Believable Exploration Agents

Extracted patterns of behavioral differences provide insights for the design of believable exploration agents. Intuitively, the believability of computer agents can be improved via bridging the behavioral gaps with human players on each aspect presented above. For instance, a hierarchical model could be devised where the *navigation* pattern and the obvious mistakes in the *sense of the mechanical* pattern reflect the low-level behavior, while *interaction with environments* and *game-goal orientation* aspects could be improved in a high-level layer. It will be discussed in Chapter 6, where I designed an *integrated agent* to play exploration games in a human-like way.

4.7 Conclusion

In this chapter, I present the experimental framework to evaluate the believability of computer agents in spatial-exploration contexts. A third-person observation approach was employed to distinguish human and computer agent gameplay, in which Likert scale responses and written comments were collected from judges. Semi-structured interviews were also conducted to collect in-depth data after the survey sessions. The experiment was running under a pre-condition that both judges and human players in the subjective gameplay were average players who had some experience of RTS games. The game environments were three self-designed exploration games based on the StarCraft: Brood War platform.

The results of the experiments provided substantial insight for the three research questions presented in the Introduction. Third-person observation assessment identified significant variances between the human and computer agents (**Q2.1**). Believability scores from judges indicated that the state-of-the-art computer agent exploration behavior demonstrated a big gap with human exploration behavior. It is notable that the variances become more distinct when game environments increase in complexity. This third-person observation method was also shown to be a practical assessment method in distinguishing believability, where human players were clearly distinguished from computer agents via observing and comparing excerpts of gameplay videos.

Performing thematic analysis on qualitative questionnaire responses and interview records enabled us to extract human-and-computer behavioral differences, which constitute a framework of believability criteria on aspects of *interaction with environments*, *game-goal orientation*, *navigation* and *sense of the mechanical*. The behavior of computer agents, according to our analysis results, tend to perceive, recognize and react to environmental elements in an inappropriate way. The exhibited behavior sometimes did not align with the orientation of game goals.

Movement did not have an acceptable "stop-and-go" pace, and failed to exhibit clear purposes after moving backward-and-forward. Observable programmed behavioral patterns, ultra-fast movements, and obvious mistakes illustrate a *sense of the mechanical* (**Q2.2**). In contrast, human players exhibited sense-making *interaction with environments* and goal-oriented strategic behavior patterns. Their navigation behavior was much more natural and appeared purposeful. Random behavior, hiding behavior patterns and altering strategies make humans' behavioral patterns look natural and non-programmed (**Q2.3**).

In this Chapter, I designed a framework of experiments to evaluate believability in virtual environments, which are used to evaluate own developed computer agents in the following chapters. The extracted patterns construct a structured framework of believability criteria which provides a lens to understand the behavioral differences between humans and computer agents, and an extendable foundation to evaluate and develop computer agents in playing virtual-environment-based video games. The patterns of behavioral differences also contribute to the development of believable intelligent exploration agents. They are integrated to develop believable agents in Chapter 6. In next chapter, I investigate the way of creating believable agent by mimicking human exploration patterns discovered in Chapter 3.

Chapter 5. Developing Believable Exploration Agent: A Heuristic Approach

This chapter seeks to answer **Q3**: “How do the behavioral patterns of human exploration contribute to believable exploration?” This question is divided into three sub-questions:

Q3.1 How can heuristic methods be applied in developing spatial exploration agents?

Q3.2 Do heuristic methods contribute to the believability of an exploration agent?

Q3.3 Does the heuristic exploration agent perform efficiently in exploring virtual environments?

To answer these three questions, I firstly investigate the process of exploration, and apply heuristic methods to prune useless options of decision-making in the exploration process. Search spaces that are currently costly in terms of time and resources are pruned, and search spaces that have heuristic attractions to humans are given high priority when searching (**Q3.1**). Then, a third-person observation method is used to assess the believability of our exploration agent in specially-developed exploration games by comparing its gameplay with that of the state-of-the-art exploration agents as well as human players (**Q3.2**). Finally, I test the efficiency of our developed agent in several abstracted maps of simulated environments, where time-consumption and distance-travelling are adopted as the evaluation-criteria (**Q3.3**).

5.1 Problem Description

Spatial exploration is an activity where subjects search around an unknown environment to acquire information or resources. Subjects normally have a limited visual range. Situations where subjects have unlimited visual range within the environment are outside the scope of this research because subjects acquire all the information of the environment without moving. In this research, the subjects specifically refer to a game unit controlled by a computer agent. The problem is described as: A game unit with limited visual range travels in a spatial environment which is unknown to the unit, to acquire spatial information and search for special items based on spatial information acquired. The environment is gradually revealed to the unit completing the activity of exploration, as the unit detects areas which are within its visual range when travelling. Based on that, the tasks of spatial exploration are often exhibited as outlining spatial environments, collecting special items and searching hidden objectives.

The normal objective of design of automated-exploration agents is to complete the tasks efficiently (travelling less distances, spending less time and costing less energy etc.). The problem of developing an optimal solution of this issue is of equal complexity to the problem of finding shortest tours/paths for “lawn mowing” and “milling” problems. Arkin has proved that the later problem is a NP-hard problem (Arkin, Fekete & Mitchell 2000), where we can infer that the former one is also a NP-hard problem. It is much more challenging to develop an exploration-agent whose exploration behavior optimally approaches human-likeness, while still having a good performance in solving the classic problem of automated exploration.

5.2 Methodology

In this section, I introduce the algorithm framework of exploration that the *heuristic agent* follows, the three heuristics (i.e. *hierarchical*, *region based* and *field of view*) and how they are used to filter candidate positions. This section also includes the description of the environment representation and the evaluation method of candidate positions.

5.2.1 Algorithm Framework

The general process of exploration is different from the traditional path-planning algorithm. In the problem of traditional path-planning, a clear initial position and a goal position have been set. The algorithms aim to find the shortest path from the initial position to the goal position. The exploration algorithm does not, however, aim to tackle the issue of finding a path from the initial location to the goal, but rather seeks to manage the overall reconnaissance task. The core issue of the exploration problem is to decide where to travel during the entire working period.

Our algorithm follows the framework described in section 4.2 Computer-agent Objects. From the general exploration framework, I abstract that the essential methodology of exploration is that of greedily searching an optimal position for the next movement. The selection of next position is a two-step process. The first recognizes candidate positions from the game map. The second selects an optimal position from the candidate positions accordingly.

5.2.2 Heuristic Component

In-between the two-step process described above, I insert a heuristic component to pre-process the identified candidate positions in the first step, filtering sets of positions which are intuitively not good for the agent to choose in terms of believability. Heuristics are efficient cognitive processes that ignore part of the information, which are commonly employed by humans in making decisions (Tversky & Kahneman 1975). Gigerenzer & Gaissmaier (2011) present that heuristics can be more accurate than more complex strategies even though they process less information. According to the human' behavioral patterns revealed in Chapter 3 (see 3.4 Results), I present three position-filtering heuristics: *hierarchical*, *region based* and *field of view*.

Hierarchical

Humans naturally use a hierarchical structure to represent their spatial environment (see 3.4.1 Player Exploration Archetypes)(Si et al. 2017). I replicate this insight by dividing the environment into local levels and the global level, according to distances between places and the position of the exploration unit. This means places near to the exploration unit are defined as local, while the global level covers all the areas within the environment. I employ the hierarchical mechanism to filter candidate positions when evaluating how to identify the best position. Candidate positions in local levels are allocated high priority for evaluation, which mimics a human's tendency to give high priority to local options (see 3.4.1 Player Exploration Archetypes) (Si et al. 2017). Positions which have higher priority will be evaluated prior to those with lower priority. I define four levels - three local levels and a global level (Figure 5.1). Evaluation priorities of positions in inner local levels are higher than outer levels.

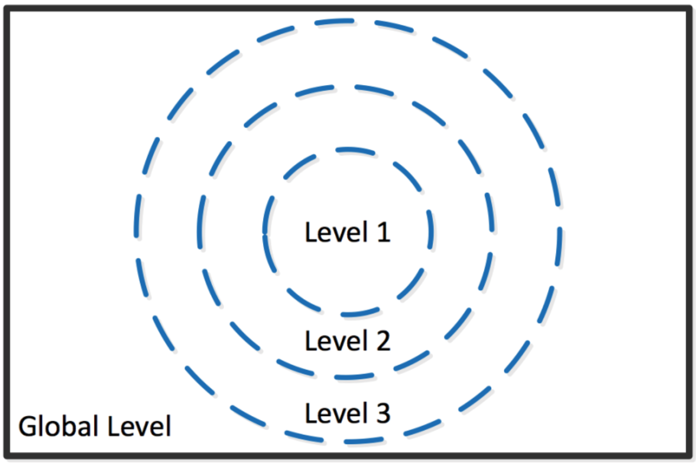


Figure 5.1 Hierarchical position-filtering levels

Region Based

Decomposing game terrain into regions, which are walled up by obstacles and cliffs and connected by narrow paths ('choke points') is a common gameplay of RTS games. RTS players reason explicitly about controlling, crossing and occupying regions of space. Building on this insight, I define the region-based algorithm where regions are walled-up by obstacles and connected by narrow paths. Region-based exploration is also the featured behavior of *Pathers (Si et al. 2017)*, the exploration archetype defined in the Section 3.4.1. Artificial intelligence researchers have pervasively realized the fundamental role of region-decomposition, where they developed algorithms to automatically decompose RTS game maps into regions and choke points (Forbus, Mahoney & Dill 2002; Halldórsson & Björnsson 2015; Perkins 2010) (see Figure 5.2).

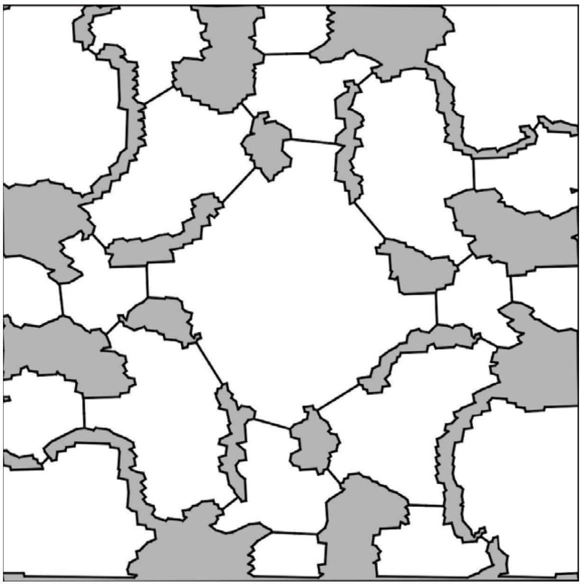


Figure 5.2 An example of region decomposition (Perkins 2010)

The *region based* approach is the second position-filtering heuristic, which works together with the *hierarchical* heuristic in-between the two-step process of position selection. Positions are grouped according to the regions where they are located. It then makes sure positions within the same region are consistently visited, which avoids the behavior of repeatedly travelling among different regions that are less likely to affect players' behavior.

Field of View

Directional consistency is defined as the preference to continue travelling in the current direction rather than changing directions frequently or travelling back and forth. Human players display a high degree of directional consistency (Si et al. 2017), whereas computer agents choose optimal destinations (see 3.4.2 Behavioral Aspects of Archetypes). This is because the human players can instantly observe the potential positions located within their *field of view* which is a restricted range that the human eye can see at any given moment. Human players then select the next position to move to within the *field of view* of the direction the exploration unit is heading to. I divide the environment into three areas: *field of view*, *forward area* and *backward area* according to the sequence where humans observe the surrounding environments (Figure 5.3). In the Figure 5.3, vector - *OF* is the direction of movement; area – *a* is the *field of view*; area – *b* is the part where the *forward area* excludes the *field of view*; area – *c* is the *backward area*.

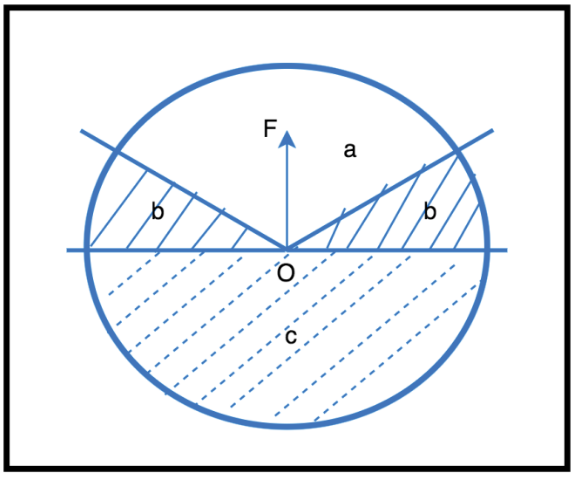


Figure 5.3 Field of view

Heuristic Candidate Position Filtering

Heuristic position-filtering is executed between the Step c) and the Step d) of the algorithm frameworks (see 4.2 Computer-agent Objects), after the candidate positions have been identified from the frontiers of the environment. The heuristic algorithm (see Algorithm 1) filters candidate-positions by combing the heuristics of *hierarchical*, *region based* and *field of view*. Within the condition that there are candidate positions at the local-level 1, the algorithm filters candidate positions by the *region based* heuristic and then *field of view* heuristic. If there are no candidate positions at the first local-level, the algorithm filters candidate positions by the *hierarchical* heuristic and then the *field of view* heuristic. The candidate-position set selected from this algorithm will be evaluated in Step d). The next best position is then chosen from the set.

Algorithm 1

```
WorkingSet ← Empty
GlobalSet ← IdentifyCandiatePositions ()
LocalLevel1, LocalLevel2, LocalLevel3, GlobalLevel ← HierarchicalDecomposeMap ()
LocalSet1, LocalSet2, LocalSet3 ← SeparatePositions(GlobalSet)

Do EnquireRegionInfo(LocalLevel1)

If LocalSet1 is not empty, then
        For all positons in LocalSet1 do
                If pos j is in region i then
                        Put pos j into regionSet i
                End if
        End for
        If the regionSet(currentRegion) is not empty, then
                FovSet, ForwardSet, BackwardSet ← Fieldofview(regionsSet)
                If the FovSet is not empty, then
                        WorkingSet ← FovSet
                Else if the ForwardSet is not empty, then
                        WorkingSet ← ForwardSet
                Else
                        WorkingSet ← BackwardSet
                End if
        Else
                WorkingSet ← regionSets – regionSet(currentRegion)
        End if
Else
        SetList ← LocalSet2, LocalSet3, GlobalSet
        For all Sets in SetList do
                If the Set is not empty, then
                        FovSet, ForwardSet, BackwardSet ← Fieldofview(Set)
                        If the FovSet is not empty, then
                                WorkingSet ← FovSet
                        Else if the ForwardSet is not empty, then
                                WorkingSet ← ForwardSet
                        Else
                                WorkingSet ← BackwardSet
                        End if
                Break For
                End if
        End for
End if
```

Where the *WorkingSet* is the filtered set of candidate positions that are evaluated in Step d); *LocalLevel1, LocalLevel2, LocalLevel3* and *GlobalLevel* are the levels of maps (see Figure 5.1); *LocalSet1, LocalSet2, LocalSet3* and *GlobalSet* are the set of candidate positions corresponding to each level of the map. The function *IdentifyCandidatePositions* identifies candidate positions from the frontiers at the specific moment when the computer agent needs to decide where to explore next. The function *HierarchicalDecomposeMap* divides the entire game map into levels based on the position of the unit's location. The function *SeparatePositions* separates a certain position set into three local sets and a global set according to the position located in each level. The function *EnquireRegionInfo* enquires about the region information of the candidate positions in a certain range. The variable *currentRegion* is the region that the exploration unit is currently located in. The function *regionSet* is the return a set of candidate positions located in a certain region. The function *Fieldofview* divides the candidate positions into the three sets: *FovSet*, *ForwardSet* and *BackwardSet*, based on the relative positions within the location of the exploration unit (see Figure 5.3).

There are three benefits for filtering set of the candidate positions before evaluation in a heuristic way. First, it promotes the efficiency of computation. Within the algorithm frameworks, it is necessary to have a step-look-ahead for evaluating the information expected to be gained in the next possible position. Computational resources (for example time and central processing unit (CPU)) need to be assigned to the evaluation activities according to the specific algorithm that is used. Obviously, for utility-based evaluation approaches, the cost of computational resources increases when the number of utilities goes up. The circumstance becomes severe if candidate positions are massive, as in large-scale game maps.

Secondly, the position-filtering method decreases the travel distance, moving from the current unit's location to the next best position. It is unavoidable to travel a long distance for exploration of an unknown region, even if areas around the exploration unit have not been completely explored, and when all of positions on the global frontier are evaluated in step d). This leads to the need for areas which were temporarily ignored to be revisited in the later exploration process when travelling for longer distances. Even though some automated-exploration strategies (Amigoni & Caglioti 2010; Li, Amigoni & Basilico 2012; Stachniss & Burgard 2003) consider the travel cost during evaluation, a candidate position with rich expected information in a relatively long distance away is commonly chosen. Alternatively, if the impact factor of distance cost is increased manually, the possibility of unreasonable prediction for the information gained in the next potential positions goes up.

The final reason is that heuristic methods, which reduce the options for decision-making according to common sense, are frequently used by humans to make decisions. The three key heuristics of *hierarchical*, *region based* and *field of view* used by human players in exploring the virtual environment have been discovered in Chapter 3 (see 3.4 Results). Therefore, applying them into the exploration of computer agents will contribute to an increase in the believability of these agents by mimicking the behavior of human players.

5.2.3 Environment Representation

The exploration strategy works on 2.5D environments. In this article, I employ a multiple map-representation methodology (i.e. the combination of grid-based, segment-based and feature-based) to re-organize map-information for exploration agents to understand the environment, as well as provide search clues.

Grid-based Representation

The grid-based method divides game maps into square tiles. Each tile is marked *unknown*, *free-movement* or *occupied*. *Unknown* tiles refer to the tiles that have not been explored, and players do not know whether they are walkable or occupied by solid obstacles or other game units. *Free-movement* tiles can be walked through. If a tile is flagged *occupied*, the tile is un-walkable. The exploration unit only walks through walkable tiles. Tiles that are close to unit and in the visual range of the unit are not *unknown*, and should be either *free-movement* or *occupied*. An *unknown* tile is changed into a walkable or un-walkable tile when it is detected by the unit, i.e. it spatially falls into the unit's visual range.

Segment-based Representation

Candidate positions are identified on the boundary between explored areas and unexplored areas. Segment-based representation, then, acts as the boundary identifier. Areas are presented by boundary polygons composed of line segments. Globally, the frontiers which separate unknown areas and unexplored areas are identified by an algorithm that recognizes polygons from the border of detected region (Perkins 2010). The algorithm converts the two-dimensional exploration array into a geometric polygon-boundary representation. This process is also called "vectorization". In each exploration step, the vectorization process is conducted when the exploration unit arrives at the previous next-best position. Hence, the new frontier vertex set is updated before evaluating the next next-best position. Normally, some frontier segments overlap with obstacle segments. As a requirement of candidate evaluation, the overlapping parts need to be identified. In other words, frontier segments that are on the border of obstacles are recognized before evaluation.

An analysis approach on its 8-trajectory tiles is used to deduce whether a frontier vertex is on obstacle or on unknown area.

Feature-based Representation

Special elements such as unique buildings and landmarks play an important role in terms of spatial information in both the real world and virtual environments. For example, in the domain of RTS games, the development of game situations basically depends on the reconnaissance of these featured elements. Special elements like gases and minerals provide economical support to StarCraft gameplay. Given that, all the bases are built in mineral areas in StarCraft. Similarly, neutral campsites, stores and taverns in Warcraft III affect gameplay by recruiting neutral heroes or offering special properties. Thus, it is necessary to gather information of these elements during exploration. I define these elements as special objects with specific geometric and functional properties.

5.2.4 Candidate Position Evaluation

When considering the computation of potential-position evaluation, I borrow ideas from the A* algorithm, which combines a goal-evaluation component and a heuristic component to evaluate candidate nodes. To gather more information costing less time or resources (travelling distance), the algorithm needs to balance these two aspects. Hence, two components are developed: the distance-based component and the utility component.

Distance-based Component

The Euclidian distance is employed to compute the distance in this component, which calculates the length of straight line between two points as the distance. In order to constrain the value of the heuristic component to the same magnitude as the utility component, the equation below is developed:

$$h(p) = e^{-[d(c,p)-r]} = e^{r-d(c,p)} \qquad (5.1)$$

where *d(c, p)* represents the estimating distance from the current position c to the candidate position *p*. The term - *r* denotes the radius of the exploration unit. For the requirement of component combination, the value of each component is limited to between 0 ~ 1. The feature of the exponential function indicates that its value is positive, and less than 1, when the variable is less than 0. The equation above guarantees that nearer candidate points acquire higher heuristic value, because the variation of the distance and the exponential function value follows an inverse proportion trend.

Utility Component

The acquisition of three types of environmental information is computed in this component. They are the walkability of map tiles, the outline of obstacles and special game elements. Technically, the knowledge of walkability of map tiles helps the game system make better path-finding decisions. It includes not only the troop maneuvering in later combat scenarios, but also supports further exploration tasks. The outline of obstacles plays a pivotal role when helping computer agents functionally divide game maps into different regions. The state-of-the-art methodologies typically separate map space into free-movement regions (allowing large groups of troops to move through side-by-side, or building extension locations on), narrow corridors (where ambushing always happens), and corridors. These region divisions are the foundations for strategy and for predicting opponents' possible options by just considering spatial factors. Special game elements vary in different RTS games and shape player strategies.

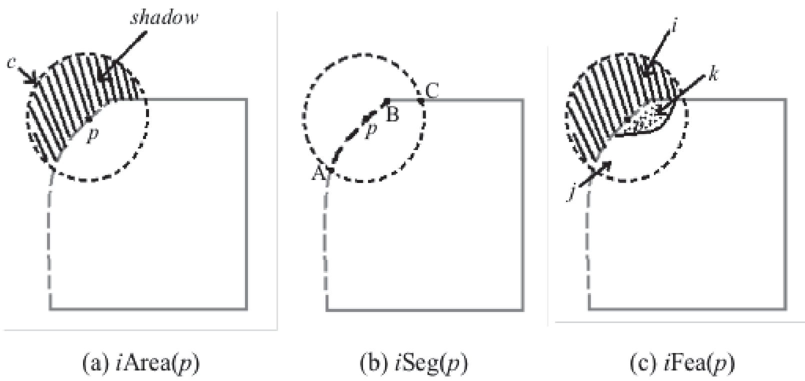


Figure 5.4 Information gain estimated with different criteria

Then, the evaluation of information gained for these three types of data is introduced. To unify the value of each utility, the circumstance of each criterion is presented by percentage. *iGrid(p)* presents the possible un-walkable tiles gathered in the candidate position *p*. As shown in Figure 5.4 (a), point *p* is the candidate position, while circle *c* illustrates the edge of unit's visual range if it is located on *p*.

Tiles in the shadow area are expected to be gained. The equation to calculate *u(iGrid)* is:

$$u(iGrid) = \frac{areaof(shadow)}{areaof(c)} \qquad (5.2)$$

In the second estimate, the amount of the potential edge line that is visible in position *p*, is computed by *iSeg(p)*. I assume that the frontier line segments, which are falling in the visual range of the exploration unit, are obstacle segments. Figure 5.4 (b) illustrates that AB is a frontier line segment, and BC is a line segment of obstacles. The computation equation is:

$$u(iSeg) = \frac{lengthof(AB)}{lengthof(AB)+lengthof(BC)} \qquad (5.3)$$

For the third elements, the expectation of obtainable game features in position *p* is predicted based on an area of gathered features, which fall within the visual range of *p*. It is illustrated by *iFea(p)* (see Figure 5.4 (c)). The computing follows the equation:

$$\mathrm{u(iFea)} = \frac{areaof(k)}{areaof(j)} * \frac{areaof(i)}{areaof(i)+areaof(j)} \qquad (5.4)$$

where area *j* includes area *k*, and *k* is the patch of explored features in the current view point, while *j* is the explored area. The term - *i* is the area, which is expected to be revealed in position *p*. A weight-based utility combination approach is used, which is demonstrated by:

$$u(p) = \sum_{i=1}^{n} u_i(p) * A_i(p) \qquad (5.5)$$

where $u_i(p)$ means the utility value of the candidate position *p* with criterion *i*, $A_i(p)$ is the weight of each utility. It satisfies the formula below:

$$\sum_{i}^{n} A_i(p) = 1 \qquad (5.6)$$

Combination of Components

A linear model is developed to combine the two components. It is illustrated by:

$$f(p) = \alpha * h(p) + \beta * u(p) \qquad (5.7)$$

The parameters (α and β) mean the weights that the two components have separately in the summary evaluation value. Their values satisfy the equation ($\alpha = 0.4$, $\beta = 0.6$ in following experiments):

$$\alpha + \beta = 1 \tag{5.8}$$

5.3 Case Study - Believability Assessment

Having a game agent with heuristic mechanisms based on common sense exploration will contribute to generating the illusion of believability. Hence, I design a believability-assessment experiment to evaluate it, which is based on the design from Chapter 4 (see 4.3 Experiment Design). It is based on a third-person observation. Judges watch videos of gameplay from each participant, and distinguish human players from computer agents.

A theory that is embedded in the believability evaluation is that of judges comparing their expectations of believable entities with the performances they observe in the videos (see 4.3.1 Judges). Given that, I consistently select average players who have similar gameplay knowledge and skills to the judges. It also includes our considerations of the fact that this player group constructs the major population of game players. In this experiment, I evaluate how the heuristic (hierarchical) method reflects believability in spatial exploration activities. The game environments are consistent with Chapter 3 and Chapter 4.

Along with the *heuristic agent* developed in this chapter, the computer agents (1) multiple criterion decision-making (MCDM), (2) topological and (3) random, which are developed in Chapter 4 constitute the computer-agent objects.

5.3.1 Human Subjects

Human players involved in this experiment, and their playing of the three games were recorded acting as reference objects when evaluating the believability of computer agents. The playing videos were selected from the experiment of Chapter 3 (see 3.1.3 Participants) to categorize how players do spatial exploration in virtual environments. They were invited via University mailing list. As the responses to the demographic survey illustrate, their skills and expertise vary from novice to game guru. I filtered the extremes on the two ends and left the mid-ranges, in which players have mid-level playing skills, spend moderate hours (5 ~ 10) playing video games a week and have medium degrees of familiarity with RTS games. Players who have mid-level skills and moderate playing-time allocation make up the majority population in both games in terms of consuming and playing markets. This fact encouraged us to select this group of people as the subjects in this experiment.

5.3.2 Judge Selection

I invited video game players, who have substantial domain knowledge and regularly play video games. They were neither novice players nor game gurus, but average game players who make up a significant proportion of the population of players. They were invited via the university e-mail list, social media and direct invitations in public areas. Their demographic information and experience of gameplay are illustrated in Table 5.1. The same methodology of recruiting is also used in the Chapter 6. For preventing judges getting access to the game-video contents before the experiments, I deliberately employed different judges in the experiments of Chapter 5 and Chapter 6 respectively. Because these two experiments share same computer agents and human subjects.

ID	Gender	Age	Years of gameplay	Gameplay hours per week	Game types usually played
J1	M	30	2-5	1-5	Strategy, CB, RPG
J2	M	28	> 10	10 - 20	RPG
J3	M	36	> 10	6 - 10	FPS, Strategy, RPG, Puzzle, Sports, CB, RLS, Simulations
J4	M	31	> 10	10 - 20	FPS, Strategy, RPG, Simulations, CBG, Sports, PBG, RLS, W&T, Social
J5	M	26	6 - 10	6 - 10	FPS, Strategy, RPG
J6	M	27	> 10	10 - 20	Strategy, Social, Sports, RLS
J7	F	36	> 10	> 20	Strategy, RPG
J8	M	25	> 10	1 - 5	Strategy, Simulations, CB, Sports, RLS
J9	M	25	6 - 10	1 - 5	FPS, Strategy, RPG, CB, Sports, RLS
J10	M	28	> 10	6 - 10	FPS, Strategy, RPG, CB, PBG, RLS

FPS	First-person Shooter	RLS	Real-life Sports	CB	Chance - based
PBG	Physical-Board Games	RPG	Role-playing Games	W&T	Word & Trivia

Table 5.1 Demographic information and gameplay experience of judges

5.3.3 Procedure

The entire experiment is conducted online via a Google questionnaire form.

1. The participant reads a paragraph about a brief introduction to the experiment, then watches an embedded online video which introduces the three games.
2. The participant fills in the demographic questions.
3. The participant reads an information board to remind him/her of the player characteristics and the tasks to be completed:
    a. Watch 18 videos, evaluate human likeness for each of them and present a reason for the judgment.

b. Answer questions to summarize their video-watching-and-evaluating sessions.

c. Human subjects are mid-level RTS players and the computer agents are designed to imitate mid-level players.

4. The participant watches videos and answers questions.

5.3.4 Believability: Ranking Results

Figure 5.5 illustrates the ranking results collated from questionnaire responses. The five Likert scale options (i.e. *definitely a computer agent*, *most likely a computer agent*, *unsure if it is a computer agent or human*, *most likely human* and *definitely human*) for rating human-likeness are mapped to numerical integer values (1 ~ 5).

In Figure 5.5, the value represents the average score for each player. It is calculated via Formula (4.1). Figure 5.5 shows that the average believable score of the *heuristic agent* across the three exploration games is higher than that of the other three computer agents. Meanwhile, it is in-between the two human players.

The value in Figure 5.6 demonstrates the average score for each player in playing each game. It is computed via Formula (4.2). Figure 5.6 illustrates that the believability of the *heuristic agent* is significantly higher than that of other three computer agents in all three games. Its believability scores are in-between those of the two human players in the *pure exploration* game and the *killing game*. Even though, it is lower in the *searching game*, the difference values, comparing to the scores of the two human players, are quite small with 0.4 (3.9 – 3.5) and 0.5 (4.0 – 3.5) respectively.

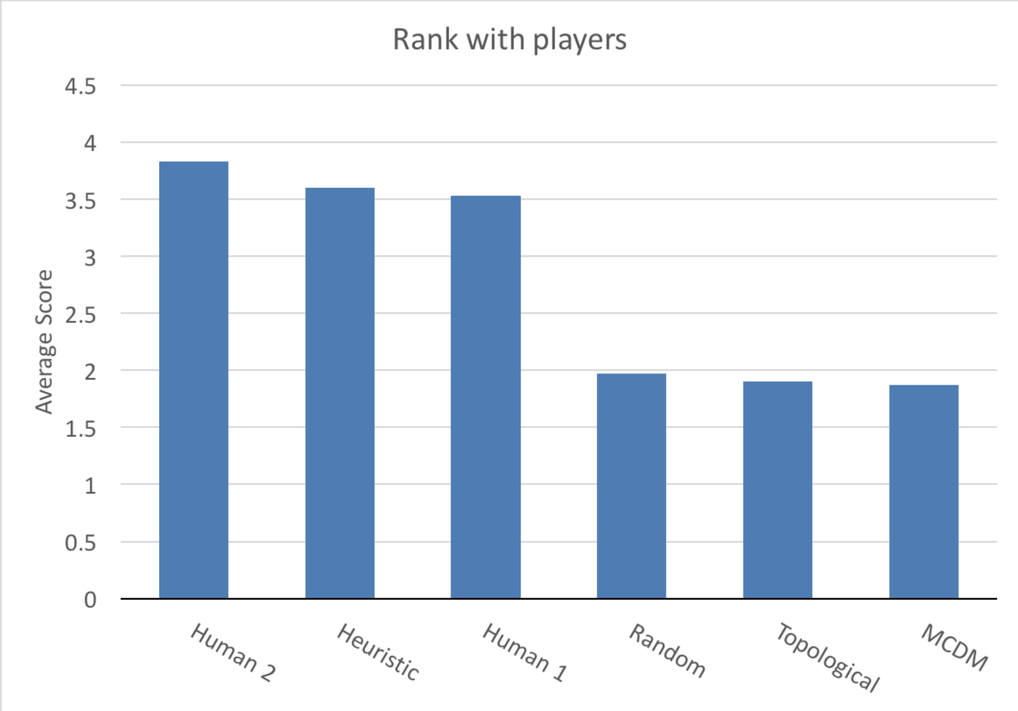


Figure 5.5 Believability of the *heuristic agent*

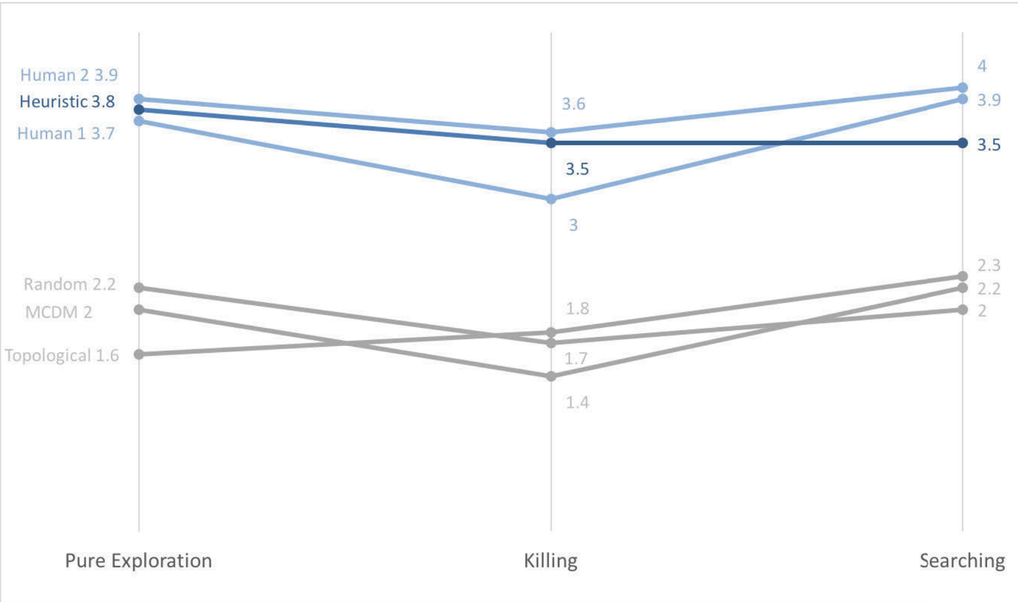


Figure 5.6 The believability scores of the *heuristic agent* are significantly higher than other computer agents, and between two human players

5.3.5 Human-like Behavior and Non-human-like Behavior

On the questionnaires, judges were required to explain their decisions about the believability of each subject. Judges' responses about this question were processed and classified by the category of descriptions of human-like behavior and descriptions of non-human-like behavior. Table 5.2 shows how the ten judges responded to the subject (*Heuristic agent –Pure exploration* game).

I arrange the judges' responses to the three kinds of subjects, humans, *heuristic agent* and other computer agents. Then, the judges' descriptions of playing behavior are analyzed by using the thematic analysis method (see 3.2 Thematic Analysis). Themes are extracted from the descriptions, where each theme represents several common descriptions of playing behavior. For example, the *stop-and-think* theme represents all the statements that describe the behavior of stopping, which illustrates a sense of thinking.

Human-like Behavior

Reasonable behavior around landmarks means that the unit exhibits human-like behavior near landmarks, such as bridges, narrow slopes and enemy buildings. The unit normally shows proper awareness and reactions to these landmarks when it perceives them.

Natural movements refer to the fact that the movements look natural and human-like. For example, "The movements were very natural. It looked like the player was always looking for the clues." (J3 – Human1 – *Searching game – most likely human*)

Human-like behavior		Non-human-like behavior	
J1	No fault was shown in searching a map.	The unit spanned in a small corner at 1:42, which looked unnatural.	J3
J2	It stopped sometimes. I think it would be thinking.	1. SCV tried to explore areas which were obvious boundaries of the map. 2. SCV got stuck on the left side of the bridge	J4
J5	1. Searching path is random. 2. The unit revisited the path that was just explored.	Sometimes, the behavior was too smooth.	J8
J6	The SCV moved towards to the enemy side before completely discovering the friendly side.		
J7	The unit expressed deliberate movement combing with some backtracks to get a missed few pixels.		
J8	Basically, the unit explored by the best paths.		
J9	1. The unit went in straight lines. 2. It made decisions very quickly.		
J10	1. The robot just walked along the map. 2. The mind was clear for the game goal. 3. It almost never wasted time.		

Table 5.2 Human-like behavior and non-human-like behavior observed in the playing of the *pure exploration game* by the *heuristic agent*

Fluent actions mean the process of game playing is fluent. For example, "This should be a human player since it moved freely and smoothly." (J5 – Human 2 – *Searching game – most likely human*)

Revisit incompletely-explored areas shows that the unit changes its current moving direction *and* returns to the places which it has visited but not completely explored. The unit normally goes back to incompletely-explored areas with specific purposes. For instance, "[The unit] double checked the area after finding the supply depot. [It then] found the enemy base quickly." (J4 – Human 2 – *Searching game – most likely human*)

Stop-and-think behavior exhibits the intention of selecting path around conjunction points of paths. For instance, "According to the behavior of the SCV, it stopped sometimes. It would be thinking. I feel it was like humans' behavior." (J2 – *Heuristic agent – Pure exploration game – most likely human*)

Deliberate exploration represents exploration behavior that the unit rigorously explores the current area before moving to others. For example, "Deliberate movement combined with some backtracking to get a missed few pixels makes me fairly sure it was a human." (J7 – *Heuristic agent – Pure exploration game – most likely human*)

Reasonable killing behavior represents behavior that is expected as human players when the game character confronts enemy units in the *killing game*. For example, "The way of looking for enemies looked like humans. The shooting process was random without any certain patterns. It should be a human player." (J8 – Human 2 – *Killing game – most likely human*)

Consistent movements mean the direction of movements keeps a certain consistency. For example, "[The unit] went straight lines, and made decisions very quickly." (J9 – *Heuristic agent – Pure exploration game – most likely human*), and "The robot just walked along the map. The mind was clear for the game goal. It almost never wasted time." (J10 – *Heuristic agent – Pure exploration game – most likely human*)

Random path selection means the unit exhibits the sense of randomness in selecting a path. For example, "The searching path was random. … It took the path just searched." (J5 – *Heuristic agent – Searching game – most likely human*)

Ignore uninformative areas represents the unit ignore some areas, such as small corners, outlined boundaries, and completely explored areas, which do not provide useful information. For example, "The player acted in a deliberate manner and abandoned exploration of an area once he could see no base in range." (J7 – *Heuristic agent – Searching game – most likely human*)

Non-human-like Behavior

Idle behavior represents the scene where judges hardly recognized the purposes of the behavior. It normally is exhibited by blind and limited local exploration. For instance, "The object walked in an idle way around the base area. It definitely was not a human." (J8 – Random – *Searching game – definitely a computer agent*)

Revisit explored areas includes behavior of visit an area repeatedly or of travelling back to an area which has been explored before from a place where there many obvious potential points to explore. It is normally regarded as redundant behavior. For example, "The unit seemed to return and check places that have already been covered. It kept making many small returns." (J4 – Random – *Pure exploration game – definitely a computer agent*)

Unreasonable stops represent the behavior of pauses when moving with no understandable purposes or a high frequency. For example, "The SCV stopped a lot and had weird behavior near the bridge." (J3 – MCDM – *Searching game – definitely a computer agent*), and "The robot walks slowly on the plain, and stops near the tree." (J10 – Topological – *Searching game – definitely a computer agent*)

Stick to boundaries represents the behavior that the unit still moved forward to explore boundaries when they were obviously revealed and easily recognized by the human. For instance, "The SCV checked against the map edge too closely when it has already been revealed that it is an edge." (J4 – MCDM – *Pure exploration game – definitely a computer agent*)

Fixed patterns mean game playing videos exhibit easy recognized behavioral patterns which are regarded as programmed behavior. For example, "I can tell searching patterns. The searching path followed the map margin. Regular pauses were exhibited when searching." (J5 – Topological – *Searching game – definitely a computer agent*)

Unreasonable killing behavior constitute behavior that is not convincing as human players when the game character confronts enemy units in the *killing game*. Ignoring enemy units or exhibiting hesitations are typical *unreasonable killing behavior.* For example, "Some unnecessary movements appeared before or after shooting, such as going further to the corner where there is no SCV [enemy units] after shooting, sudden stops and going forward a bit before shooting." (J3 – Human 2 - *Killing* game - *definitely a computer agent*)

Unreasonable behavior around landmarks means that the unit expresses unexpected behavior near landmarks, such as bridges, narrow slopes and enemy buildings. For example, "The behavior that the object rigorously approached *supply depots* with a certain distance looked like machines." (J8 – Topological – *Searching* game – *most likely a computer agent*)

Unnatural movements represent unexpected movement trajectories. For example, "The object hesitated several times and went with strange paths." (J9 – Human 1 – *Pure exploration game – most likely a computer agent*)

Spin in a corner represent the situation that the unit appears temporally stuck in a corner. For example, "Overall [its behavior was] natural, but spinning in a small corner at 1:42 looked unnatural." (J3 – *Heuristic agent – Pure exploration game – most likely a computer agent*)

5.3.6 Behavior-based Evaluation

The content from transcripts is labelled via themes of behavior generated above. Labelled pieces of content for each theme are counted within each group of subjects. I employ the "pie of pie" chart to represent the themes of both human-like behavior and non-human-like behavior for each group of subjects, and the frequency of each theme in the transcripts. Each pie represents the percentages taken by themes of non-human-like behavior or human-like behavior. The right pie is smaller and takes lower percentages. It shows the group of behavior themes (i.e. human-like behavior or non-human-like behavior) that takes lower percentages for a certain subject group (i.e. humans players, computer agents or the *heuristic agent*).

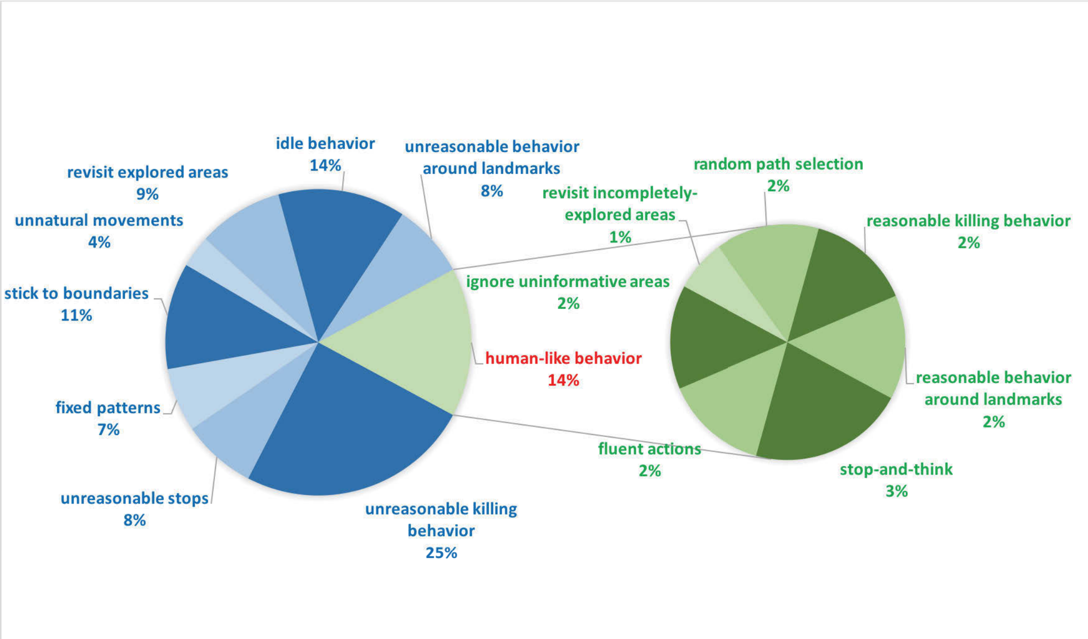


Figure 5.7 Distributions of behavior themes for computer agents (Percentages are computed based on the counts of statements in each theme.)

Figure 5.7 shows the human-like behavior and non-human-like behavior of the three computer agents. They are presented by the ten judges' responses to the questionnaire. It also illustrates how many times one type of behavior is recognized and mentioned by percentages. The count of human-like behavior is 14 percent while the statements of non-human-like behavior is 86 percent. For obviously recognized computer agents, non-human-like behavior is significantly more than human-like behavior.

The highlighted non-human-like behavior are *unreasonable killing behavior*, *stick to boundaries* and *idle behavior*. Several themes evenly share the rest pie of human-like behavior. Each of them only takes a small percentage of the total pie.

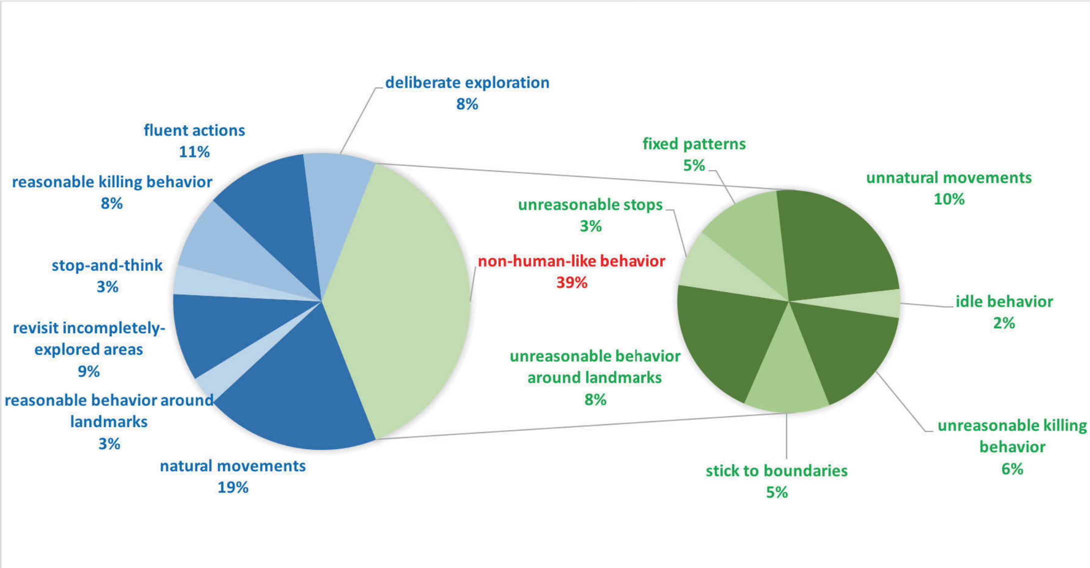


Figure 5.8 Distributions of behavior themes for human players (Percentages are computed-based on counts of statements in each theme.)

Figure 5.8 shows the human-like behavior and non-human-like behavior of human players. Human-like behavior occurs more than non-human-like behavior as it takes 61 percent of the total.

The highlighted human-like behaviors are *natural movements*, *fluent actions*, and *revisit incompletely-explored areas*. The count of these three themes takes the major part of human-like behavior. They are followed by themes of *deliberate exploration* and *reasonable killing behavior*, which take 8 percent each. Meanwhile, the highlighted non-human-like behaviors are *unnatural movements*, *unreasonable killing behavior* and *unreasonable behavior around landmarks*.

Figure 5.9 shows the human-like behavior and non-human-like behavior of the *heuristic agent*. Human-like behavior is more than non-human-like behavior as it takes 66 percent of the total. This demonstrates how the *heuristic agent* achieves high scores in believability.

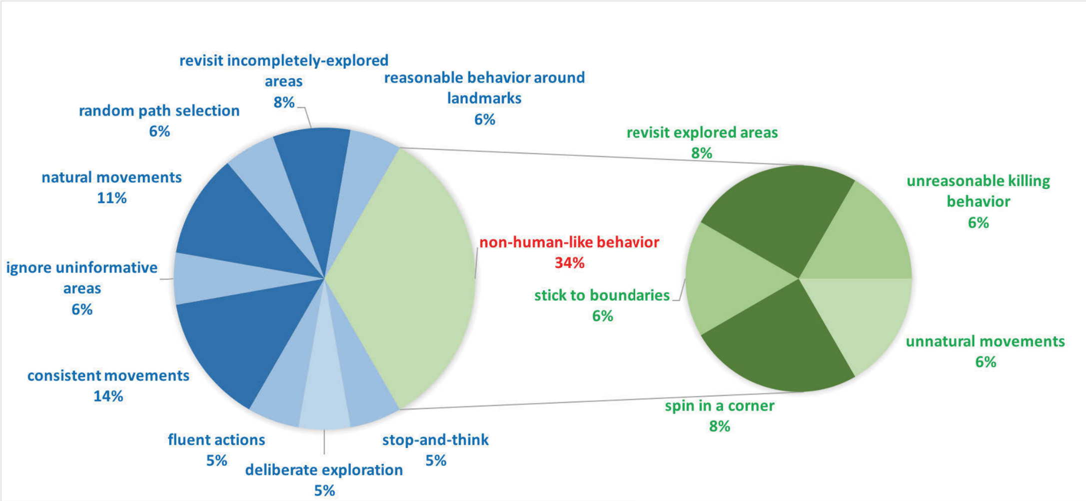


Figure 5.9 Distribution of behavior themes for the *heuristic agent* (Percentages are computed-based counts of statements in each theme.)

The highlighted human-like behaviors are *consistent movements*, *natural movements* and *revisit incompletely-explored areas*. Other themes of human-like behavior almost evenly share the rest of the percentages. Meanwhile, the highlighted non-human-like behaviors are *revisit explored areas* and *spin in a corner*.

5.*3.7 Discussion*

The believability scores shown in Figure 5.5 and Figure 5.6 show that the *heuristic agent* I developed is believable in playing exploration games. Within the experiment, the score that the *heuristic agent* achieved is significantly higher than the other computer agents and in-between human players. The position-filter-based heuristic method is valid in achieving believability for the exploration of virtual environments.

According to Figure 5.9, several themes with relatively high percentages of human-like behavior are generated by the heuristic factors. In general, the heuristic method filters potential positions before making decisions, which leads to the illusion of *revisit natural movements* and *fluent actions*. The *field of view* heuristic factor gives a high priority to potential positions which are in front of the exploration unit. The unit changes movement directions only when there are no potential positions that it faces, which generates a sense of *consistent movements*. The *region based* heuristic factor guarantees the exploration unit visits all the potential positions before heading to other regions, which is regarded as *deliberate exploration* and *revisit incompletely-explored areas*. The *heuristic agent* normally keeps a local exploration strategy where it consistently explores local areas if there are potential positions in local areas. It occasionally does employ a global strategy to search potential positions globally, when there are no positions to visit in local areas. In this sense, it may travel to the places that it has partially explored. Since the global exploration behavior happened reasonably, the *revisit incompletely-explored areas* in many cases are regarded as human-like behavior.

The design of the *heuristic agent* matches the pattern of human exploration behavior. Humans are *hierarchical* when making spatial decisions like the *Seer* archetype who does local exploration but with a global conception. Human players may not strictly follow the rule of considering global choices only if there are no local choices. They may also revisit a partially explored place when they occasionally would like to gather more information or evaluate the knowledge they acquired about the area previously. Generally, however, keeping to local exploration most of the time and doing global searching occasionally is the behavioral pattern of the human. In this research, I employ a restricted hierarchical-heuristic method, where the unit evaluates candidate positions only if there are no local choices (Algorithm 1). It is a simple and efficient way to create believability in exploration. Nominated human-like behavior such as *revisit explored areas* and *make decision* *quickly* exhibit this mechanism.

As the *Pathers* archetype reveals (see 3.4.1 Player Exploration Archetypes), having *region based* perception of spatial environment is also a highlight feature of players. Human players perceive, represent and memorize spatial environments with a *region based* structure, where a game map is divided into regions which are connected by choke points (narrow paths). Players make decisions based on the map of region connections. In the chapter, the *heuristic agent* employs a *region based* heuristic component. It compulsively makes the agent primarily evaluated potential points that are in the same region as the exploration unit. If there are no potential points in the same region, it then evaluates those in the nearest region. That contributes to generate *deliberate exploration*.

Hesitations, referring to the behavior of travelling back and forth, are also one kind of common behavior of human exploration. Reasons that cause hesitation behavior vary among different archetypes. According to our experiences, the reasons are not easily figured out by purely observing. Complex and unreadable hesitations may appear unreasonable because they could not be understood by observers (see 4.5.3 Behavioral differences defined by judges). The *hierarchical* heuristic has generated a kind of hesitation behavior – *revisit explored areas*, which occasionally happens. More frequent hesitations would make them incomprehensible, since observers need more time to discover exhibited purposes. The *field of view* heuristic helps to keep the agent in a consistent direction when exploring (*consistent movements*), and it also reduces hesitations.

In the case study, the results illustrate that the *heuristic agent* passed the believability test. I evaluate the efficiency of the *heuristic agent* in abstract environments to see whether it could have a good performance in terms of efficacy.

5.4 Case Study - Efficiency Evaluation

In this section, I evaluated whether the heuristic approach that filter candidate positions conducted exploration tasks efficiently. This experiment emphasis on testing whether the position-filtering heuristic approach was efficient in the corresponding tasks or not. Hence, I implemented a simple version of the *heuristic agent* with the *hierarchical* heuristic, instead of its full version in this study. Additionally, abstract environments were developed where each computer agent was tested many times in each game map, and started with different positions in each round of exploration.

5.4.1 Experiment Design

To test the efficiency of our method, I developed a simulator in C++ using openFrameworks (Lieberman, Watson & Castro 2016). I collected 45 game maps from three commercial RTS games (StarCraft: Broodwar, StarCraft II and Warcraft III (Entertainment 2002)), analyzed them, and extracted five common patterns: *base-location pattern*, *base-location-and-the-first-extension pattern*, *turtle-shape pattern*, *corridor pattern* and *extensions pattern (Si, Pisan & Tan 2014b)*.

This simulator is independent to any specific platforms. The developed game maps represent the common traits of maps in different commercial games. The simulated system also satisfies the requirements of simulations that have a balance of test maps, where the exploration units need to start the exploration at different start points.

- *Base-location pattern* represents the starting area, where the player's base is located in RTS games. It is often surrounded by obstacles or un-walkable terrain elements, such as seas and cliffs. A passageway, usually referred to as a choke point, connects this region to the rest of the map.

- *Base-location-and-the-first-extension pattern* presents a pattern where a starting area connects to a resource-rich area. The resource-rich area is frequently explored in the first several minutes of gameplay.

- *Turtle-shape pattern* defines terrain where there is a large free-movement space in the center of the region and small regions containing resources connected to the main region through narrow corridors.

- *Corridor pattern* is a corridor-shaped common area, where narrow passageways are twisted.

- *Extensions pattern* is used to summarize a specific type of terrain frequently observed in Warcraft III. A group of semi-open extensions (i.e. regions rich in resources close to the base-location) are connected by an open space. This inner-connected large area is normally reachable from other regions through one or two narrows.

I have created abstract maps (Figure 5.10) based on these patterns. In these abstract maps, areas in black represent walls and obstacles, while areas in white represent walkable spaces. Resources are represented by blue polygons. The purpose of the experiment is to test the ability of our strategy to explore the spatial environment. Therefore, there is no enemy designated on these maps.

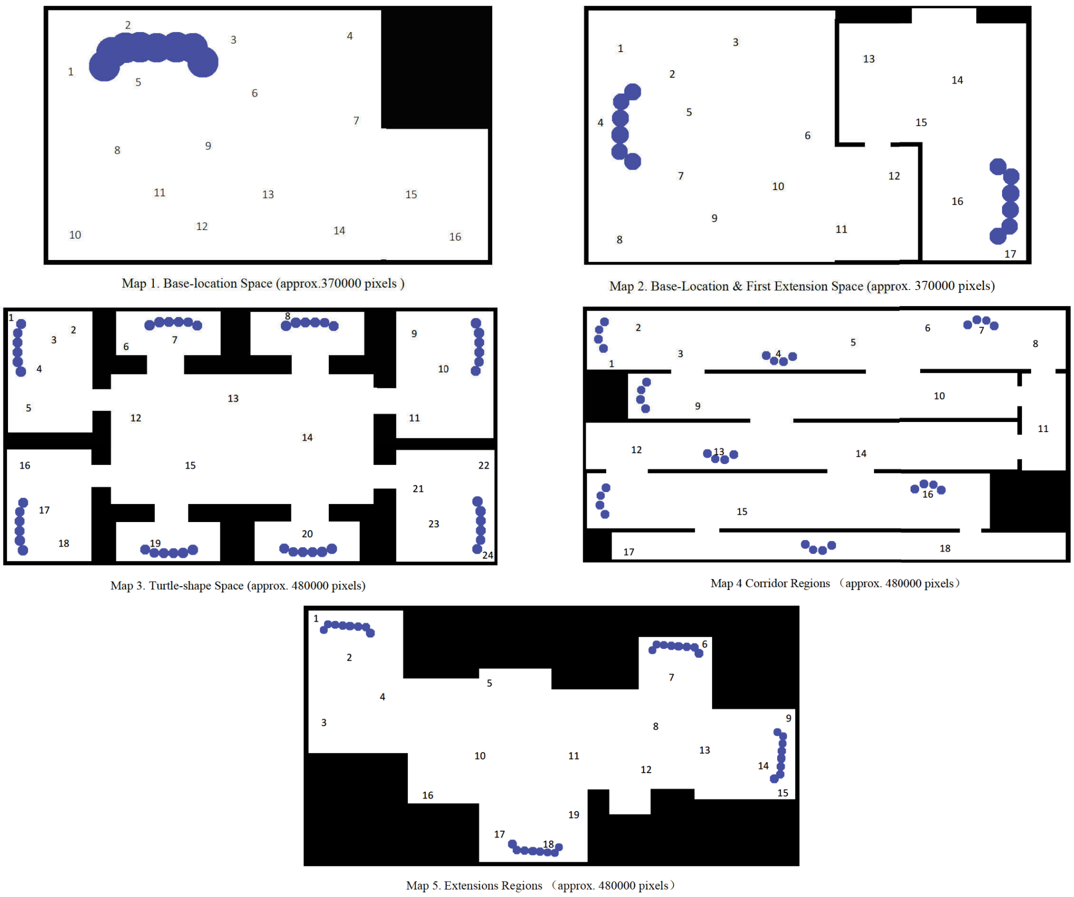


Figure 5.10 Game maps used in experiments (numbers represent starting locations)

For all experiments, I chose the visual range of exploration units as 40 pixels, which forces recon units to make a significant number of steps to complete the exploration. Simulation is terminated when 99.5% area of the map has been explored or when the allocated time (800s) for exploration runs out. This percentage is enough to reflect the completeness of space information gathering. It is meaningless to compare the remaining 0.5% exploration in evaluating exploration algorithms. I describe the four strategies used in our experiments below.

Random Strategy

The candidate positions are randomly selected from explored areas, and the next movement position is randomly selected from the candidate positions i.e. the evaluation function is not used. This strategy represents an uninformed agent intended as a worst-case strategy for exploration.

Visual Strategy

In the visual strategy, candidate positions are chosen from the current unit's visual range, and often along the edge of visual range to maximize the new area. Candidate positions are evaluated using the same MCDM strategy as the Heuristic-Frontier Strategy described below. Integrating this strategy gives us a chance to compare the performance of exploration algorithms between frontier-based and non-frontier-based.

Frontier Strategy

This strategy is a modified version of the Gonzáles-Baños and Latombe's exploration strategy (GB-L strategy) (Gonzalez-Banos & Latombe 2002) and is used to determine the performance contribution that can be attributed to the hierarchical position filtering mechanism. As part of MDCM, candidate positions from frontier vertices are identified and evaluated by the following formula:

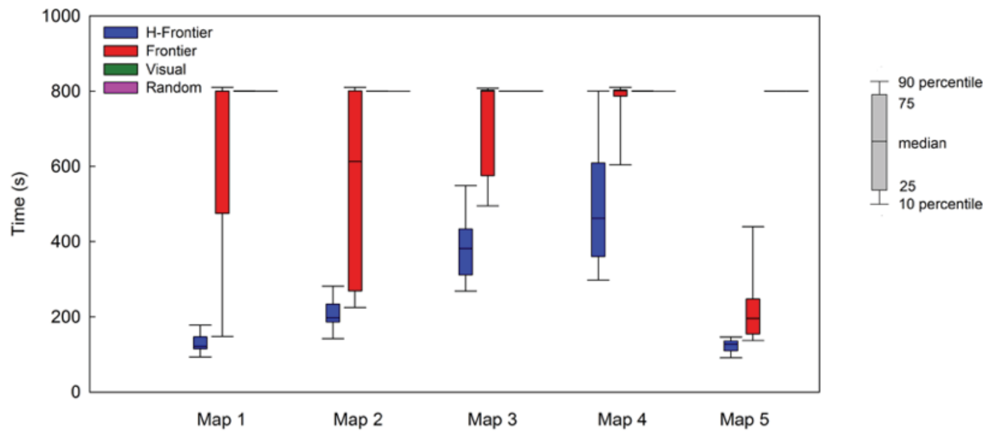
$$f(p) = A(p) * \exp(-\lambda * L(p)) \qquad (5.9)$$

where *A(p)* is an estimate of the unexplored area visible from *p*, *L(p)* represents the real distance from the current location of the exploration unit to the candidate position *p*. λ denotes the weighting between exploring large areas and travelling less distances. The value of λ is set to 1/300, meanwhile the value of *A(p)* is constrained to [0~1], and the value of *L(p)* is in [0~1000]. That helps to balance *A(p)* and *L(p)* at the same magnitude as well as to keep their contribution for the total evaluation value in a proportion of 2/3. The value of λ is empirically chosen and varying this value is part of our future research. In terms of unexplored area estimation, two criteria are taken into account: unknown map-grid gathering and obstacle-segment collecting. This strategy is a representative example of the state-of-art in NBV-based strategies used to solve robotic exploration problems.

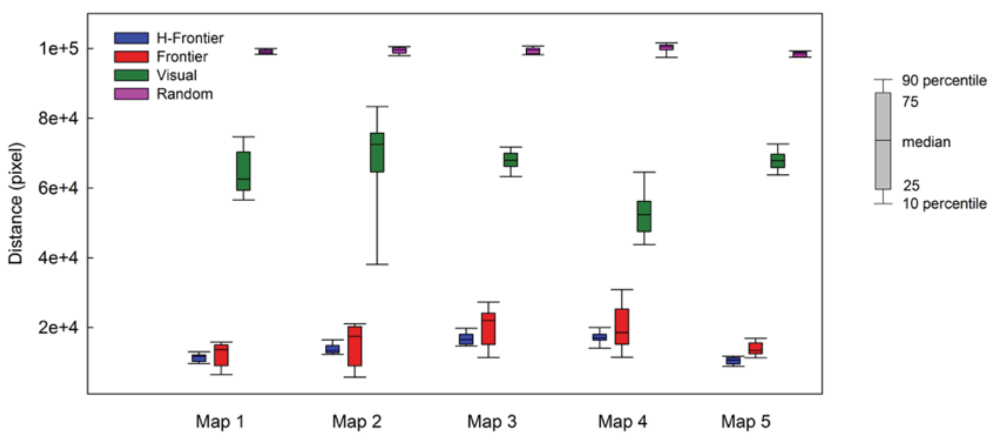
Heuristic-Frontier Strategy

It employs Heuristic-Frontier (H-Frontier) candidate identification strategy to filter potential positions before evaluation (Si, Pisan & Tan 2014b). H-Frontier strategy is a simple version of the *heuristic agent*, where it mainly uses a *hierarchical* heuristic. In terms of the weights of position evaluation, I focus more on grid gathering and segment gathering, since these two kinds of information are used to reconstruct the outline of the map territory. Then, the parameters of utility component (Equation (5.5)) are set as: 0.4, 0.4 and 0.2 for *A(iGrid)*, *A(iSeg)* and *A(iFea)* respectively. Compared to distance travelling, I give priority to information gathering in the next view. In equation (5.7), the weights I have chosen give priority to information gathering over travelling less distances with α set at 0.4 and β set at 0.6.

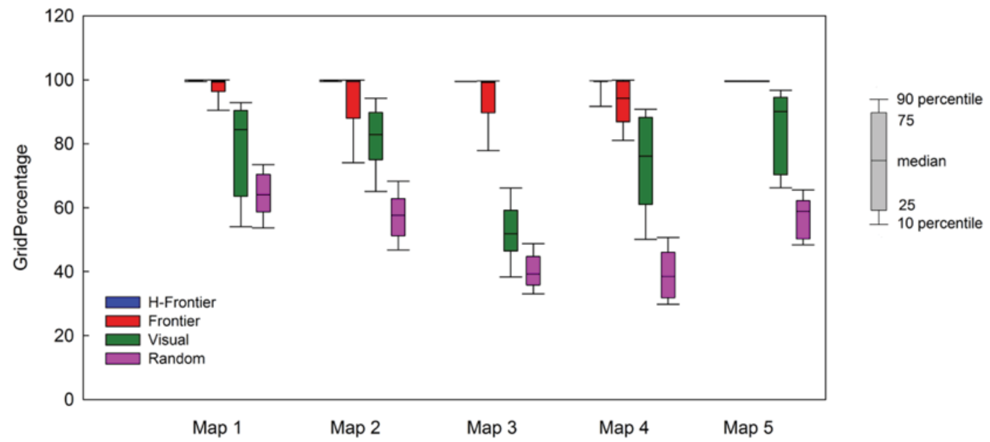
5.4.2 Results



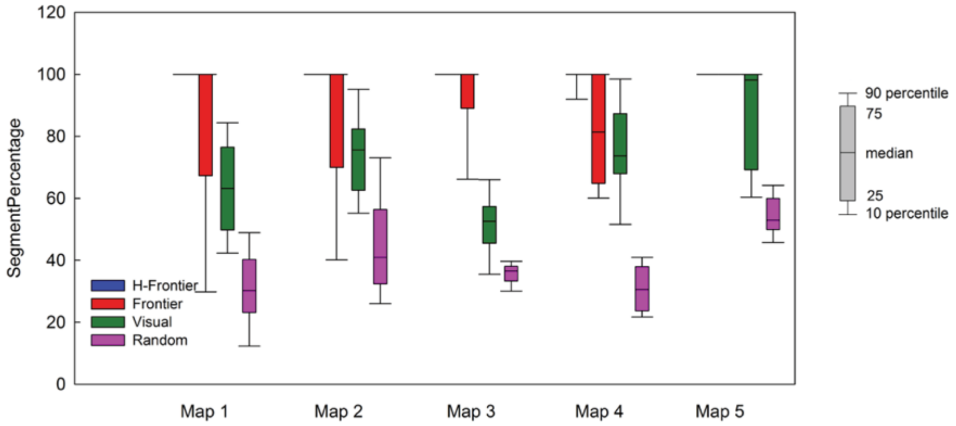
(a) H-Frontier spent relatively less time to complete the exploration task in each map comparing to other three algorithms.



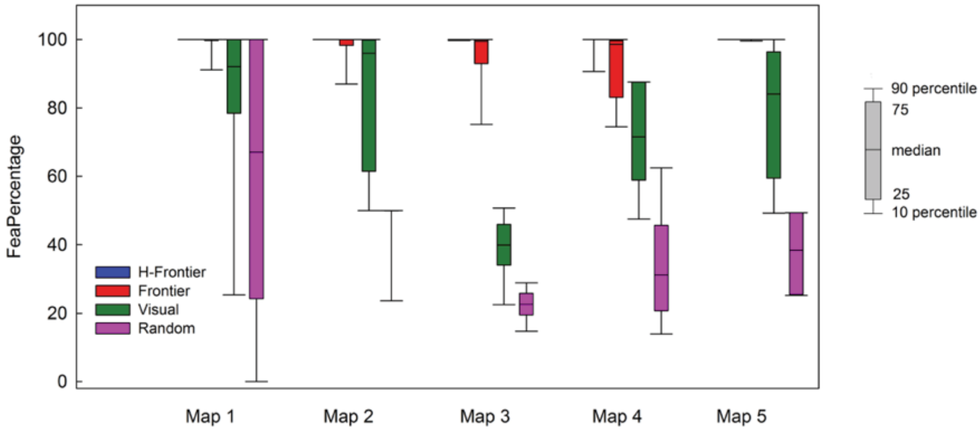
(b) H-Frontier travelled relatively less distance to complete the exploration task in each map comparing to other three algorithms.



(c) H-Frontier achieved the most percentage of grid in all the five maps.



(d) H-Frontier achieved the most percentage of segment in all the five maps.



(e) H-Frontier achieved the most percentage of features in all the five maps.

Figure 5.11 Performance of strategies in different criteria

For each map, I have chosen 16-24 possible starting positions (shown in Figure 5.10), determined by the complexity of the map. Each game map is evaluated using the four different strategies with all the different origin positions. Box plots, shown in Figure 5.11, aggregate the results from simulation runs with different origin positions. The five criteria used to evaluate the performance of the strategies are: time cost (seconds), travelling distance (pixels), percentage of free-movement grids collection, percentage of obstacle segments, and percentage of game features (such as resources) gathered during exploration. The horizontal line in the box plot indicates the median value, box-boundaries are the 25th and 75th percentiles, and whiskers are the 10th and the 90th percentiles.

The percentage plots illustrate that the H-Frontier strategy is the only one that is able to statistically complete exploration tasks in all the game maps and for all the origin positions. Figure 5.11(c), 5.11(d) and 5.11(e) illustrate that the 10-percentile value of map information-gathering percentage for H-Frontier strategy is over 99.5% in map 1, 2, 3, and 5, and that the 25-percentile value is over 99.5% in map 4. The 10-percentile value of the Frontier strategy is just over 99.5% only in map 4. The other two strategies perform even worse, rarely completing exploration tasks. In terms of time spending, the H-Frontier strategy performs significantly better than other strategies in each map. Almost all the time spent on the H-Frontier is less than the other three strategies in all the maps (Figure 5.11(a)). Furthermore, the H-Frontier also travels less distance in completing the exploration tasks in all the maps (Figure 5.11(b)).

For a few cases in maps 1, 2, 3 and 4 the Frontier strategy travels less distance than the H-Frontier strategy, but in these cases the Frontier strategy fails to complete the exploration mission. As demonstrated by the percentage plots, the 90-percentile value of distance of the H-Frontier strategy is even lower than the median value of the Frontier Strategy in maps 1, 2 and 3. To summarize, the Heuristic-Frontier-Based strategy I presented performs better than the others for exploration in RTS game environments based on the five different criteria outlined above.

5.4.3 Discussion

In this case study, I evaluated our algorithm with other four strategies, and demonstrated that our algorithm performs the best within each criterion. Generally, a good strategy is gathering more terrain information (revealing grid, segment and features) and spending less resources (time and travelling distance). Figure 5.11 indicates that frontier-based strategies achieved overwhelmingly better results that the other two strategies. Because candidate positions are on frontiers, where there are the closest places to unknown areas. Intuitively, exploring these places as a priority can also save time.

Among the frontier strategies, the H-Frontier performs better than Frontier strategy in all five criteria, which means the former can collect more spatial information whilst travelling less distance during less time. In most position evaluation processes, the H-Frontier only computes the utility value of local positions, while the Frontier strategy conducts it globally. Obviously, time spent on evaluating computation is saved. Additionally, evaluating all candidate positions globally may cause a phenomenon of back-and-forth movement. It is common that a candidate position that is far away from the current spot with potential to gather more environmental data is selected as the next-best view. The fact is, however, that the unit must travel back again for the completeness of exploration. In this experiment, the exploration settings (such as α, β and the visual range for the unit) have been kept constant. In our algorithm, since the local candidates are given high priority, the phenomenon of back-and-forth across long distances is eliminated.

5.6 Conclusion

In this chapter, I applied the heuristic method in solving the problem of spatial exploration, where a heuristic approach is used to pre-process the set of candidate positions before estimating each step by using A*. To be specific, the heuristics of *hierarchical*, *region based*, and *field of view* are used to reduce the choices when making decisions. The idea was generated from common sense human navigation, where they intuitively consider local areas rather than taking the global view in each step. The pattern of terrain is another common-sense area where humans prefer to go to the places that are easier to move to, and humans prefer looking forward within the field of vision first rather than looking around elsewhere (answer **Q3.1**).

I organized two experiments to evaluate both the believability and efficiency of our method. The results in the experiment of believability assessment illustrate that our heuristic method can achieve believability in the spatial exploration field (answer **Q3.2**). The results in the experiment further demonstrate that the heuristic method contributes to saving time and resources in terms of travelling because it effectively reduces the behavior of moving back and forth. The performance of our method also shows that coverage of environments (segment, grid and resources) is better than algorithms in the control group (answer **Q3.3**).

In this chapter, I developed a *heuristic agent* by mimicking the way that humans do exploration, discovered in Chapter 3. The *heuristic agent* was evaluated within the experimental framework developed in Chapter 4 for assessing its believability. The results illustrate that it achieves believability in exploring virtual environments. The *heuristic agent* was also tested in an abstract simulated environment, where its performance was proved to be efficient for doing exploration. In next chapter, I will investigate the way of integrating players' expectations of human-like gameplay in a computer agent, and evaluate its believability in the three exploration games.

Chapter 6. Development of Believable Spatial Exploration Agents – An Integrated Approach

This chapter aims to answer **Q4**: "How do we bridge the gap between human and computer agents' exploration via a computer agent?" I divide this question into two sub-questions.

Q4.1 How can we implement believable expectations of spatial exploration from mid-level players in an integrated architecture?

Q4.2 Does the believability of intelligent exploration agents increase when it meets the expectations of mid-level players?

For answering **Q4.1**, I employ the methodology that create a believable agent by satisfying mid-level players' expectations of believability. Hence, I firstly extract the expectations about believable spatial exploration agents from mid-level players which act as the requirements of believable agents. The expectations are collected from the experiments conducted in Chapter 4 (see 4.5.3 Behavioral Differences Defined by Judges). The requirements then are transferred into three components: *environmental knowledge*, *behavioral rules* and *controller rules*, which are implemented in the integrated frameworks of the exploration agent. The developed exploration agent is then evaluated by the questionnaire-based third-person-observation assessment used in Chapter 4 and Chapter 5 (aiming to answer **Q4.2**). In the experiments, I employ three self-developed exploration games: *pure-exploration game*, *killing game* and *searching game*, where the gameplays reflect three different aspects of exploration skills.

6. 1 Judges' Expectations

From the experiment conducted in Chapter 4, I summarize the judges' (mid-level players) expectations of believable exploration-behavior in four aspects: *Interaction with Environment*, *Game-goal orientation*, *Navigation*, and *Sense of the mechanical*, which map to the four types of behavioral differences (see 4.5.3 Behavioral Differences Defined by Judges). The expectations are then summarized as the requirements of the believable exploration agents.

6.1.1 Interaction with Environment

1. Complex Environment
    a. Computer agents keep a stable and determined performance in complex environments, where they should have a high-level perception of environments and a sense of orientation without exhibiting inconsistencies.
2. Special Objects
    a. Computer agents perceive enemy units immediately when enemies appear within the field of vision of the exploration unit.
    b. Computer agents express the awareness of perceived objects by reacting to, interacting with and making decisions about them within a proper time interval.
    c. Computer agents avoid colliding with edges or obstacles when travelling.
    d. Computer agents keep a certain distance from edges when walking along.

e. Computer agents have well-planned behavior around choke points like bridges, passing them in a determined and quick way or exploring unknown surrounding areas before passing through.

6.1.2 Game-goal Orientation

3. *Pure exploration game*
    a. Computer agents have well-planned strategies without too much undetermined behavior.
    b. Computer agents allocate time reasonably to visit areas based on how much information can be gained.
4. *Killing game*
    a. Computer agents are sensitive to enemies, and they normally kill enemies immediately within a spatial sequence upon perceiving them.
5. *Searching game*
    a. Computer agents exhibit the behavior of exploring around discovered clues (for example enemy buildings).

6.1.3 Navigation

6. Stop and go rhythm
    a. Computer agents move smoothly without frequent stops.
    b. Computer agents sometimes have a brief stop on intersections, pretending to make decision among several paths.
7. Forward and backward
    a. Computer agents keep a low frequency of moving forward and backward.

   b. Computer agents make forward and backward behavior reasonable. Each forward and back movement needs to end up with a determined purpose which means it should be explicitly shown that the behavior has a clear destination to visit.

6.1.4 Sense of the Mechanical

8. Obvious mistakes
   a. Computer agents do not walk or stand in an idle manner.
   b. Computer agents do not exhibit failure in taking actions, for example failing to kill enemy units.
9. Over planning
   a. Computer agents do not exhibit over-planned behavior. For example, a structured exploration, where the exploration unit visits places around a center within the same distance, was easily recognized as a computer agent in the experiment of Chapter 4.

6.2 Environmental Knowledge

Environmental knowledge refers to the short-term memory that the computer agent keeps when exploring.

1. Computer agents have a cardinal direction system, which demonstrates the relative locations where the exploration unit is located. It maps to players' oral expressions of "left-top", "right-top", "left-bottom" and "right-bottom" of the map (see Chapter 3). Hence, computer agents maintain knowledge about their relative locations which represent the relative part (i.e. "left-top",

"right-top", "left-bottom" and "right-bottom") of the map. It helps to make global decisions when the computer agent decide to give up local exploration and plan to select the next-best position globally.

2. Computer agents also acquire knowledge about the boundaries of obstacles, edges, and frontiers perceived as the exploration progresses. The frontiers refer to the boundaries between locations, exploration areas and unknown areas.

3. Computer agents have knowledge about the decomposed map with the representations of regions, choke points and relationships among them. It is an important cognitive way of spatially reasoning the strategy that players normally use (Halldórsson & Björnsson 2015; Perkins 2010).

4. Computer agents acquire and store knowledge of enemy units discovered. In the memory of the computer agents there is the location of enemy units that appear in the visual range of the exploration unit. Their information (location, type and status of life) is maintained in the memory of the computer agents.

6.3 Behavioral Rules

Behavioral rules are rules that computer agents follow to exhibit human-likeness during exploration.

1. Computer agents explore the environment with collision-free behavior. The behavior of consistently knocking obstacles and edges was explicitly marked as that of computer agents in Chapter 4. The exploration unit's knocking

edges behavior illustrates its unawareness of edges and obstacles. A behavioral rule set for the computer agent is to navigate the exploration unit with a collision-free model, where I simply make the computer agent ignore candidate positions which are too close to edges.

2. Computer agents have a proper way to interact with discovered special objects. Ignorance of them may be clearly identified as computer agents' behavior. To be specific, interacting with special objects refers to killing enemies in a natural way in the *killing game*. It also refers to immediately looking around to search for further clues when enemy buildings are discovered in the *searching game*.
3. Computer agents have a consistent direction of movement. Going frequently back-and-forth is easily recognized as the behavior of computer agents. A behavior rule set for computer agents is to keep a certain consistency of direction during exploration. I implement that rule by using the *field of view* heuristic (see 5.2.2 Heuristic Component).
4. Computer agents illustrate the behavior of doing reasoning about the location of the enemy base according to the explored clues in the *searching game*. The experiment in Chapter 4 indicates that behavior of exploring surroundings after discovering enemy buildings is normally regarded as the gameplay from human players. Hence, the surrounded unexplored areas are given a high priority to be explored in following steps when enemy buildings are found by the computer agent in the implementation of the behavioral rule.
5. Computer agents stop and express an illusion of making decisions around highlighted connections, such as bridge or ramps, among regions. Frequent stops are distinguished as the behavior of computer agents, while a few stops

around intersections are regarded as the behavior of human player. This behavioral rule exhibits the tendency of thinking about where to move next, which is normally the behavior of humans.

6. Computer agents allocate differentiated priority to candidate positions according to the informative possibility that they have. For example, ignoring the non-informative corners is a common behavior of humans in doing exploration. Hence, enabling computer agents to mimic this behavior would help to create the sense of humanness.

6.4 Controller Rules

Controller rules act as supervision rules which control and correct computer agents' behavior in a higher level.

1. Computer agents exhibit flexible plans when conducting exploration tasks. Exhibiting fixed and structured planning is easily recognized as computer agents' behavior. This fact encourages developers to implement randomness into computer agents. Unfortunately, too much randomness exhibited takes the performance to another level which is regarded as the performance of a computer agent. Hence, a mechanism that controls randomness well is necessary to be implemented. It determines when and how randomness is applied within the system.

2. Computer agents have a natural movement rhythm. Controlling the movement of the exploration unit through a natural "stop and go" rhythm is another key factor to make it believable. As the judges suggested in Chapter 4, computer agents normally have a disordered and unreasonable "stop and

go” rhythm. Hence, having a reasonable “stop and go” rhythm for intelligent exploration agents would be a distinct feature of believable agents.

3. Computer agents correct their behavior when errors occur. Recognized computer agents sometimes exhibit behavior that is marked by systematic errors, such as being stuck, moving in an idle fashion, and failing to shoot. Therefore, implementing a mechanism of behavior-status evaluation, which could help diagnose issues when computer agents go wrong, would contribute to preventing exploration agents from making such errors.

4. Computer agents react to special objects in the right time. When the exploration unit observes one or a group of special objects, the controller can determine when to pause the ongoing process and react to special objects.

6.4 Relationship between Implementation and Requirements

The implementation of *environmental knowledge*, *behavioral rules* and *controller rules* satisfies judges’ expectations (see 6.1 Judges’ Expectations) of believable agents. Judge’s expectations act as requirements of developing believable agents in this chapter. Each instance of the implementation maps to one or more requirements. Table 6.1 illustrates the map, where R is short for requirement, EK is short for *environmental knowledge*, BR is short for *behavioral rules* and CR is short for *controller rules*.

6.5 Design of the Architecture of the agent

The design of the architecture consists of six components (see Figure 6.1).

Exploration Pipeline refers to the framework of the exploration algorithm described in the section 4.2 Computer-agent Objects.

Implementation		Requirements
Environmental Knowledge	EK1	R1.a
	EK2	R2.c, R2.d
	EK 3	R3.a, R1.a, R2.e
	EK4	R2.a, R2.b, R4.a, R5.a
Behavioral Rules	BR1	R2.c, R2.d
	BR2	R2.b, R4.a, R5.a
	BR3	R1.a, R3.a, R7.a, R7.b
	BR4	R5.a
	BR5	R2.e
	BR6	R3.b
Controller Rules	CR1	R3.a, R9.a
	CR2	R6.a, R6.b
	CR3	R8.a, R8.b
	CR4	R2.a, R2.b

Table 6.1 Mapping implementation to requirements

Environment Recognition & Analysis conducts environment analysis where knowledge about detected environments is extracted and maintained. It provides recognized patterns and objects to components of *Global Controller*, *Goal Controller* and *Navigation Controller*.

Global Controller can pause, recover and jump forward among the exploration loops in the *Exploration Pipeline*.

Goal Controller rules the behavior of exploration agents to achieve the game goal in each exploration game.

Navigation Controller controls the track of movement when the agent is doing exploration.

Error Controller monitors the status of the computer agent. It also keeps detecting the behavior errors of the exploration unit, and then, handles the errors.

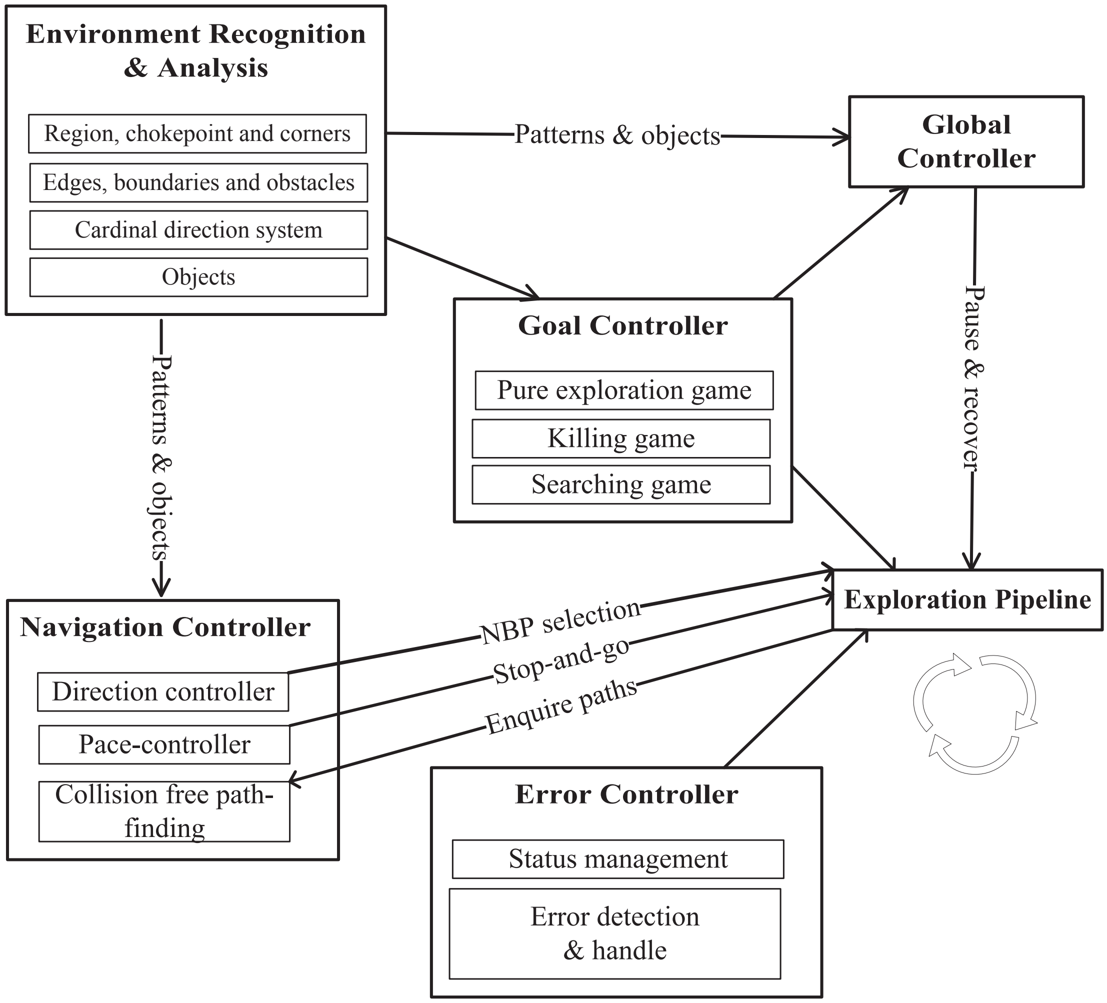


Figure 6.1 The integrated architecture of the exploration agent

Except for the *Exploration Pipeline*, each of the other five components provides mechanisms for the implementation of believable exploration agents. Table 6.2. shows the map of which implementation is contained within which component.

Components	Implementation
Environment Recognition & Analysis	EK1, EK2, EK3, EK4
Global Controller	CR1, CR4
Goal Controller	BR2, BR4, BR5, BR6
Navigation Controller	BR1, BR3, CR2
Error Controller	CR3

Table 6.2 Map of implementation in the components

6.6 Experiment

In this experiment, I have the same human subjects and experimental procedure as the 5.3 Case study – Believability Assessment (see 5.3.1 Human Subjects and 5.3.3 Procedure).

Along with the *integrated agent* developed in this chapter, the computer agents (1) multiple criterion decision-making (MCDM), (2) topological and (3) random, which are developed in Chapter 4 constitute the computer-agent objects.

6.6.1 Judge Selection

Believability relies on the judgments of observers who watch the behavior of characters or playing bots in video games. Completely distinguishing human players and computer agents is technically impossible at the current time. I invited video game players who have substantial domain knowledge and regularly play video games. They are neither novice players nor game gurus but normal game players who make up the significant population of players. Their demographic information and experience of gameplay were illustrated in Table 6.3.

ID	Gender	Age	Years of gameplay	Gameplay hours per week	Game types usually played
J1	M	29	2 - 5	1 - 5	FPS, Strategy, Sports
J2	M	24	> 10	6 - 10	FPS, Strategy, Simulations, RPG, CB, Sports, PBG
J3	M	26	2-5	6 - 10	Strategy, CB
J4	F	25	6 - 10	6 - 10	RPG, Puzzle
J5	M	28	>10	10 - 20	Strategy, RPG, Simulations, CB
J6	M	25	6 - 10	1 - 5	FPS, Simulations
J7	M	32	>10	6 - 10	FPS, RPG, CB, Sports, PBG
J8	M	28	2 – 5	10 - 20	FPS, Sports
J9	M	28	<2	6 - 10	FPS, Strategy, Sports
J10	M	25	2 - 5	6 - 10	FPS, Strategy, Sports, RLS

RTS	First –person Shooters	RLS	Real-life Sports	CB	Chance - based
PBG	Physical Board Games	RPG	Role-playing Games		

Table 6.3 Demographic information and gameplay experience of participants

6.6.2 Believability: Ranking Results

In Figure 6.2, the value represents the average score for each player. Average scores are computed via Formula (4.1). The believability of the *integrated agent* across the three exploration games is higher than the other three computer agents. It almost approaches the believability of human 2, and is in fact higher than that of human 1.

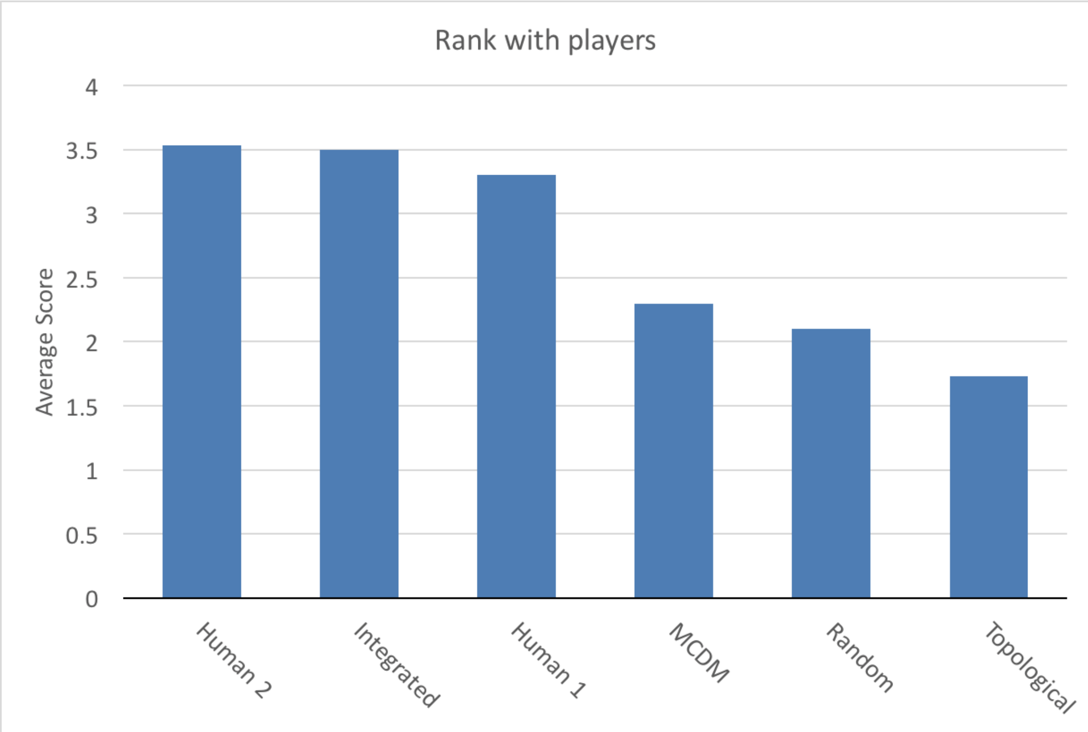


Figure 6.2 Believability of the *integrated agent*

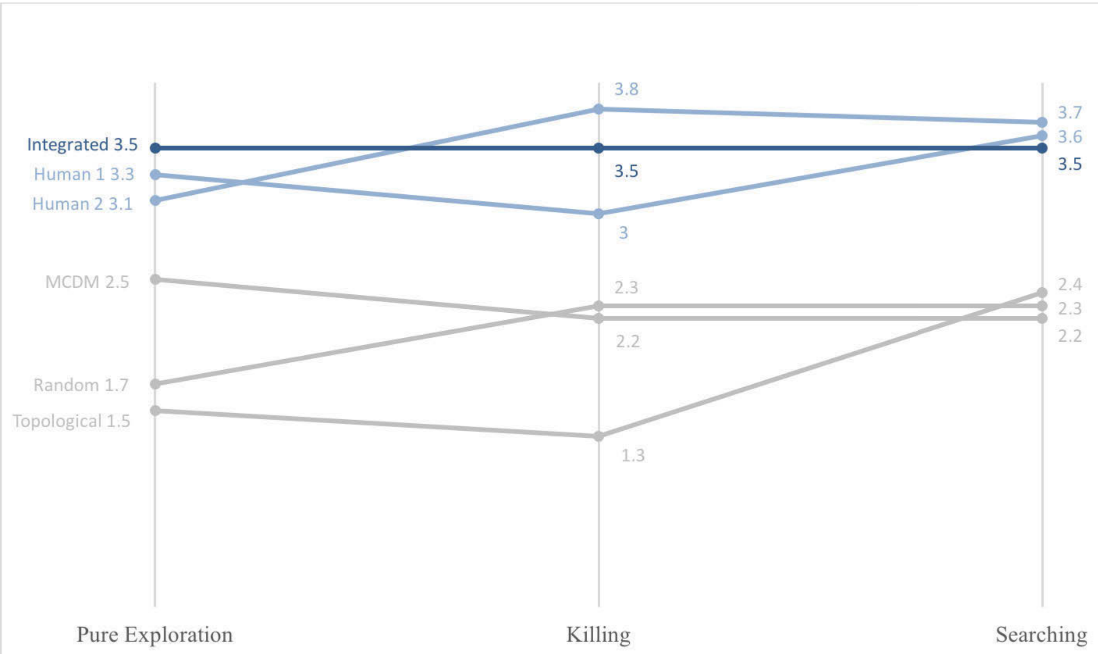


Figure 6.3 The believability scores of the *integrated agent* are significantly higher than the other computer agents, and between two human players

In Figure 6.3, the average score of each player in each game is calculated via Formula (4.2). The believability score of the *integrated agent* is significantly higher than the other three computer agents in all three games. The *integrated agent* is regarded as more believable than the two human players in the *pure exploration game*. Its believability is in-between the two human players in the *killing game*. The believability score of the *integrated agent* is quite near to that of the human players with small differences of 0.1 (3.6 – 3.5) and 0.2 (3.7 – 3.) respectively in the *searching game*.

Figure 6.2 and Figure 6.3 underscore the fact that the *integrated agent* I developed is believable in terms of playing exploration games.

6.6.3 Human-like Behavior and Non-human-like Behavior

In this chapter, the themes of human-like behavior and non-human-like behavior are extracted from questionnaire responses via thematic analysis as well. The process is same as that in Chapter 5 (see 5.3.5 Human-like Behavior and Non-human-like Behavior).

Most themes extracted in this chapter have been observed and identified in Chapter 5 (see 5.3.5 Human-like Behavior and Non-human-like Behavior). The thematic analysis conducted in this chapter discovered two more themes which do not appear in Chapter 5.

Human-like Behavior

Have a global view means the unit exhibits the sense that it has a global view when finding paths and making decisions. For example, "When the player saw an edge of the map, he turned right away to the other side. The player had a clear view of the whole map that made it like a human player." (J3 – *Integrated agent – Pure exploration game – most likely human*)

Non-human-like Behavior

Explored uninformative areas represents the unit explores some areas, such as small corners, outlined boundaries, and completely revealed areas, which do not provide useful information. It illustrates a sense that the unit strictly explores everywhere without an ability to recognize outlined terrain. For example, "The unit, sometimes however, visited very narrow areas where buildings were very less likely to be built. That makes me feel it was an AI." (J5 – *Human 1 – Searching* game – *unsure if it is human or a computer agent*)

6.6.4 Behavior-based Evaluation

The count for each theme is represented by percentage it takes from total and visualized by "pie of pie" chart within each object group.

Figure 6.4 shows the human-like behavior and non-human-like behavior of the three computer agents. The count of human-like behavior takes 16 percent while the statements of non-human-like behavior takes 84 percent. As obviously recognized computer agents, non-human-like behavior is observably more than human-like behavior.

The highlighted non-human-like behavior is *unreasonable killing behavior*, *idle behavior, revisit explored areas* and unreasonable stops. Several themes evenly share the rest of the pie of human-like behavior. Each of them only takes a small percentage of the total pie.

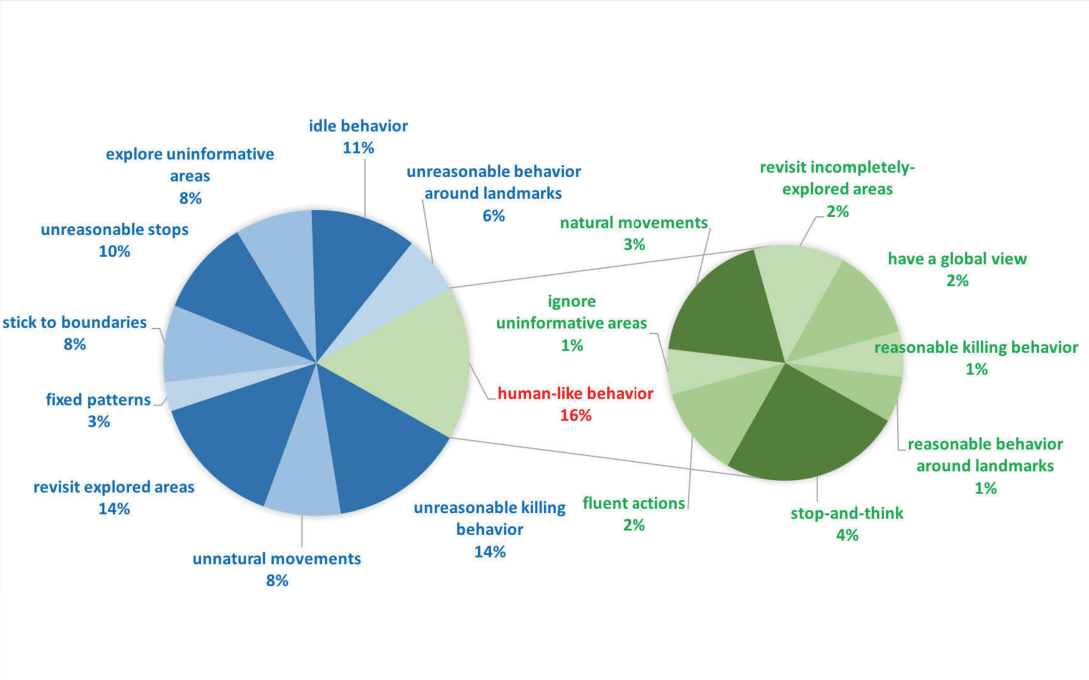


Figure 6.4 Distributions of behavior themes for computer agents (Percentages are computed based on the counts of statements in each theme.)

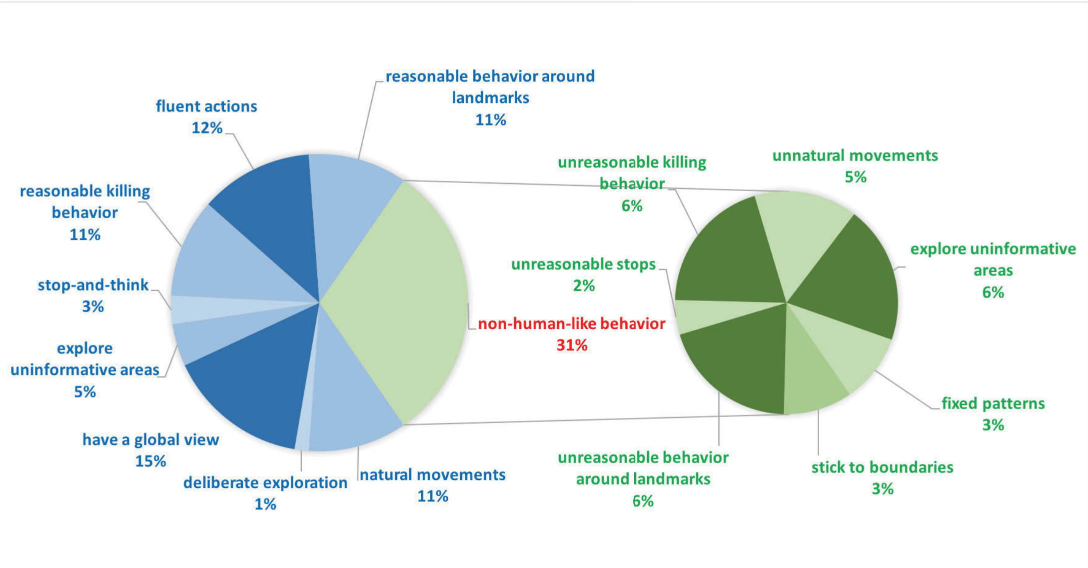


Figure 6.5 Distributions of behavior themes for human subjects (Percentages are computed based on the counts of statements in each theme.)

Figure 6.5 shows the human-like behavior and non-human-like behavior of human players. Human-like behavior occurs more than non-human-like behavior as it takes 69 percent of the total.

The highlighted human-like behaviors are *fluent actions*, and *have a global view*. They are followed by themes of *natural movements, reasonable behaviors around landmarks* and *reasonable killing behavior*, which take 11 percent respectively. Meanwhile, the highlighted non-human-like behaviors are *explore uninformative areas*, *unreasonable killing behavior* and *unreasonable behavior around landmarks*.

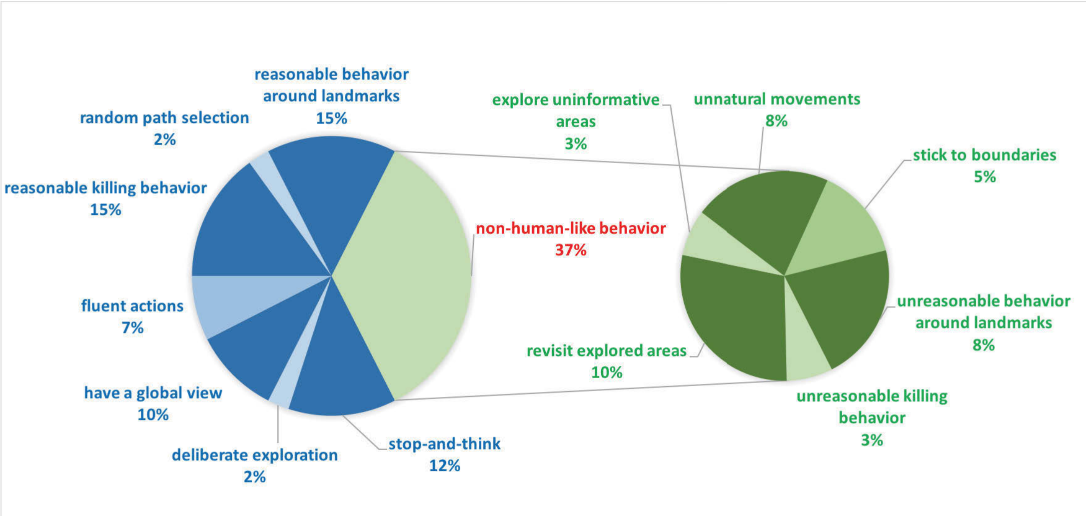


Figure 6.6 Distributions of behavior themes for the *integrated agent* (Percentages are computed based on the counts of statements in each theme.)

Figure 6.6 shows themes of the *integrated agent's* human-like behavior and non-human-like behavior and the frequency of them appearing in the judges' comments. Human-like behavior takes 63 percent of the total counts of themes, while non-human-like behavior gets only 37 percent. That is consistent with the fact that the *integrated agent* achieved a high score in the believability ranking.

Outstanding human-like behavior constitutes reasonable behavior around landmarks, reasonable killing behavior, stop-and-think and have a global view. Meanwhile, the highlight non-human-like behaviors are unnatural movements, unreasonable behavior around landmarks and revisit explored areas, which take the major percentages of non-human-like behavior.

6.7 Discussion

6.7.1 Believability of the Integrated Agent

The believability scores shown in Figure 6.2 and Figure 6.3 reveal the fact that the *integrated agent* I developed is believable in playing exploration games. Within the experiment, the score that the *integrated agent* achieved is significantly higher than other computer agents, and on the same level with human players. The *integrated agent* which integrates components that fill the behavioral gaps between humans and computer agents is valid for achieving believability in exploring virtual environments.

According to Figure 6.6, several themes (i.e. *reasonable behavior around landmarks*, *reasonable killing behavior*, *stop-and-think*, and *have a global view*), which take relatively large percentages of human-like behavior are controlled by components of the agent. *Reasonable behavior around landmarks* was primarily led by the component of Environment Recognition & Analysis, where landmarks are recognized. The proper behavior is also controlled by the components of the Goal Controller and Global Controller. Similarly, *reasonable killing strategies* are generated by the component of Goal Controller and Global Controller. *Stop-and-think* behavior is driven by the Pace Controller, which is part of the Navigation Controller. The components of Environment Recognition & Analysis and Global Controller contribute to the behavior of *have a global view*.

6.7.2 Different Human-like Behavior between the Integrated Agent and the Heuristic Agent

Believability assessment experiments recruited different judges to evaluate same human subjects and same computer agents in Chapter 5 and Chapter 6 respectively. Even though the themes labelling behavior are not exactly same, the patterns outlined do not show big differences.

Next, I look at the similarity of distribution of themes in the major type of behavior (either human-like behavior or non-human-like behavior) between the corresponding group of objects. The similarity is evaluated via two criteria. One is the number of overlaps between the top four themes, which take higher percentages. More overlaps mean high similarity. Another is the number of mismatches. One mismatch means a theme appears in one group but does not in the other. More mismatches mean low similarity. The bold numbers highlight top four themes for each group, and one dash means one mismatch in Table 6.4, 6.5 and 6.6. The raw data where how many times was each theme counted in judges' statements are shown in Table A.7-A.9 and Table A.11-A.13.

Non-human-like behavior	Computer Agents (Chapter 5)	Computer Agents (Chapter 6)
unreasonable killing behavior	**25 %**	**14 %**
stick to boundaries	**11 %**	8%
idle behavior	**14%**	**11%**
revisit explored areas	**9%**	**14%**
unreasonable stops	8%	**10%**
revisit explored areas	9%	-
unreasonable behavior around landmarks	8%	6%
fixed patterns	7%	3%
unnatural movements	4%	8%
explore uninformative areas	-	8%

Table 6.4 Comparison of non-human-like behavior between computer agents in Chapter 5 and Chapter 6

Table 6.4 illustrates the groups of computer agents has 3 overlaps in themes of *unreasonable killing behavior*, *idle behavior* and *revisit explored areas* and 2 mismatches in themes of *revisit explored areas* and *explore uninformative areas*.

Human-like Behavior	Human (Chapter 5)	Human (Chapter 6)
natural movements	**19%**	**11%**
fluent actions	**11%**	**12%**
revisit incompletely-explored areas	**9%**	**-**
reasonable killing behavior	**8%**	**11%**
deliberate exploration	8%	1%
reasonable behavior around landmarks	3%	11%
stop-and-think	3%	3%
have a global view	**-**	**15%**

Table 6.5 Comparison of human-like behavior between human subjects in Chapter 5 and Chapter 6

Table 6.5 represents the group of human subjects has 3 overlaps in themes of *natural movements*, *fluent actions* and *reasonable killing behavior* and 2 mismatches in themes of *revisit incompletely-explored areas* and *have a global view*.

Human-like Behavior	Heuristic Agent	Integrated Agent
consistent movements	**14%**	**-**
natural movements	**11%**	**-**
revisit incompletely-explored areas	**8%**	**-**
reasonable behavior around landmarks	**6%**	**15%**
random path selection	6%	2%
ignore uninformative areas	6%	**-**
fluent actions	5%	7%
deliberate exploration	5%	2%
stop-and-think	5%	**12%**
have a global view	**-**	**10%**
reasonable killing behavior	**-**	**15%**

Table 6.6 Comparison of human-like behavior between the *integrated agent* and the *heuristic agent*

Table 6.6 shows that the *heuristic agent* and the *integrated agent* have 1 overlap in the theme of reasonable behavior around landmarks and 6 mismatches in themes of consistent movements, natural movements, revisit incompletely-explored areas, ignore uninformative areas, have a global view and reasonable killing behavior. Table 6.4 and Table 6.5 show that the subject groups, human players (in

Chapter 5 and Chapter 6) and computer agents (in Chapter 5 and Chapter 6), achieved same and relatively high similarity in comparing the marks of their major behavior (i.e. non-human-like behavior for computer agents and human-like behavior for human players). That means same subjects group achieved relatively high similarity. Meanwhile, the similarity between the *heuristic agen*t in Chapter 5 and the *integrated agent* in Chapter 6 is relatively much lower shown in Table 6.6. The comparison of the similarities demonstrates the fact that the human-like behavior of the *heuristic agent* is obviously different from that of the integrated agent, even though both have passed the believability test. That is because the mechanisms of their implementations are different as discussed in 5.5.2 Design of Heuristic Agent from Humans' Behavioral Patterns and 6.7.1 Believability of the Integrated Agent. Here, I just used judges' statements about subjects' behavior to explore the difference of these two algorithms in exhibiting behavior. The exploration in this topic could help to formulate further investigations. The initial conclusions also need to be evaluated by statistic evidences from more specialized experiments.

6.8 Conclusion

In this chapter, I transferred players' expectations to believable exploration agents, which were identified in Chapter 4, into *environmental knowledge*, *behavioral rules* and *controller rules*. Then, an integrated framework was developed, in which I implemented these requirements by integrating them into a generally accepted exploration pipeline (answer **Q4.1**). The *integrated agent* was evaluated in the experimental framework of believability assessment developed in Chapter 4. The results show that our integrated framework can achieve believability in the spatial exploration field (answer **Q4.2**). Even though, both the *heuristic agent* and the *integrated agent* have passed the believability test, the different mechanisms implemented made them exhibit different believable behavior.

Chapter 7. Conclusion

In this thesis, I studied one type of common human behavior – spatial exploration. People do spatial exploration to gather information, locate resources and map environments. Human beings, as large-scale collaborative groups, have a long history of exploration, where civilized societies organize to discover unknown lands. Nowadays, they have expanded the exploration to deep oceans and space. Exploration is a way that humans discover themselves and interact with the environment. It is a complex decision-making problem for an individual to decide where to visit and then observe continually according to their perceptions, understandings and purposes. This research is driven by the insufficient examination of human exploration behavior, and the importance of that behavior on human development. Furthermore, the boom of artificial intelligence technology accompanying societal demands hastens the need to develop human-like computer agents. Even though autonomous exploration has become an active research area, human-like exploration has rarely been mentioned by researchers. These facts have motivated this thesis to explore the patterns of how human spatial exploration and to present effective ways to design human-like exploration agents.

To understand how humans doing spatial exploration, three exploration-based modifications were developed on top of the StarCraft video game. An experiment was conducted by having human players play the games and verbalize their feelings, strategies and descriptions of their behavior both simultaneously and after reviewing gameplay videos. Thematic analysis was used to identify behavioral archetypes of human players (see Chapter 3).

To define gaps between normal human players and computer agents in doing exploration, a third-person observation-based believability assessment was developed to evaluate the human-likeness of the computer agent as well as the human players in exploring virtual environments. Comments from evaluation questionnaires and interview records were deeply mined to summarize the behavioral gaps between humans and computer agents on several aspects of exploration activities (see Chapter 4).

To explore methods to develop human-like exploration agents, the heuristic method was employed as it aims to mimic humans' heuristic decision-making. I developed three heuristic option filters—*hierarchical*, *region based* and *field of view*—which were extracted from the mechanisms that humans exhibit in doing exploration (see Chapter 5).

I also employed another way to develop human-like exploration agents, where players' expectations were integrated. Based on the behavioral gaps between human and computer agents identified in this research, the requirements of human-like exploration agents were generated. Then, *environmental knowledge*, *behavioral rules* and *controller rules* were developed. An integration framework was designed to integrate them into an exploration agent. Both the *heuristic agent* and the *integrated agent* were assessed by the believability assessment method developed in this thesis (see Chapter 6).

7.1 Discussion

7.1.1 Heuristic Agent Mimicking an Average Person

Four archetypes (*Wanderers*, *Seers*, *Pathers* and *Targeters*) were developed in Chapter 3, and the design of the *heuristic agent* was generated by mimicking the four archetypes. The behavioral pattern of the *heuristic agent* does not match any individual in the four archetypes. That means it mimics an average person of four archetypes, where the *heuristic agent* takes behavioral features across the four archetypes. The three heuristic filters *hierarchical*, *region based* and *field of view* are applied in the *heuristic agent*, and are extracted across the four archetypes instead of from any one of them.

The results of evaluating the *heuristic agent* indicate that it achieved believability in doing spatial exploration. Its human-likeness has the same level of two human players. Since the *heuristic agent* mimics an average person, its human-likeness to an average person instead of a specific individual or an archetype is accepted by normal players. In fact, there might not be an individual who has exactly same behavior as the *heuristic agent*, even though it was believed to be the human player. The characteristics and preferences of the *heuristic agent* should be quite different from that of a real human player. To create a human-like exploration agent which has the behavior of a real human is an interesting topic to explore further.

7.1.2 Humans' Non-human-like Behavior

Human players have also exhibited behavior which is regarded as non-human-like (see 5.3.6 Behavior-based Evaluation). It reflects some uncertainty that exists in believability assessment. One kind of behavior could not be strictly confirmed to be human-like behavior or non-human-like behavior. It mostly depends on whether the intentions of the behavior can be understood by observers or not. Having observers and players with similar common sense and backgrounds would reduce the rate of misjudgments. The misjudgments, however, cannot be thoroughly eliminated.

One possible reason is that different people have different preferences and behavioral patterns. As Chapter 3 revealed, human players exhibited four different archetypes in playing the exploration game. Their behavioral differences were exhibited in several aspects. The intentions of behavior might not be mutually understood among players in different types. A *Seer* hardly understands why a player always searches the environment locally – a common behavior of a *Wanderer*. Even though *hesitation* behavior was exhibited by all four archetypes, they could still be mutually misunderstood across archetypes because of different underlying purposes.

7.1.3 Benefit to Human-like Computer Agents

Exploration is a kind of basic behavior. The spatial information gathered contributes to many other forms of decision-making. Almost any of behavior within an unknown environment relies on discovered spatial information. For example, a computer agent needs to know spatial information to assist it to maintain resources and define defensive and offensive strategies in play scenarios of RTS games. The computer agent needs to know the information of the surrounding terrain to deploy defensive forces, mineral sites to build up expansions, and the location of enemy bases to attack. As an important part of a computer agent, believable exploration plays an essential role in creating a human-like computer agent.

Believable exploration agents can be integrated into a general human-like computer agent seamlessly without leading to other systematic problems. As discussed in the literature review, one popular way of developing a computer agent is to divide the task that the computer agent does into sub-tasks, and then develop components separately to fulfil them. For example, a gameplay bot needs to fulfil tasks like gathering resources, producing units, upgrading techniques, harassing etc. The believable exploration agents developed in this thesis can be retrieved by a general human-like computer agent as an independent component when it needs to do exploration. Moreover, the *integrated agent* could be integrated into a general computer agent on the component level. A simple example is that the *Exploration Pipeline* component stays independent. Other components can be integrated into the corresponding components (if there are any) of the general computer agent; otherwise they can be kept independent. The *Goal Controller* is revised according to the requirements of the tasks.

7.1.4 Benefit to Game Design

The findings in the thesis will also benefit game design, especially the design of game maps and navigation systems. The four exploration types (defined in Chapter 3) reveal how players mentally map game environments and devise strategies to find their way. The types also outline differences in player behavior. This contribution enables game designers to produce user-centered navigation-assistant systems. For example, since *Seers* have a direction-based mental map, game designers could create mutual-mapping compasses for the window of the mini-map view and the main window respectively. They could also develop an assist mechanism that can automatically generate the structure of discovered areas of the map to enhance the *Pathers'* ability to structure game environments.

Our research can also help designers produce more immersive game maps. Taking the *Targeters'* feature as an example, their reasoning in terms of environments and way-finding relies on the key items found. This requires map designers to place conspicuous and informative items, which act as important navigation guidance aside from other existing mechanisms, in the maps.

The enhancements of game design suggested above not only provide a better navigation experience for *Seers*, *Pathers*, and *Targeters*, but also stimulate *Wanderers* to learn to use external tools to explore. According to the findings about hesitation behavior, the improvements might also be expected to reduce players' hesitation when exploring maps to improve the flow experience.

7.1.5 The Number of Judges

The population of judges (seven in Chapter 4, ten in Chapter 5 and Chapter 6 respectively) might be statistically weak in doing the evaluation. 2014 University of Reading Competition employed thirty judges, and the Super Mario AI competition had sixty judges. There isn't, however, a standard setting of the number of judges. More judges could intuitively decrease the error rate in estimating the convinced believability of an object. For having a deep exploration and understanding of objects, judges need to observe objects in multiple scenarios and give comprehensive statements, which is not practical to invite a large number of judges. The Loebner Prize, where organizer increased the interaction duration many times, have four judges. In the BotPrize 2014, the five judges were required to observe the objects in different scenarios. In our experiments, judges observed the behavior of each object in three different games. They were encouraged to identify the evidence of their judgements from the videos, and to give deeper statements of their findings via the questionnaire and the interview.

7.2 Limitations

Studies in the thesis focus on exploratory research with qualitative analysis to build a theoretical and practical foundation in the field and help in formulating relevant hypotheses for more definite investigation. Once a theoretical framework has been established, quantitative analysis can be used to fine-tune the parameters of the framework using a larger set of participants. The experimental data in Chapter 3 is not suitable for quantitative analysis. I collected players' demographic backgrounds and preferences for diverse terrain features to establish the theoretical framework on how these parameters affect archetypes. The experiment was intended to establish insights into this new domain not for performing quantitative analysis. However, I did run one-way ANOVA tests to analyze how real-life navigation abilities impact archetypes as well as the preferences of archetypes to terrain features by generating p-values via the SPSS (Corporation 1968) software. After reviewing the tests, as expected, I found that the results with the given groups sizes broke the homogeneity assumption of the ANOVA test (Keppel 1991) and would not be reliable. My contribution is in establishing the theoretical framework in understanding spatial exploration and how believable agents can be built based on these principles. Further fine-tuning of this framework will be part of future research.

The process of classifying gameplay instances into archetypes is also a limitation for future researchers wishing to repeat this work in other genres. When categorizing an instance into an archetype, the think-aloud, interview as well as in-game data were comprehensively collected and analyzed. This requires coders to meticulously observe and read players' behavior and statements within the context of the genre across the data set. Due to the complexity and variability of behavior and responses, focusing on coding is difficult and time consuming. Hence possible future work would be to investigate better ways of collecting and coding such data.

The experiment environments were developed based-on StarCraft: Brood War, which has a direct top-down 2.5D view. It provides high-level views to players, hides some details of objects which would be shown in three dimensional environments and allows players to have spatial information of extended areas. These features intuitively assist players to make clear strategies in doing exploration. However, players' behavior may differ from the behavior of those in full three-dimensional environments. Furthermore, players have a third-person view in the top-down model of StarCraft. Players' visual ranges are more open than those of the first-person view. The accompanying visual attention is also different from that of the first-person view. Those constraints limit the findings in this research to be directly transferred to other genres, for example, first-person shooters games, where players have first-person views for during the major gameplay.

In the three exploration games: *pure exploration game*, *killing game* and *searching game*, players concentrated on the tasks closely relevant to spatial exploration. They provided us with chances to observe and analyze players' behavior which is exclusively about exploration. In real scenarios, even though a lot of gameplay behavior (such as offence, defense and harass) is based on information gathered from exploration, those behaviors affect exploration. Therefore, the exploration behavior which is affected by other behavior cannot be observed and included in the conclusion.

The experiment participants were invited within the university. They were all students, although enrolled in different courses throughout the university. This fact indicates that the knowledge about human exploration that I gained in this study might not correspond exactly to a broader cross-section of players. Despite this limitation, it is common and widely-accepted research practice that university students are used in experiments across many domains.

7.3 Closing Remarks on Research Questions

In this thesis, I deeply understand humans' spatial exploration behavior in virtual environments by classifying their behavioral patterns. The spatial exploration behavior of humans is categorized into four archetypes: *Wanderers*, *Seers*, *Pathers* and *Targeters*. The behavioral features of these four archetypes is exhibited through the lenses of *strategy*, *reasoning*, *perception*, and *hesitation*, which are the four main aspects of understanding exploration behavior. Categorizing gameplay instances in the three exploration games allows us to confirm that factors of *gender*, *weekly gameplay time* and *real-life navigation abilities* also affect how a players' behavior is classified in which archetype within a specific type of exploration game (answer **Q1**).

Evaluation from third-person observations of normal players indicates that state-of-the-art exploration computer agents have a gap between normal human players in terms of human-likeness in playing exploration games. Behavioral differences are evident on aspects of *interaction with environments*, *game-goal orientation*, *navigation* and *sense of the mechanical*, which observers are commonly drawn to when watching gameplay videos of exploration games (answer **Q2**).

Humans often heuristically consider groups of options with high priorities when making decisions, especially in fulfilling spatial exploration in complex decision-making tasks. Based on the pattern of humans doing exploration discovered in Chapter 3, I developed a *heuristic agent* with mechanisms of *hierarchical*, *region based* and *field of view* position filtering. The results of believability assessment illustrated that the agent achieved believability, where each position filtering mechanism created outstanding human-like behavior. The agent also proved to be able to acquire information efficiently with less time expenditure and travelling distance than in another abstracted simulation experiment (answer **Q3**).

The behavioral gaps between human and computer agents identified in doing spatial exploration are regarded as requirements for developing human-like exploration agents. Based on the algorithm framework of identifying and approaching next-best-position as the basic exploration pipeline, I designed an integrated architecture. Requirements were mapped to *behavioral rules*, *controller rules* and *environmental knowledge*, which were then implemented and folded into the integrated architecture. The results of the believability assessment illustrated that the *integrated agent* approached believability. Several forms of highlighted human-like behavior created by components of the *integrated agent* were recognized by judges. The assumption that humans compare the behavior observed and the expectations of the human-like agent when evaluating the human-likeness of a computer agent was correct (answer **Q4**).

A major research methodology employed in this research is exploratory research. I used thematic analysis to identify behavioral patterns of exploration and behavioral gaps between humans and computer agents from content data from interviews, thinking aloud and a questionnaire. The number of participants ranged from seven to twenty-one. The findings from our experiment have not been statistically verified. One of our future tasks is to design experiments which are easily run within a large population to verify and solidify the theory I have presented about behavioral patterns and behavioral gaps.

In this thesis, I have identified several expectations of human-like exploration agents. Integrating them in an agent generates a valid way to create human-like exploration agents. The major studies conducted are exploratory research, where I aim to establish a fundamental theory and practice of the field in developing human-like agent for doing spatial exploration. The contribution made in this thesis encourages people to investigate further regarding this field. For example, it is still not clear how each expectation affects the human-likeness acquired by the exploration agent. As a fundamental exploratory research, this thesis will also lead to formulate relevant hypotheses for more definite investigation (Kothari 2004, p. 4). For instance, a potential hypothesis could be "Believability is determined by several expectations of judges instead of any individual criterion in spatial exploration field." This research may also initiate many other research topics in the future. What is the weight of each criterion when they work together to evaluate the human-likeness of a computer agent? It would be valuable to design a standard protocol to evaluate the human-likeness of a computer agent by scoring it with each criterion respectively. Based on such a protocol, the design of human-like exploration agents could achieve detailed confirmed-scientific guidance. It would be a meaningful extension of thesis.

Overall, this work is a significant contribution to the field of gamer research, game design, and believable agents. It deepens our understanding of exploration behavior in gameplay, provides classifications of exploration behavior, frames and extracts structured believability criteria, develops heuristics to mimic human exploration, integrates requirements of believability to bridge the gap between human and computer-generated exploration behavior.

Appendix

Materials appended in this section are examples of full transcribed think-aloud and interview conversations, which provide additional insights into how the experiments are conducted, and what kind of data prepared for thematic analysis. Presenting all the transcribed data would extend this thesis too long, and generating redundant information. Hence, I give three typical conversations to achieve the purpose.

A.1 A Sample of Think-aloud Data in Chapter 3

A think-aloud conversation which from the participant 9 during playing the *killing game*, is listed below where P represents participant, and E presents experimenter.

Speaker	Start Time	End Time	Manuscript
P	0′00.0″	0′41.4″	I suppose any directions at this point. Move down, a little.
E	0′41.4″	0′43.5″	Why did you go down?
P	0′43.5″	2′24.5″	Oh, that's a different thing [click and observe the creature for a while.] I don't down, just seem like a thing I can do. I am wondering there are more minerals near there. It looks like I see me at the edge, that probably not, at the point, wondering around too much in that area. I am thinking. So, go back out. I guess keep going before knowing more than that. OK, that's another one. OK, I guess going this way let's fill out the entire below area what's before. OK, let's see somewhere. I assume it should be down somewhere. I am on the way out. So, I am going this way to find the way to the entrance, which looks like I did miss one back up there. OK, let's see where that is. Kill this one. Enter the map there. I guess it is worthwhile to clear up the bit blank area. There might

			be something in there. Oh, a good choice. Looks like I am near the bottom of the map. I am trying to find some new areas. And go up, from where I started. It looks like a bit of unexplored on the top in the general map. From my experience, there possibly be a life in the down. This area is that I can go anyway.

A.2 A Sample of Interview Data in Chapter 3

An interview conversation which from the participant 9 after playing the *killing game*, is listed below where P represents participant, and E presents experimenter.

Speaker	Start Time	End Time	Manuscript
P	0′00.0″	0′22.8″	At this point, I didn't really have any strategy. I was trying to explore.
E	0′22.8″	0′24.0″	Why did you directly go right? I mean there was a whole blank here.
P	0′25.6″	0′31.0″	I don't know. I think probably I directly head to.
E	0′31.0″	0′35.1″	Then, you found the slop, right?
P	0′35.1″	1′00.7″	Yeah. And I started to think they might be located near to minerals. Generally, minerals probably were down this area, for some example, but, didn't know that were consistent. Yes, as I mentioned before, it looked like a container area, I just saw too many points around there.
E	1′00.7″	1′09.7″	So even though you found this slop that you could go through. But you chose to go down [side of the map].
P	1′09.7″	1′10.1″	I ignored that one.
E	1′10.1″	1′11.4″	Oh, you just ignored it.

P	1′11.4″	1′34.9″	I ignored to see anything. I wanted to complete this area. I found another one near mineral site that seems I felt deliberative at that point. I guess I was just following the edge around.
E	1′34.9″	1′37.1″	Following the edge?
P	1′37.1″	1′45.2″	Yeah, well. Tried to find a way down. Already the knew the edge above that area.
E	1′45.2″	1′46.0″	OK, here, you already saw some enemies, right?
P	1′46.0″	1′58.4″	Yes. So now I was trying to find a way down.
E	1′58.4″	2′05.5″	So, are you just focusing on finding a path to go down?
P	2′05.5″	2′13.7″	Yes. I know there are some objectives down there. So, it has to be somewhere around this edge. I tried to path down, finish those off and head back out. At this point, there were [areas] just a bit of explored above. So, I can go to make sure there was nothing there. I found something. I guessed they were enemies just down and upside areas. I was going down to, basically, find the bottom of the map to make sure there were enemies or anything there. I was going where [was a] bit of completion.
E	3′26.4″	3′31.8″	Here is a slop. But, you just ignored it.
P	3′31.8″	3′38.9″	I probably missed. I didn't observe it.
E	3′38.9″	3′42.0″	You haven't recognized it, right?
P	3′42.0″	3′48.3″	No. I don't remember, liberally, ignoring it or going around it.
E	3′48.3″	3′54.6″	At that point, there was only one enemy left. And what were you trying to do?
P	3′54.6″	4′10.8″	I just tried to find external unexplored base, you know. I notice that I have kind of assume I have done anything below, I just was going up to do the top.

E	4′10.8″	4′19.2″	I assumed that the overall strategy you used is to explore the middle of the map first, right?
P	4′19.2″	4′46.5″	Yes, well it is kind of, not really, I am looking for [in] random direction. And I guess, once, once, I explored and found some. It was kind of looking for minerals, and immensely just trying to pick up areas by haven't seen yet.

B.1 A Sample of Interview Data in Chapter 4

An interview conversation which from the judge 4 in the experiment of Chapter 4, is listed below where P represents participant, and E presents experimenter.

Speaker	Start Time	End Time	Manuscript
E	0′00.0″	0′22.7″	Do you think it is easy to distinguish AI players from the videos?
J	0′22.7″	0′44.3″	I think there are signs in some videos [which] help me to judge whether they are human or AIs. But, for some videos, they didn't have significant signs. In those cases, I was not quite sure whether they were computers [or not].
E	0′44.3″	0′50.3″	Do you have some specific strategies to make the judgements?
J	0′50.3″	2′00.0″	Yeah, generally I think the computer behave poor in complex environments. In narrow areas, computers did not act smoothly. Sometimes I could not figure out what they were trying to do, since they usually got stuck there, without any explicit strategies. But for human players, they were clever and quick. They could act precisely by observing surroundings. My conclusion is that human behaves much better than machines in complicated environments.

E	2′00.0″	2′17.6″	Let's move into the three games. For each game, have you recognized some highlight behaviors, which indicate human or machine players?
J	2′17.6″	3′11.7″	For the *pure exploration* [game], I think AIs behaved much poor in corner areas. They normally went into and hanged around corners. It takes quite a long time for computers to get out. But for humans, they quickly went into corners and recognized them [corner patterns]. Then went out very quickly.
E	3′11.7″	3′13.4″	For the *killing game*?
J	3′13.4″	4′05.5″	For the *killing game*, I think the main highlight behavior is: for humans, they saw enemies and killed them, it's simple, while for computers, they saw enemies but ignored them. I don't know why it happened. But it made computers look so stupid. For the *searching game*, there are no specific highlight signs. But issues are quite similar to the *pure exploration game*.
E	4′05.5″	4′51.7″	OK. I see. Let's get rid of these three exploration games and consider much more general scenarios. According to what you mentioned, you have good gameplay background and played many games. When you played with or against players, did you found any highlight behavior that could indicate whether they were human or machine players, in commercial games?
J	4′51.7″	6′15.7″	According to my experience, I played Counter-Strike and DotA (Eul, Feak & IceFrog 2003). They all have AI bots. When considering whether I could tell they are AIs, there are two facts. AI acted very precisely in small-scale behaviors. For example, they shoot more precise than human, and react more precisely than human. The speed is abnormal. On the other hand, computers do not have strategic behavior. They only kill and run, without strategies. But for human, we group together, collaborate with each other and kill enemies, which is much better than computers.

C1. Raw data

Category	Percentage		
	Male – 50 instances	Female – 19 instances	Total – 69 instances
Wanderer	8%	37%	16%
Pather	22%	16%	20%
Targeter	34%	32%	33%
Seer	36%	16%	30%

Table A.1 Data visualized in Figure 3.5 a

Category	Percentage		
	Male – 15 instances	Female – 16 instances	Total – 31 instances
Wanderer	20%	44%	32%
Pather	27%	13%	20%
Targeter	20%	25%	23%
Seer	33%	19%	26%

Table A.2 Data visualized in Figure 3.5 b

Category	Percentage		
	Less than 1 hour – 31 instances	1 to 5 hours – 22 instances	More than 5 hours – 16 instances
Wanderer	91%	9%	0%
Pather	43%	29%	29%
Targeter	30%	26%	43%
Seer	38%	52%	10%

Table A.3 Data visualized in Figure 3.6 and Figure 3.7

	Average Score
Human 1	3.62
Human 2	4.14
Random	1.48
APF	1.86
MCDM	2.33
Topological	1.62

Table A.4 Data visualized in Figure 4.3

	Pure exploration game	Killing game	Searching game
Human 1	3.71	3.86	3.29
Human 2	3.43	5.00	4.00
Random	1.86	1.29	1.29
APF	3.14	1.14	1.29
MCDM	2.57	1.86	2.57
Topological	2.14	1.00	1.71

Table A.5 Data visualized in Figure 4.4

	Average Score
Human 1	3.62
Human 2	4.14
Random	1.48
APF	1.86
MCDM	2.33
Topological	1.62

Table A.6 Data visualized in Figure 5.5

Themes	**Count**
unreasonable killing behavior	22
unreasonable stops	7
fixed patterns	6
stick to boundaries	10
unnatural movements	3
revisit explored areas	8
idle behavior	12
unreasonable behavior around landmarks	7
stop-and-think	3
fluent actions	2
ignore uninformative areas	2
revisit incompletely-explored areas	1
random path selection	2
reasonable killing behavior	2
reasonable behavior around landmarks	2

Table A.7 Data visualized in Figure 5.7

Themes	Counts
natural movements	12
reasonable behaviors around landmarks	2
revisit incompletely-explored areas	6
stop-and-think	2
reasonable killing behavior	5
fluent actions	7
deliberate exploration	5
stick to boundaries	3
unreasonable behavior around landmarks	5
unreasonable stops	2
fixed patterns	3
unnatural movements	6
idle behavior	1
unreasonable killing behavior	4

Table A.8 Data visualized in Figure 5.8

Themes	Count
stop-and-think	2
deliberate exploration	2
fluent actions	2
consistent movements	5
ignore uninformative areas	2
natural movements	4
random path selection	2
revisit incompletely-explored areas	3
reasonable behavior around landmarks	2
spin in a corner	3
stick to boundaries	2
revisit explored areas	3
unreasonable killing behavior	2
unnatural movements	2

Table A.9 Data visualized in Figure 5.9

Participant	Average Score
Human 2	3.53
Integrated	3.5
Human 1	3.3
MCDM	2.3
Random	2.1
Topological	1.73

Table A.10 Data visualized in Figure 6.2

Themes	**Count**
unreasonable killing behavior	14
unnatural movements	8
revisit explored areas	14
fixed patterns	3
stick to boundaries	8
unreasonable stops	10
explore uninformative areas	8
idle behavior	11
unreasonable behavior around landmarks	6
stop-and-think	4
fluent actions	2
ignore uninformative areas	1
natural movements	3
revisit incompletely-explored areas	2
have a global view	2
reasonable killing behavior	1
reasonable behavior around landmarks	1

Table A.11 Data visualized in Figure 6.4

Themes	Count
natural movements	7
deliberate exploration	1
have a global view	10
explore uninformative areas	3
stop-and-think	2
reasonable killing behavior	7
fluent actions	8
reasonable behaviors around landmarks	7
stick to boundaries	2
unreasonable behavior around landmarks	4
unreasonable stops	1
unreasonable killing behavior	4
unnatural movements	3
explore uninformative areas	4
fixed patterns	2

Table A.12 Data visualized in Figure 6.5

Themes	Count
stop-and-think	5
deliberate exploration	1
have a global view	4
fluent actions	3
reasonable killing behavior	6
random path selection	1
reasonable behavior around landmarks	6
unreasonable killing behavior	1
revisit explored areas	4
explore uninformative areas	1
unnatural movements	3
stick to boundaries	2
unreasonable behavior around landmarks	3

Table A.13 Data visualized in Figure 6.6

D1. Ethic application

UTS Creativity and Cognition Studios
2-page Ethics Approval Application

From: *Chen Si*
HREC 2013000135 Project Number 2015-x*

1. Title
Exploring Players' Behaviours of Unknown-environment Exploration in Real-time Strategy Games

2. Aims
The purpose of this study is to investigate players' preferences and strategies for performing exploration tasks in a PC game environment. A secondary purpose is to explore how domain and common knowledge play a role in players' decision making on navigating in unknown environment.

3. Methodology
The following method will be applied:

- Online questionnaire
  - To collect participants' demographical data.
  - To find out participants' past experiences in playing exploration games for evaluating the degree of data validation.
  - To find out participants' decision-making patterns in exploring an unknown environment.
- Game replay records

Participants are asked to play three games described below. Then, each game-play data is recorded in a replay file.

  - Searching Game: navigating a game unit to search the opponent's base.
  - Collection Game: controlling a battle unit to kill a certain amount of enemy units with constraint time.
  - Map Construction Game: navigating a game unit to perceive and discover the unknown game terrain with constraint time.

4. Significance
This is part of a series of experiments to investigate the preferences, navigation and strategies of human in fulfilling spatial exploration tasks. The outcome would take the form of design guidelines for humanoid exploration agents.

5. Number of participants and justification of numbers
up to 40.

The research aims to get an initial understanding of the performance of participants in a series of exploration games, which are based-on the StarCraft engine. Roughly even groups of participants separated by properties of age, gender and background in game-play are expected to attend the trials. So a moderate size is chosen.

6. Selection/exclusion criteria

Participants will be students and colleagues related to the investigators and their team. They will consist of primarily individuals who may or may not have any gaming experience, and may or may not have any experience with real-time strategy games such as the StarCraft : Brood War.

7. Children under 18 years of age will participate in the evaluation.
No.

8. Procedures
Participants will be:
1. contacted and briefed on the nature of the study;
2. asked to provide their consent an online consent sheet (see 11.);
3. asked to engage in a trial as defined in section 3, if they agree.

9. Time commitment for participants
The entire session will take about 40 minutes.

10. Location of research
The study will take place in the Game Studio (11.06.401).

11. Consent procedures
Online consent sheet(s) (see attached)

12. Additional Risks (additional to those noted in the CCS Generic Approval)
Nil.

13. Strategies to cope with risks mentioned in 12.
N/A.

14. Other issues
No other issues perceived as being problematic.

*Number obtained from CCS Ethics Administrator

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