Modeling Player-like Behavior for Game AI Design

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ABSTRACT

The design of artificial intelligence in computer games is an important component of a player's game play experience. As games are becoming more life-like and interactive, the need for more realistic game AI will increase. This is particularly the case with respect to AI that simulates how human players act, behave and make decisions. The purpose of this research is to establish a model of player-like behavior that may be effectively used to inform the design of artificial intelligence to more accurately mimic a player's decision making process. The research uses a qualitative analysis of player opinions and reactions while playing a first person shooter video game, with recordings of their in-game actions, speech and facial characteristics. The initial studies provide player data that has been used to design a model of how a player behaves.

Categories and Subject Descriptors

H.5.2 [**Information Interfaces and Presentation**]: User Interfaces – *User-centered Design*; I.6.8 [**Simulation and Modeling**]: Types of Simulation – *Gaming*; K.8.0 [**Personal Computing**]: General – *Games*.

General Terms

Design, Human Factors.

Keywords

Video games, AI, player model, user study, design.

1. INTRODUCTION

The inclusion of artificial intelligence (AI) controlling non-player characters (NPC) in video games has been commonplace for nearly two decades. As the visual and interactive components of games become ever more life-like, we are beginning to see how traditional AI designs hamper the playability and engagement of modern games. This is especially the case in games where the AI is designed to provide adequate competition for human payers. NPCs can come across as unrealistic, with their behavior, choice of actions and performance affecting the believability of the gaming scenario. This is particularly evident in the first person shooter (FPS) genre. NPCs can be viewed as flawed, both because their behavior is seen as too predictable and also because their actions can be unrealistically effective.

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On one hand, players commonly consider the AI as cheating or unbalanced. NPCs, for example, know where their enemies are, or know where to find weapons or ammunition without seeing them [17]. On the other hand, AI implementation in many games is programmed to respond to situations in a certain way, with objectives and goals based on static rule sets [17]. Actions become predictable and repetitive. As a result, NPC AI is open to exploitation by players.

In this paper we examine how experienced players respond to current AI implementations of FPS opponents to better understand the problems and issues that arise. We also study how players behave while playing a first person shooter game. The concept of creating AI which incorporates 'player-like' behavior underpins this research. Our investigation into how a player performs and behaves when interacting during a game aims to provide a basis for improvement in the design of game AI.

This study is a continuation of research undertaken recently [7] in the same domain. However, this paper proposes a model which introduces a more player-like approach to AI design. The objective is to effectively simulate how a player behaves. Within this model is a general attempt to understand a player's ability to make decisions in uncertain environments and the tendency to react unpredictably as threatening game play situations arise. The model is designed to simulate player-like decision-making, measuring certainty or 'threat' within a game situation and applying it to AI behavior, altering how readily the AI will change its current action. The paper proceeds by designing a player-like model of AI based on the issues uncovered in two separate studies. The first study looks primarily at player expectations and opinions of an AI system and details some of the problems concerning unrealistic, unfair and predictable game play. The second study looks more deeply into how experienced players interact with a game, detailing the actions and decision-making processes of the participants. The data from both of these studies provides a model of player-like game AI design that addresses important aspects of player decision making processes, uncertainty and threat assessment.

2. BACKGROUND

Artificial intelligence in games has, in the past, been included as an afterthought [20]. AI was left until the last stage in a game's development cycle as it is difficult to develop game AI until details on how the game is going to be played are known [10]. Due to the time-pressure inherent in games production, developers rarely have the opportunity to explore or implement innovative AI techniques [12].

While AI has the potential to enhance game play, many implementations can detract from the game play experience [19] with agents performing unrealistic behaviour. The environments, objects, and agents in game worlds are often static, lifeless, and afford limited interaction [23]. Today's players are seeking more realistic and interactive behavior from these game elements.

2.1 Game AI

Examples of innovative Game AI design and development have appeared slowly in the last decade. Laird and Duchi's [16] Soar Quakebot is an early attempt at creating synthetic 'human-like' characters with varying levels of skill. The research included a method of evaluating the humanness of the AI; assessing the aggressiveness, aiming skill, decision time and tactical knowledge of the agents. Results showed that variations in decision time lead to changes in ratings of humanness, with the best performance coming with a decision time similar to that hypothesized for humans. Similarly, Bauckhage et al. [2][3] used the game Quake 2 to mimic player-like behavior. They used both neural networks [2] and a 'neural gas' algorithm [3] to map human states and actions to representational data. These studies demonstrated the potential for novel AI implementations to model human behavior for use in enjoyable gaming experiences. Hingston and Soni [9] also address the need for player-like AI. Using neural network AI trained using data from an experienced human player they created bots[1] that play testers competed against. These bots were rated on criteria such as challenge and predictability. Results showed that testers found them more player-like, less predictable, more re-playable, and more challenging compared to a traditional hand-coded bot.

Researchers have also been examining the use of inexpensive AI techniques for computer games. For example, the 'Groo' project [15] attempted to create an efficient agent that plays a deathmatch[2] style FPS game in a tactically intelligent manner. The emphasis in this project was on the efficiency of simpler, more visual mechanics. More recently research by Arrables et al. [1] addresses the idea of consciousness in game AI. Designing with the idea of implementing 'embodiment' and 'situatedness', their CERA-CRANIUM model of executing conscious-like behavior is a high-level control mechanism. It focuses on the AI's awareness of the environment, its interpretation of occurring events and its decision making process.

2.2 Player-like AI

According to Hallam and Yannakakis [8] a player's interest in any video game is directly related to the interest generated by the opponents' behavior rather than the graphics or the player's own behavior. A player's issues with non-player characters can usually be attributed to how the underlying AI operates. Performance of the AI is usually compared to a player's own ability to perform similar actions in the same situation. Anything that may seem out of place, unrealistic or impossible is likely to be deemed as 'cheating' [12]. This cheating refers to the AI agent's knowledge of the game world and ability to perform certain tasks with mechanical ease. In the past, game AI has often 'cheated' to provide the illusion of player-like behavior.

More than anything else in the game world, players identify with and expect life-like behavior from game characters [24]. Yet how a player experiences a game is very different to how modern AI acts within the game world. Player decision-making is based on all aspects of the interaction, from input and output methods, observable game world states and evaluation of the current situation. As players interface with the game differently than any form of AI system, there are discrepancies in performing even simple motor mechanics necessary for play [6]. Players also retain a level of uncertainty while gaming. This uncertainty may be caused by an inability to remember a previously encountered feature of the game or not knowing something in general [22]. Given that decision making is considered the core concept behind artificial intelligence [14], understanding player uncertainty is important.

It has been suggested that for maximum enjoyment, the skill level of a NPC opponent should roughly match that of the player [9]. Yet players do not have a fully intuitive sense of orientation and action in virtual environments and must invest time and energy to master the control interface and learn the mechanics of a game [21]. Developing AI that more closely mimics player behavior in first person shooters should result in better gaming experiences.

2.3 Modeling Player Interaction

As people play games, patterns of behavior emerge. Player actions, their usage in game play scenarios, as well as the consequences and relationships to other actions can be identified [4]. Identification of action and event patterns in FPS games will allow us to better understand and articulate in-game player behavior.

Norman's Seven Stages of Action [18] has been used to model human interactions with both physical and computational objects. This interaction driven model details the process of executing and evaluating actions enacted by a person to achieve a particular goal. The execution of actions involves the intention to act, the sequence of actions to be performed and the physical execution of that action sequence. The evaluation process, which can change the current goal, involves a person's perception of the world, the interpretation of that perception and an eventual evaluation of those perceptions [18]. As FPS actions are generally goal oriented, the model allows us to decompose the interactions of players within a game play scenario. Identified action and event sequences can be analyzed using Normans stages of action.

3. GAME PLAY INTERACTIONS

In order to better understand player interactions in FSP games two user studies were conducted. The first study explores players' views of AI behaviors and the second study examines the details of player goals, actions and interactions as they work through a game play scenario.

3.1 Study 1

Study 1 is designed to assess player's expectations of game AI. It examines players' feelings, thoughts and opinions related to the experience of competing against game AI.

3.1.1 Method

The game chosen for study 1 was Quake 3: Arena (or Quake Live) (ID Games, 1999). It was selected for its open source capabilities and its portability, accessibility and ease of use. Twenty-one expert game players were observed while playing this popular 3D FPS game. The participants were aged between 18 and 23, and all had experience playing FPS games before. Approximately 50% of players had played the game chosen for the user study, with over 80% having played similar game (i.e. arena shooter).

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1 Bot - Computer controlled robot, usually referred to in First Person Shooter games.

2 Deathmatch - A game mode in FPS games where it is every person for him or herself. No teams.

Participants were required to play a single 30 frag (kill) death-match session against seven bots of the same skill type. The bots they competed against were chosen specifically for their varied play styles which ranged from reckless to cautious. The play sessions were recorded in-game. The participants were given a questionnaire designed to elicit opinions on their play session and the AI they competed against. Questions related to the perceived difficulty of the bots to kill, the suitability of AI behavior and the level of challenge encountered. Participants were also given the option to rate their own level of aptitude and their ability to perform to the same degree again, given the opportunity.

3.1.2 Data Analysis

The questionnaire contained a mixture of multiple choice and open-ended questions. The multiple choice questions dealing with player performance and AI behavior covered five categories:

- predicting enemy player's behaviour: including AI behavior related to area awareness and use of line of sight;
- aiming: including perceptions of the AI's ability to acquire targets and shoot accurately;
- moving through the environment: including attributes of movement and navigation;
- weapon usage; and
- pick-ups / resources.

Data analysis was based on these categories. It should be noted that because the AI does not behave like the player (i.e. states in a finite state machine) players were asked to critique some of the aspects of AI in additional detail. The open-ended question asked players to comment on their game play experience, particularly with respect to competing against the game AI. All comments were analyzed with the view of identifying consistent themes.

3.1.3 Results

The questionnaire results showed that participants were concerned with the level of believability and execution of certain AI behaviors. Player responses to the open-ended question were analyzed to extract common themes and identify unifying issues. Of the 21 participants, two had no comments about the game AI. Three more participants indicated that they had no issues with the AI. Of the 16 remaining participants, 81% commented on unrealistic AI behavior, 37% flagged issues with AI 'cheating' and 37% indicated they felt there were issues related to the predictability of AI behavior. Table 1 provides examples of player comments from the questionnaire.

A majority of participants mentioned some aspect of the AI's navigation, aiming and tracking of other players. One participant commented that "*… I felt their tracking and accuracy was slightly too good, and their movements in combat were a bit too robotic and precise*". Concerns about aiming and the bots' ability to use certain weapons were identified by 66% of study participants in response to the multiple choice question that addressed this topic. Another irregular behavior identified was a bot's enhanced ability to see the player character. Approximately 62% of participants were uncomfortable with the AI's ability to lock onto their presence and found that even when they were occluded from direct line-of-sight, the AI could still find and target them without error.

Of particular interest was a comparative analysis of two questionnaire items. The first asked participants to identify aspects of AI behavior that they felt was unrealistic (question 1). The second asked players to reflect on their own game play performance, looking for details of game play experience that was challenging or hard to master (question 2). In both questions players were asked to comment on key areas of FPS game play such as predicting enemy behavior, targeting and aiming, movement, navigation, weapon usage and resource acquisition. Table 2 details the percentage of positive responses to both questions. The highlighted sections show aspects that were seen to be both difficult for players and unrealistically represented in the AI. This is important to recognize as it denotes a perceived imbalance between the activities by the participants.

Table 1: Player Comments about Game AI

Topic	Example Player Comments
Unrealistic AI behavior	Sometimes they shoot at you when they have no reason to. …even fewer duck in and out of cover like I would. …a few of the shots they did were a bit 'far out'
AI 'cheating'	They are able to tell where you are if you attempt to sneak up on them. It almost feels as if you are merely activating the bot's ability to see you through walls … They see and engage other players too quickly around corners.
Predictable behavior	I noticed that the bots didn't change up their movement. Bots seem to congregate in a specific area making them easier to kill. Humans would mix up their movements more.

Table 2: Responses to questions on key areas of game play

<table>
<tr><th colspan="2">Aspect</th><th>% Yes Question 1 (Unrealistic AI)</th><th>% Yes Question 2 (Challenging for Player)</th></tr>
<tr><td rowspan="2">Predicting enemy behavior</td><td>Area awareness</td><td>61.9%</td><td rowspan="2">61.9%</td></tr>
<tr><td>Use of line of sight</td><td>57.14%</td></tr>
<tr><td rowspan="2">Aiming</td><td>Target Acquiring</td><td>66.67%</td><td rowspan="2">42.85%</td></tr>
<tr><td>Accuracy</td><td>47.61%</td></tr>
<tr><td rowspan="2">Moving through the environment</td><td>Movement</td><td>52.38%</td><td>38.09%</td></tr>
<tr><td>Navigation</td><td>33.33%</td><td>66.67%</td></tr>
<tr><td colspan="2">Weapon Usage</td><td>23.8%</td><td>33.33%</td></tr>
<tr><td colspan="2">Pickups/Resources</td><td>28.57%</td><td>38.09%</td></tr>
</table>

3.2 Study 2

Study 2 aimed to better understand players' in-game interactions, examining how a player performs and behaves when interacting within a FPS game scenario.

3.2.1 Method

Unreal Tournament 3 (UT3), a competitive multiplayer first person shooter by Epic Games was used in study 2. UT3 was chosen because it is a modern game that has a game engine that is relatively customizable and includes features such as a prebuilt AI system and level editing tools.

Four participants were involved in the study. These participants were experienced players of FPS games. They had an above average level of proficiency playing this genre of games. All had experience in playing either Unreal Tournament 3 or the Unreal

Tournament franchise. Experienced participants were chosen so that little direction was needed in terms of educating them in the game's objectives, goals and mechanics

Participants were involved in a single death match game against a difficult (adept or greater) level AI opponent for 30 frags or 10 minutes. Ten minutes of prior practice was permitted and encouraged. The level used was 'Rising Sun' as it is a relatively open map with multiple routes for players to take with pick-ups scattered all over the map. It is a map that all participants were familiar with and had no difficulty navigating. The single bot used was Lauren on adept difficulty.

Throughout study 2 demonstration recording and footage capture technologies were used. A digital video camera was set up behind the player to capture their pose and body language, as well as what was happening on screen. A smaller secondary camera was placed in front of the player on top of the monitor to capture facial expressions during play. The game play was initially recorded via UT3's in-game demo recording tool, but later recorded to a media file. All three video streams were collated in a final video compilation (see Figure 1). Player intentions and goals were elicited using the talk-out-loud technique [13] during game play. This technique was used in combination with interviews with participants while examining game play footage after the game play session.

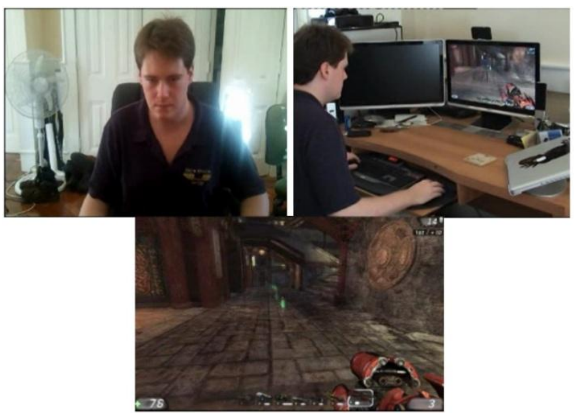

Figure 1: Data captured during study 2.

3.2.2 Data Analysis

The analysis of the data captured during study 2 was undertaken to extract player behavioral patterns. Noticeable player actions and decisions were examined. The technique used to extract the data from the videos was a process of both time and event sampling [5]. The process was designed to record player actions, the frequency of the action, the state prior to the action and the consequence of the action. Figure 2 is an extract from a data analysis record obtained using this process. Comments from players as they played the game were also recorded.

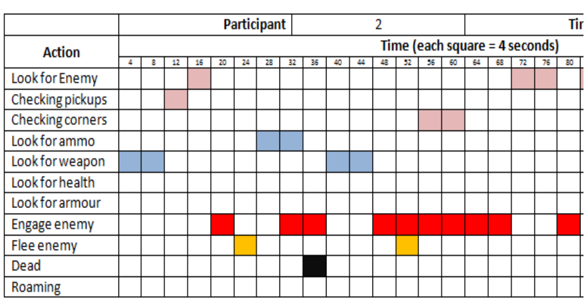

Figure 2: Example of a data analysis record.

3.2.3 Results

The following is the list of viewable player states/actions that were found in the data.

- Looking for enemy: visibly panning and searching around the map looking for presence of enemy.
- Checking pickups/observing key locations: players would return to or observe locations where desirable items/weapons were located.
- Checking corners with weapon fire: often participants would fire blindly around corners without having made visual contact with the AI opponent. Usually performed with explosive or area-of-affect weapons.
- Looking for ammunition: actively searching for or heading towards specific pick-ups to refill currently equipped weapons.
- Looking for weapon: actively searching for or heading towards more desirable weapons to equip the player character.
- Looking for health: actively searching for health pick-ups to restore hit points. This usually occurred when the participants were low on health.
- Looking for armor: actively searching for armor pick-ups. This appeared to be of lower priority for participants compared to health, weapons and ammunition.
- Engaging Enemy (including dodging, jumping, weapon mechanics etc): engaged in combat with opponent AI performing maneuvers to effectively take down an opponent or avoid incoming fire.
- Fleeing Enemy: engaged in combat with opponent AI and performing primarily defensive maneuvers to avoid line-of-sight and incoming enemy fire.
- Dead: participant's avatar reached less than or equal to 0 hit points.
- Roaming/Suicidal/Exploring: These states were harder to distinguish and were performed in only a few select scenarios. The causes of these states are believed to player boredom, over-confidence and general amusement.

What is noticeable about these states is that, unlike an AI opponent, a player would perform more than one of them at any given time. In certain scenarios, for example, a player would be both fleeing and engaging the enemy while concentrating on picking up health, as well as checking corners with weapons fire. This sophisticated level of play is rarely seen in any AI opponent. Player comments related to game play were used to associate goals and reasoning with the actions performed during the game.

Table 3 details the player actions and the associated goals and justifications commonly occurring for each of the four participants.

Decision making is an important component of consideration for study 2. Analysis of the data demonstrated that all four participants were involved in complex decision making at certain times during game play. These decisions generally related to transitioning between the observable actions states identified in Table 3. In many cases the decisions made given a particular circumstance were consistent for all four participants. Decision making appears to be driven by a combination of an analysis of the variables that influence a game play situation (e.g. level of health) and an assessment of the uncertainty of a situation or the perceived threat level.

Table 3: Common actions, goals and reasons identified during game play

Action	Reason	Goal
Looking for enemy	Equipped to face enemy, feels engagement will be successful	Engage enemy
Checking pick-ups /observing key locations	Check for availability of pickups and presence of enemy near them	Pick off enemy at known locations, take pickups from enemy
Checking corners with weapon fire	Cannot see enemy, waste ammo but come around corner with firepower advantage in case	Kill enemy unexpectedly, security and to feel at ease
Looking for ammo	Current weapon nearly empty	Replenish current weapon's ammunition
Looking for weapon	Current weapon undesirable	Find and use more desirable weapon
Looking for health	Low on health, may die	Replenish health, decrease chances of death
Looking for armor	Low on armor, may die	Gain armor, decrease chances of death
Engaging Enemy	Overall objective of game	Receive frags (kills) to further increase score
Fleeing Enemy	Losing engagement, caught off guard/unprepared	Prolong life
Dead	Was killed by opponent. Looking at own corpse or score screen	Get back into fight and continue trying to win
Roaming / Exploring / Suicidal	Rare. Usually when participant has high/low degree of confidence in outcome, bored, or for own amusement.	No real goal or purpose.

However, on occasion strange decisions, which appeared to have no clear reasoning, were observed. These decisions may best be described as 'bad' decisions as the success rate of achieving a particular goal were low. A trend of inconsistent and frequent decision-making in threatening scenarios was observed. In highly threatening scenarios, players have a greater tendency to change their current action, for better or for worse. As this threatening scenario continues, participants continue making different decisions, some of which appear to move the player away from their desired goal. It is believed that this sort of behavior is the player's response to:

1. Indecision on how to most appropriately handle the current situation; and
2. Danger and the need to change tactics immediately and frequently.

The sequencing and performance of actions based on player reasoning and goals has provided an insight into the FPS game play experience. The detailed analysis reveals behavior patterns specially related to self-preservation decision-making. This level of player-like behavioral analysis is an important first step in designing player-like game AI.

4. AI MODEL DESIGN

The data from study 1 shows players expectations of AI and exposes the common issues concerning the unrealistic, unfair and predictable actions they sometimes perform. The data from study 2 analyses how experienced players react and behave when playing a FPS game and how their actions and decision making processes differ from existing AI models. It is believed that many of the issues raised in study 1 can be remedied by creating an AI model that is based on the actions and behavior of players such as the participants from study 2. The problematic aspects of AI found in study 1 can be traced to both the inadequate mechanical execution of actions and inappropriate decision making made by the AI agent.

Some component of 'threat assessment' or understanding of self-preservation is necessary for an AI agent to behave similarly to a human player. This assessment of threat is an important part of player decision making, contributing to many of the actions and behaviors of the participants in study 2.To properly address the findings from both studies, the model is positioned in relation to how people act and achieve goals in the game world. Using Norman's seven stages of action [18] we have mapped AI functions to action steps (Figure 3). AI decision-making is based on feedback from a previous action which includes an analysis of threat or uncertainty and consequently prioritized action choices.

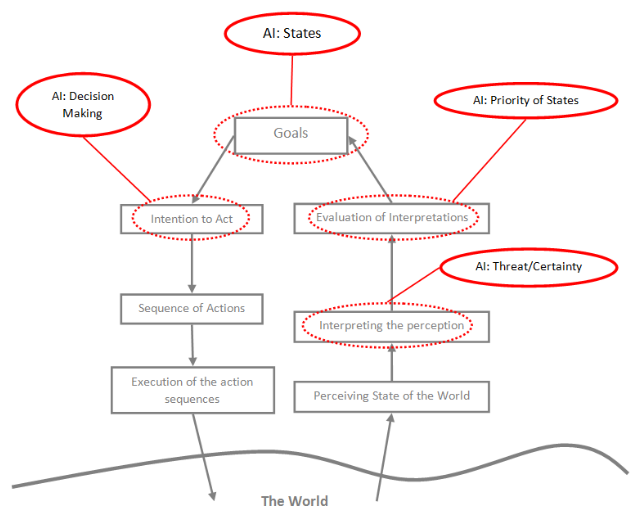

Figure 3: AI functions mapped to goal-directed actions.

The actions identified in study 2 (Table 3) form the basis of the AI states in the proposed model. These states have been categorized based on similarities in goals and reasoning (see Figure 4). The actions can be categorized into out-of-combat states and combat-related states. Within the out-of-combat states there are two identified categories, weapon-related states and uncertainty states. Health states sit between the out-of-combat and combat-related states as these states may occur simultaneously in either. In

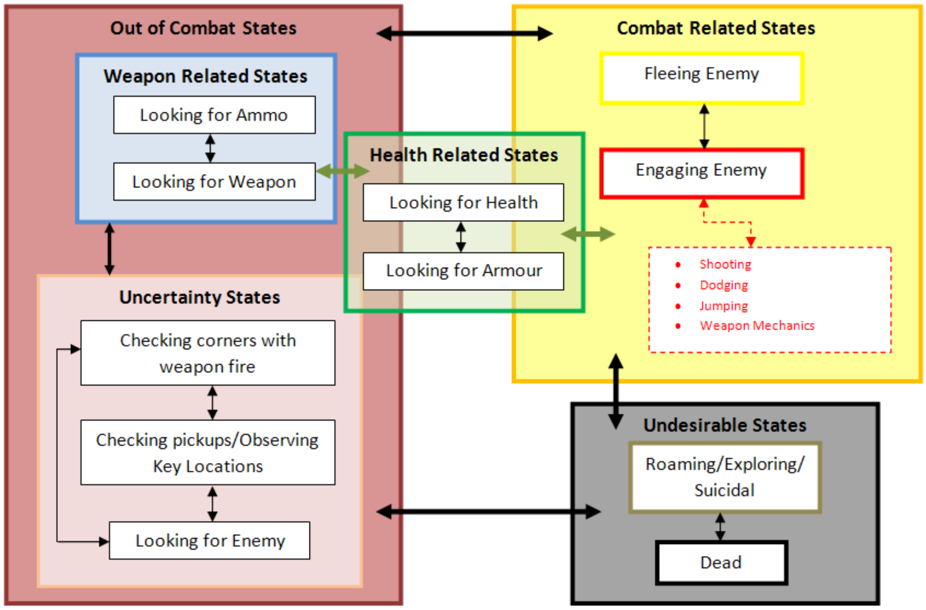

Figure 4: Action State Map

addition to these key state categories, an undesirable state category has been identified.

The model allows us to identify relationships between states. These relationships illustrate the ability of a player to transition from actions within one state to actions within another. For example, *looking for enemy* and *looking for weapon* can be considered within an out-of-combat state and therefore desirable actions should the player wish to stay out of combat. Some actions, such a *looking for health*, are shared across three states and can be both in and out of combat. The model should not be viewed as set of actions that are performed individually from one another. From the analysis in study 2, players were found to, for example, actively flee from the enemy while searching for health, checking corners with weapon fire and looking for ammo. This combined performance includes actions from a combat related, health related and uncertainty state simultaneously, guided by the goal of getting out of combat, staying alive while still being well equipped.

Analysis of study 2 data demonstrated that all players exhibited a high degree of state change and decision making when in positions of stress in the game. The behavior appears to be guided by self-preservation and a 'threat level' assessment that contributes to action priority and changeability of action states. The threat assessment component of the AI model is designed to mimic the observed threat levels in a general sense. This is because threat is assessed differently by all players. Therefore, a simplified representation is proposed. For example, a large and sudden decrease in health is mapped to a high increase in threat. A large increment in armor results in a significant decrease in threat.

Threat is addressed in this model from the perspective of 'self-preservation'. Self-preservation assessment changes the priority of logical action states that the AI might transition to depending on how threatening a situation is (see Figure 5). In a highly threatening scenario, the actions of higher priority (e.g. flee, find health) would be the opposite order of the actions during a low threat scenario (e.g. fight, find weapon). In a scenario where threat can be measured as moderate, all states would be considered equally, with no priority for one state over another. The threat assessment also determines the possible states that can be transitioned to depending on the threat level and the current state. For example, a highly threatening situation while the action being performed is *engaging enemy* will result in the action *fleeing enemy* being given the highest priority. In such a situation actions such as *looking for ammo* are ignored entirely. The frequency of state transition would increase depending on how threatening a situation is, emulating that of a human player in the same situation.

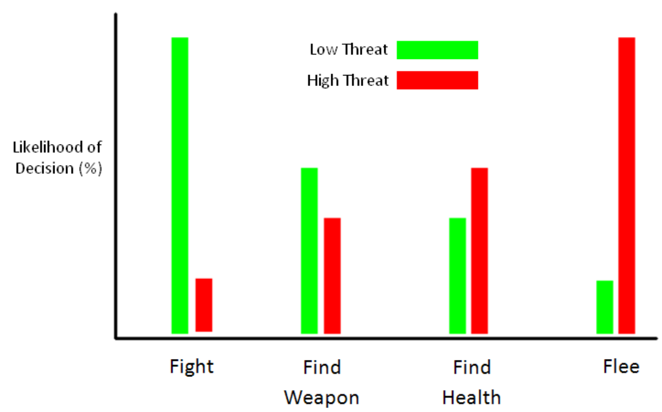

Figure 5: Threat Priority Adjustment

To make threat selection seem unpredictable, it is necessary to plot the priority of states along a distribution that would still allow for the selection of low priority states (see Figure 6). This threat meter encapsulates certain states within each other across its distribution, with a priority density algorithm determining which state is chosen at a particular time. High priority actions are chosen more often than not, but bad, low priority decisions may still be made by the bot. However, it would occur infrequently enough for it not to become routine or exploitable. For example, in Figure 6, the action *search for health* encompasses the actions *search for enemy*, *engage enemy*, *search for armor* and *flee engagement*.

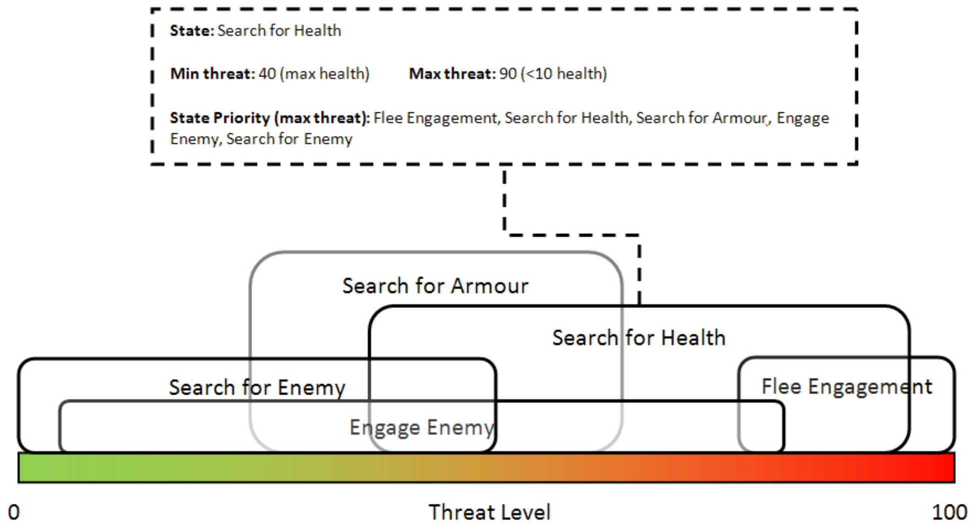

Figure 6: Threat Meter State Distribution

These distributed states have minimum and maximum threat values that determine their logical execution across a global threat range. At a high threat level, the likely course of action while looking for health would be to flee the current engagement. It is unlikely that the bot would *search for enemy* during a threatening situation as it is on the lower/less threatening end of the continuum in the *search for health* state. However, the possibility of such a transition occurring is not ruled out and may still occur infrequently. The same cannot be said for the action *flee engagement* that does not have the *search for enemy* overlap in its threat boundary. This completely rules out the possibility of transitioning to an enemy searching action from a fleeing action as they are logically opposed actions from the start. Overall, this method provides both logical control and unpredictable threat assessment based decisions.

5. DISCUSSION

The devised AI model was created with the intent of portraying aspects of how players behave in FPS games. This model is designed using data from both study 1 and study 2, which examined the interactions of experienced game players. The data analysis was used to identify the disparate qualities of AI bots and human players and to detect the subtle activities and behaviors that differentiate the two. Study 1 contained questionnaire responses that clearly identified three key issues related to game AI: unrealistic behavior, cheating and predictability. Responses to questions also showed that players found tasks like predicting enemy behavior, aiming and navigation difficult. They felt that AI was unrealistic due to the ability to track players through enhanced area awareness and the ability to 'see' occluded targets (use of line of sight), the ability to lock onto targets through superior target acquisition and accuracy and the ability to move easily around the environment. The disparity between the players' assessment of their own skills in tracking enemies, aiming and moving through the environment in comparison to that of their AI opponents was clear. The problematic aspects can be traced to both the execution of actions and the decision making processes of the AI agent.

The analysis of data obtained in study 2 has allowed for a better understanding of the nature of player behavior when playing a first person shooter. Using the observed data from the study, it was possible to formulate an initial understanding of what a generic model of player interaction looks like when playing this genre of game. This model was built on the actions and decisions made by experienced players, and incorporates an assessment of threat which affects the priority and frequency of state transitions. This priority of states or goals from the player's perspective was seen to be greatly affected by the current in-game situation. Because of the distribution of the action priorities, actions with low priority have a less likely chance of being transitioned to, but still remain a possibility. This reduces the predictability of the system which is an aspect of AI that participants of both studies had issues with. Overall, a system employing this model would provide a more player-like method of decision making.

Certain limitations of the current work should be noted. Firstly, only small sample sizes were employed (particularly in study 2) and the samples in both studies were made up of experienced FPS players. It is possible that our samples are not representative of the larger FPS playing population and future research with larger, broader samples (including players with a range of expertise) will be needed to address this issue. Additionally, the player behaviors in study 2 were only analyzed and coded by one of the one researcher. Further validation of our analysis of player behavior will be possible in future research through the use of additional coders and by cross-referencing the classifications of behaviors made by each coder.

6. CONCLUSIONS

Artificially intelligent NPCs employing a player-like method of behaving should provide a more enjoyable and immersive gaming experience to players. The threat evaluation employed by AI within the new model would appear to be more natural and more consistent with how players behave. The player should therefore be more engaged and motivated to play, which is something all games strive to achieve.

The ideas discussed in this paper address a central area of concern for modern game developers. As games become more complex and life-like, so must the underlying design decisions manipulating their technologies. In the sphere of competitive first person shooters, where players can be pitted against artificial opponents, addressing the believability of the AI has never been a more important design problem. The provision of the simple features of player-like priority of goals, assessment of threatening situations, embodiment, self-preservation and overall decision making may lead to less frustrating player experiences. It is a small step in a long journey, but one that designers of games will inevitably need to undertake.

Future work consists of expanding the current model to incorporate more aspects of player interaction from the competitive multiplayer FPS genre. This will require the input from more participants using different scenarios than the one presented in study 2, specifically analyzing aspects uncovered in both studies. These aspects include the unrealistic, unfair and predictable nature of the AI in different scenarios as well as further exploration into player decision making and assessment of threatening situations. It is expected that this larger sample size will allow for a more holistic model of player-like behavior and account for any possible discrepancies the current model may have. Additionally, this revised model will then be adapted to an existing AI system in a game to accurately test for any changes in player engagement. It is expected that the results from this future study will be analyzed comparatively to those derived from the two studies presented here with further conclusions about the functionality of the model drawn from that data.

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