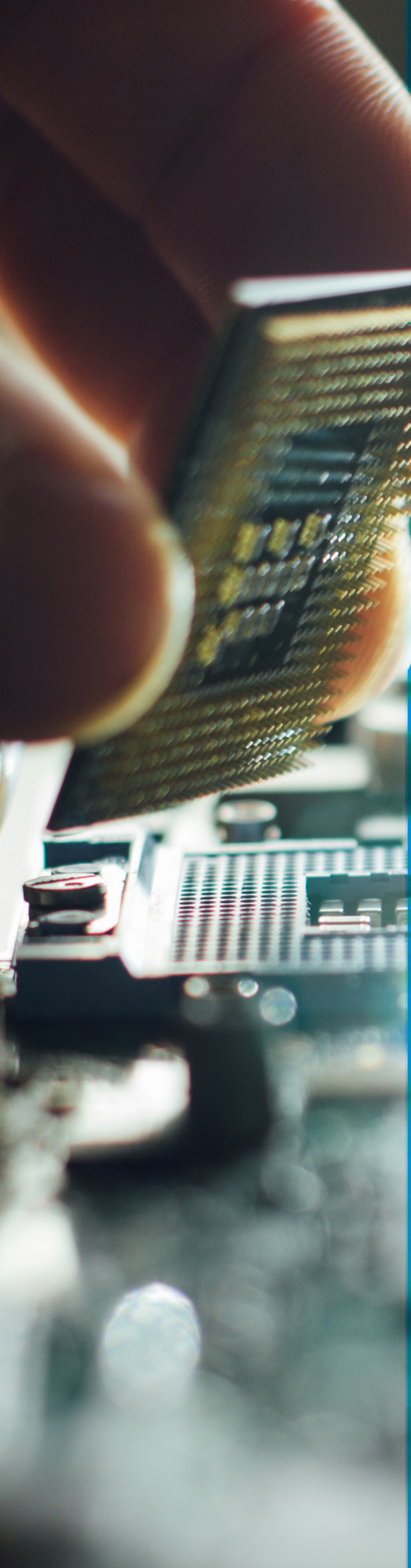

A Produção do Conhecimento na Engenharia da Computação

Ernane Rosa Martins
(Organizador)

Atena Editora
Ano 2019

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APRESENTAÇÃO

Segundo o dicionário Aurélio a Engenharia é a “Arte de aplicar conhecimentos científicos e empíricos e certas habilitações específicas à criação de estruturas, dispositivos e processos que se utilizam para converter recursos naturais em formas adequadas ao atendimento das necessidades humanas. A Engenharia de Computação é definida como o ramo da engenharia que se caracteriza pelo projeto, desenvolvimento e implementação de sistemas, equipamentos e dispositivos computacionais segundo uma visão integrada de hardware e software, apoiando-se em uma sólida base matemática e conhecimentos de fenômenos físicos.

Este livro, possibilita conhecer algumas das produções do conhecimento no ramo da Engenharia da Computação, que abordam assuntos extremamente importantes, tais como: as transformações sofridas nos processos de projeto desde a implementação das ferramentas digitais; o armazenamento, indexação e recuperação de formulários digitais; a reabilitação motora assistida por computadores; a reflexão acerca do realismo e da representação visual em jogos digitais; os padrões de players em ambientes virtuais; as soluções tecnológicas relevantes usadas em países africanos; a complexa relação existente entre jogos digitais e o humano; a dinâmica da comunicação de um grupo de Facebook criado em um processo de urbanismo bottom-up; o estado da arte das pesquisas e estudos acadêmicos acerca dos elementos visuais contidos na interface de jogos digitais; as estratégias de design que integrem tecnologia computacional digital a artefatos e instalações para a interação de visitantes em museus; os jogos que abordam o tema de mitologia e religião.

Deste modo, espero que este livro seja um guia para os Engenheiros de Computação auxiliando-os em assuntos relevantes da área, fornecendo conhecimentos que podem permitir especificar, conceber, desenvolver, implementar, adaptar, produzir, industrializar, instalar e manter sistemas computacionais, bem como perfazer a integração de recursos físicos e lógicos necessários para o atendimento das necessidades informacionais, computacionais e da automação de organizações em geral. Por fim, agradeço a todos que contribuíram de alguma forma para a construção desta obra e desejo a todos os leitores, novas e significativas reflexões sobre os temas abordados.

Ernane Rosa Martins

SUMÁRIO

CAPÍTULO 14

A BATTLING BEHAVIOR ANALYSIS OF SHOOTER GAMES BOTS BASED ON THE BARTLE'S PLAYER TYPES AND FINITE STATE MACHINES

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ABSTRACT: The players types are increasingly demanding especially in relation to the experience that the game provides. In shooter games, although the bots often have the same level of skill and follow specific rules throughout the game, not presenting their own strategies. This fact can mean a fragility in the game design process, since players expect even more realism in shooter games. In this context, the creation of bots showing believable behaviors can be decisive for the success of a shooter game next to its target audience. This work presents a proposal of revisiting the Bartle's typology in order to adapt it to bots behavior. Then, considering a shooter battle arena scenario, this work assumed that realistic and efficient bots for shooter games can be developed based on four behavior types: killer, achiever, explorer, and beginner. Each bot behavior was defined through a finite state machine based on the verification of the environment and decision making. From the experiment's results analyses, it is possible to conclude that as important as the behavior of the bots, is the interaction of this with the environment, which plays a fundamental role in the question of player experience and the believability related to immersion into the battle scenario.

KEYWORDS: Game Bots; Shooter Games; Behavior Analysis; Player Types; Finite State Machines.

1 I INTRODUCTION

The term "shooter game" refers to a combat-oriented games with firearms in which the player must control an avatar and take out enemies. Besides the combative nature, shooter games are characterized by fast action and, since early 90's, are still one of the most popular genres of games. Shooter games have sub-genres as first-person shooters (FPS), third-person shooters (TPS), tactical shooters among others.

Shooter game players face bots, computer-controlled enemies also referenced by non-player characters (NPCs) or game-playing agents, using different weapons in addition to collecting items through the scenario. While the players are undergoing a learning and training process as the game progresses, bots often have the same level of skill throughout the game and follow specific rules, not evolving into their own strategies. Bots have the ability to move around in an environment, avoid obstacles, aim, shoot, pick up items, run among other actions. For this, techniques of artificial intelligence (AI) are employed in order to perform verification of environment as well as decision making (FUNGE, 1999) (MILLINGTON, I.; FUNGE, 2009) (RABIN, 2002).

The application of AI in games differs from the problems of classical AI, since games are real-time computer graphics applications that require immediate response every fraction of a second. AI techniques used in games are related to the tactical level of bots which should be able to perform their tasks in short time, comprised between the frames of the game simulation. Some examples of AI techniques applied to games are state machine, fuzzy logic, genetic algorithms, neural networks, scripting, etc.

In shooter games, the AI is mostly controlled by finite state machines (FSM) and scripting to determine how a bot should act in diverse situations (RABIN, 2002) (BYL, 2004) (YUE; PENNY, 2006). Scripting techniques allow the player to create new types of bots (or modify an existing character according to their style of play) and are strongly based on rule systems. On the other hand, FSM techniques are logical structures composed of a set of states and a set of rules of transition between these states such as finite automata (HOPCROFT; ULLMAN, 1979).

Beyond the tactical level, players expect even more realism in shooter games through the creation of bots showing believable behaviors. According to Byl (BYL, 2004), Livingstone (LIVINGSTONE, 2006) and Ripamonti et al. (RIPAMONTI; GRATANI; MAGGIORINI; GADIA; BUJARI, 2017), some elements that increasing the believability of bots are human natural movement, mistakes and gestures during the game, character appearance and animation.

Nevertheless, Khoo et al. (KHOO; DUNHAM; TRIENENS; SOOD, 2001) discusses two potential problems with the believable behaviors approach and the increasingly complexity of the bots in shooter games. First, this method can be expensive, because generally involves highly serial computations operating on a large database of logical assertions, and second, it is unclear that the increased complexity of believable behavior in bots has added much to the final playability of the product. Laird and Duchi (LAIRD; DUCHI, 2000) suggest that, in shooter games, four main parameters influence the perception of humanness in bots: decision time, aggressiveness, number of tactics, and aiming skill. These parameters are common behaviors in shooter players and do not demand the addition of AI complexity in the game.

Then, for the definition of behaviors for bots next to the behavior of players is necessary to consider different shooter player types as beginner, competitor, killer, and explorer. In this context, the Bartle's taxonomy of player types (or archetypes) (BARTLE, 1996) involves the psychology in how they perceive and play a game. This theory corresponds to a functional model of human personality in a game playing context and was based on Multi-User Dungeon (MUD), the ancestor of Massively

Multiplayer Online Role-Playing Game (MMORPG). Although the original proposal is based on MUD, Bartle's taxonomy constitutes a more general personality model that can be extended to other gaming genres (FULLERTON, 2008) (STEWART, 2011) (FERRO; WALZ; GREUTER, 2013) (HAMARI; TUUNANEN, 2014) (see more details in the section II).

According to Bartle's player types, there are two dimensions to playing: (1) action vs. interaction, related to the degree to which the player interacts with other objects/ players in the game, and (2) players-orientation vs. world-orientation, which refers to the degree to which the player emphasizes the virtual world or other players. These two dimensions determine four player types:

- The killers seek to affirm their existence in competition with other players or with the environment.
- The achievers want to accumulate wealth and make points.
- The explorers aim to discover all aspects of the game world.
- The socializers prioritize the relationship with other players, even outside the role of your character.

While killers and achievers are mostly interested in acting on the environment, explorers and socializers prefer a deeper level of interacting with things or other people. Still, killers and socializers have emphasis on players and achievers and explorers have focus on the environment.

Some authors assert that would be difficult to use Bartle's model since it was based on compilation and observations of a forum discussion between MUD players about what they thought was fun in the game (YEE, 2005) (RADOFF, 2011). On the other hand, Stewart (STEWART, 2011) suggests that Bartle's types work because are a functional model of human personality in a game playing context, i.e., a subset of a more general personality model that works.

From these aspects, this work aims to analyze the bots behavior in a shooter battle arena developed by the authors using Unity Game Engine, considering different specificities inherent to the Bartle's typology and without the presence of a player. In this context, it is assumed that realistic and efficient bots for shooter games can be developed based on well-understood behavior-based approach. This study employs three Bartle's player types: killers, achievers and explorers' bots. Once the socializer type doesn't have a battle nature, it was replaced by the "beginner", a common type in games universe. Each bot behavior was defined through a FSM based on the verification of the environment and decision making.

From the obtained experiments results, it is concluded that as important as the behavior of the bots is the interaction of this with the environment, which plays a fundamental role in the question of player experience and the believability related to immersion into the battle scenario.

The remainder of the paper is organized as follows. Section 2 briefly reviews related work. Section 3 presents aspects of the building of bots' behavior and experimental procedures are detailed. Results are presented and discussed in section 4. Finally, section 5 contains the final comments.

2 I RELATED WORKS

In the last years, diverse works have discussed studies related to player types and games agent behavior. This section presents some of these works and their approaches.

Understanding the ways people interact with a game is essential information for game designers. As discussed in the introductory section, the Bartle's player types (BARTLE, 1996) is one of the most prominent within the areas of player typologies. This typology was later adapted to three-dimensional environments and featured another four elements in an attempt to account for the fluctuations between player types and to identify further sub-types of the initial four player typology (BARTLE, 2003).

Besides Bartle, other authors have devoted to studying types of players and their perception of games and their proposed universes.

In the early 60's, Caillois (CAILLOIS, 1961) proposed four player types: competitive, chance-based, simulation, and vertigo, respectively, agon, alea, mimicry, and ilinx. The competitiveˆ is related to rivalry, the chance-based uses luck, the simulation represents acting or taking on a role, and the vertigo describes momentous excitement.

Stewart (STEWART, 2011) highlights the fact that the best-known play style and game design models share conceptual elements and proposes a single unified model of play styles based on (KEIRSEY, 1998, (BARTLE, 1996), (CAILLOIS, 1961), (LAZZARO, 2004), (BATEMAN; BOON, 2005); (RON, 2001) and (HUNICKE; LEBLANC; ZUBEK, 2004). According to Stewart, though no model of human behavior can ever be considered perfect, the practical question is whether a given model provides sufficient explanatory and predictive power to allow game designers to understand the experience expected by the players.

The Fullerton' player types (FULLERTON, 2008) are also based on Bartle and Caillois works and are divided into ten profiles: competitor, explorer, collector, achiever, joker, artist, director, storyteller, performer, and craftsman. The author asserts that this proposed player types is not exhaustive and not all of these have been equally addressed by all digital games.

Ferro et al. (FERRO; WALZ; GREUTER, 2013) consider these tree previous works in his study: Bartle's (BARTLE, 1996), Callois (CAILLOIS, 1961), and Fullerton et al. (FULLERTON, 2008). The authors investigate the relationship between player types, personality and traits. As result, they propose a table identifying these relationships, game elements and mechanics, and discuss how this connection may impact the design of gamified systems and offer insight towards more user orientated design objectives.

Hamari and Tuunanen (HAMARI; TUUNANEN, 2014) review the types of players in relevant literature and propose a comprehensive meta-synthesis of the identified types based on segmentation of groups of people that are as homogeneous as possible, but that differ from each other in a significant way. The authors synthesize the player types into five dimensions: achievement, exploration, sociability, domination, and immersion.

Busch et al. (BUSCH; MATTHEISS; ORJI; FROHLICH; LANKES; TSCHELIGI, 2016) revise the BrainHex model (NACKE; BATEMAN; MANDRYK, 2011) by investigating the psychometric properties of this player type model in two subsequent online studies. The creation of additional items for the seeker, survivor, mastermind and daredevil player types and re-define the conqueror player type was proposed. The authors conclude that a game should provide a positive and unique player experience and, in order to do that, is necessary to investigate the relationship between players types and their experience.

Based on the presented works, it is noticed that game elements which fit the players type(s) should result in a more positive player experience. The concepts widely applied in most studies involving player types continue to be the Bartle's typology (BARTLE, 1996).

3 I BOTS BEHAVIOR APPROACH

This section describes how the behaviors of the bots were defined from the establishment of rules to interact in the environment that simulates a battle arena based on a shooter game. In this battle scenario, there is no player role, only the bots interacting against each other. At the end, the experiments procedure employed in this study is described.

3.1 Revisiting Bartle's Type

As mentioned in the introductory section, in order to evaluate the believability of bots that mimic players, the bots behavior were defined based on the Bartle's typology (BARTLE, 1996).

However, this work proposed to replace the socializer by the beginner because the socializer profile does not usually cover in shooter games, which often test the player's speed and reaction time using some kind of weapon against enemies represented by bots. On the other hand, killers, achievers and explorers are common player types related to this game genre. In this sense, it is considered interesting to evaluate the bot behavior based on the simulation of a beginner player against other bots with profiles well established.

Then, the following behavior for the bots' type proposed were defined:

- The killer: This bot walks endlessly through the battle arena, straying from its limits, and shoot whenever it detects items that are not walls.
- The achiever: This bot aims to look for items that will improve your life and,

at the same time, deviates from traps and fights some enemies.

- The explorer: This bot aims to discover all aspects of the game world, including items that damage his life.
- The beginner: This bot avoids dangerous situations, since it is still a beginner in the game. So, it does not completely explore the scenario, but shoots at all enemies.

The next subsection presents this definition applied to our scenario based on a battle arena.

3.2 Scenario and Battle Definitions

The battle scenario is formed by eight bots with behaviors defined by FSM. The purpose of the agents is to destroy any other bot detected by their radius of vision. The simulation control determines that a new round will be started if there is less than two active agents. In addition to the bots, the simulation consists of lives, which are collectible items that increase integrity, bombs, which damage bots and decrease their integrity, and missiles fired by bots in order to decrease integrity of opponents.

During the battle simulation, raycasting are used for the collision detection with objects from scenario (BLACKMAN, 2013). This is done by casting two rays outwards from the central point of the bots in each render cycle. While the first ray (shown in green color in the Figure 1) aims to detect far objects, the second (red in the Figure 1) seeks to detect nearby objects.

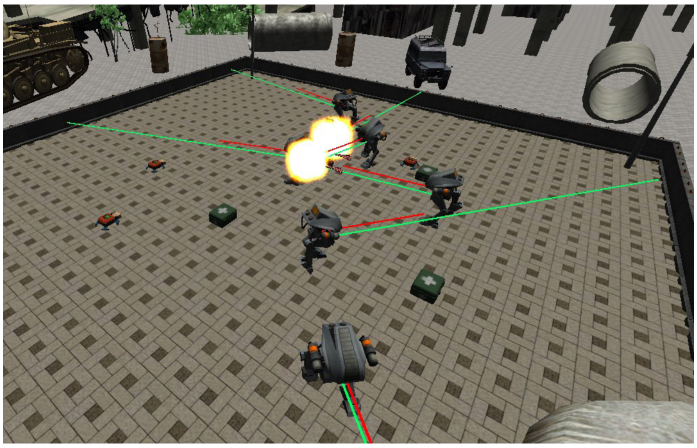


Figure 1. Bots raycasting in a battle scenario.

When defining a game environment or simulation, it is necessary to consolidate the context rules (ROGERS, 2010) (SCHELL, 2011). In this work, the constitution of battle rules were delimited in: Bots can move forward; Bots can rotate left or right; Bots can fire with a delay of ten seconds; Bots can stop their actions;;Bots can detect objects at short and long distances from their raycast; Bots cannot go beyond the scenario limits; Bots can collide with lives and bombs involuntarily, and have their integrity affected; The initial position of bots and items is set at random; A bot is destroyed when it has less than one life point; Each round will end when there are less than two active bots. The next subsection presents the FSMs that define the bots behavior.

3.3 Agents Behavior based on Finite State Machines

The construction of the bots behavior based on FSM adopts two main criteria: the player types based on Bartle's typology and the battle rules defined previously that are related to intentional actions of bots according their specific behaviors. Although Bartle's typology is related to human behavior, this feature is useful in determining the credibility of bot behavior in the context of games. However, there is no need for a growing complexity of AI for bot credibility, but rather appropriate solutions to the context of the game that allow the construction of a player experience based mainly on the fun aspect (SCHELL, 2011).

The bots architecture defines their decisions in real time, based on detection of their sensors. The implementation is made by a set of event-action rules constituted by deterministic finite automata, which classifies this architecture as reactive or non-deliberative (CASAL; GODO; SIERRA, 2011) (EHLERT; ROTHKRANTZ, 2001). The reactive bots behavior is determined by static actions (EHLERT; ROTHKRANTZ, 2001) in opposite to deliberative bots which use symbolic reasoning for planning the actions (CASAL; GODO; SIERRA, 2011).

In addition to the decisions made based on the detection of their sensors, the integrity of the bots is affected by involuntary collisions with lives and bombs randomly positioned in the environment. While the involuntary collision with bombs does damage, reducing their life time, the involuntary collision with lives causes the bots to end up collecting them, restoring their integrity. The Figure 2 presents the FSMs of the bots' type proposed.

The bot based on killer player type do not to adopt strategies that are too complex or elaborate. Essentially, what this bot focuses on is eliminating what is in his radius of vision. The strong characteristic of this bot is the ability and accuracy with which he shoots, however, these shots hit any object, including bombs and lives. In addition to the shots, the bot deflects the walls and does not have complex motion strategies. The state transition criterion in FSM of this bot is always based on the detection of objects through raycasting. Figure 2(a) shows the killer bot states: (S1) state 1 represents circular walking; (S2) state 2 is related to the deflecting; and (S3) state 3 is shooting. These three states also are present in explorer, beginner and achiever bots behaviors.

On the other hand, the explorer bot has more possibilities of state transitions than the killer. An important characteristic of the explorer is that when sighting bombs, he will try to collect them. Based on the rules defined previously, this action can be considered a mistake and contributes with the believability of this bot type (RIPAMONTI; GRATANI; MAGGIORINI; GADIA; BUJARI, 2017). Once again the criterion for transition occurs through raycastings and the states S1, S2 and S3 are the same of the killer behavior with the addition, however, of the state 4 (S4) related to collecting bomb (Figure 2(b)).

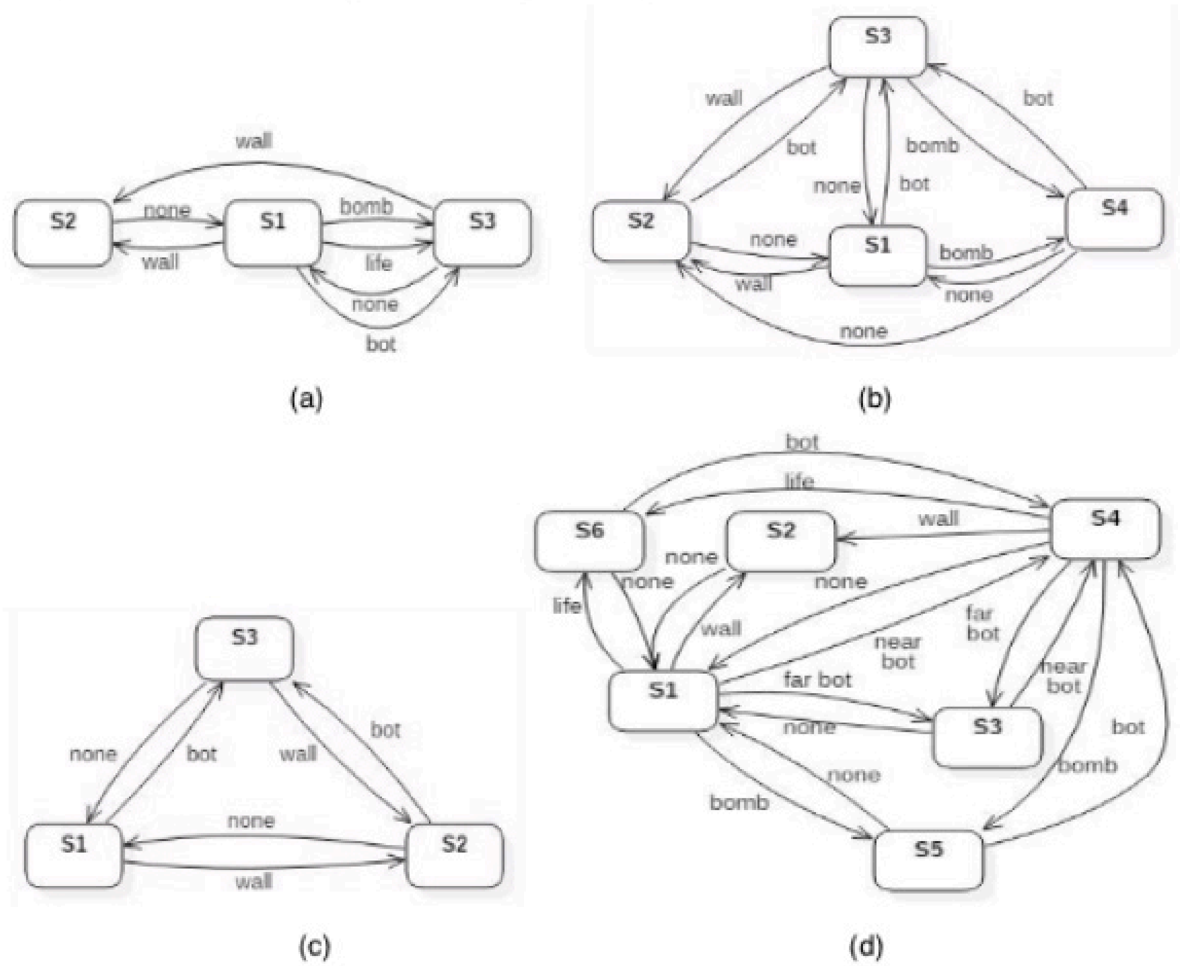


Figure 2. Bots FSMs. (a) Killer: (S1) circular walking, (S2) deflecting, and (S3) shooting; (b) Explorer: (S1) walking, (S2) deflecting, (S3) shooting, and (S4) collecting; (c) Beginner: (S1) walking, (S2) deflecting, and (S3) shooting; (d) Achiever: (S1) walking, (S2) deflecting walls, (S3) shooting, (S4) deflecting nearby bots, (S5) deflecting bombs, and (S6) collecting lives.

The beginner is the bot that presents the behavior considered the most basic. Essentially, he walks, deflects walls and shoots against bots, being able to make transitions from each state to all states (Figure 2(c)). Analyzing the diverse possibilities of interaction with the battle scenario, the bot based on the achiever player type is the one that delves deeper into the analysis of the environment and possible state-based actions. This bot is strongly based in states related to the action, as well as context analysis of the scenario.

The achiever is more assertive in recognizing the beneficial elements that can interact, distinguishing lives from bombs and nearby from distant objects. This is the only that presents different behaviors related to the distance of other bots, deflecting from those that are close and shooting at those that are far away. This fact leads the achiever to expose themselves more, not shooting at the bots that are nearby and running the risk of being hit by shots fired by these.

Thus, the achiever bot has three different states related to deflecting: wall, nearby bots and bombs. In this way, besides the initial three states common to all bots, the achiever has the states deflecting nearby bots (S4), deflecting bombs (S5) and collecting lives (S6) (Figure 2(d)). The achiever state transition criteria (also based on raycasting) consider some cases to be objects that are far or near.

The next subsection presents the experiments realized with these bots' types.

3.4 Experiments Procedure

The experiments proposed aim to identify which bot type adopts the best strategy in the battle arena as well as to observe the different behaviors. In order to do that, an evaluation study was carried out based on the automatic data collection related to the behavior of the bots and the results after 100 rounds of battle. The battle scenario is bounded by a square surrounded by walls containing 8 bots, three lives and three bombs, that are distributed in random positions of the scenario every time a new round starts (Figure 1).

After a random distribution of initial behavior for each of the eight bots, the bots assume one of four FSM types every 15 seconds. This change in bot behavior during the battle was proposed to increase the variability of presented situations. Each battle is ended when less than two bots are active in the scenario. Each bot starts the round with its life worth 100. In addition to colliding with bombs, bots can fire missiles at their enemies or be hit by missiles launched by them. Each collision with a bomb or missile causes a 40 point reduction in life. Upon reaching an life value less than one, the bot is eliminated from the round.

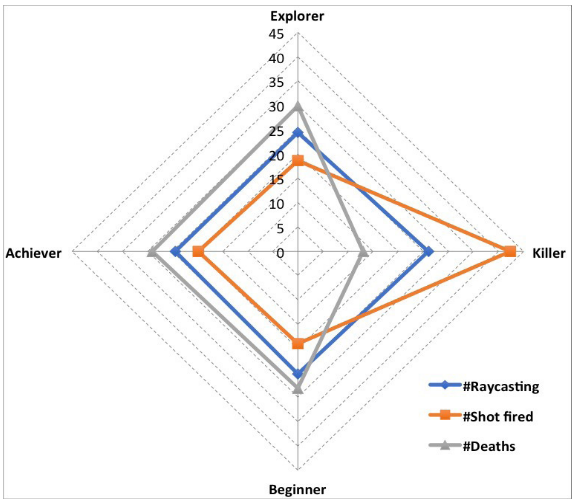
Including the round time (seconds), the data collected at each round for each bot type are: number of raycasting, shots fired, shots fired at other bots, shots fired at lives, lives collected, and number of deaths; time (seconds) of life, deflecting bombs, deflecting walls, detecting bots, and total time assuming each behavior type. The results obtained from this experiment and the discussion about these are presented in the next section.

4 I RESULTS AND DISCUSSION

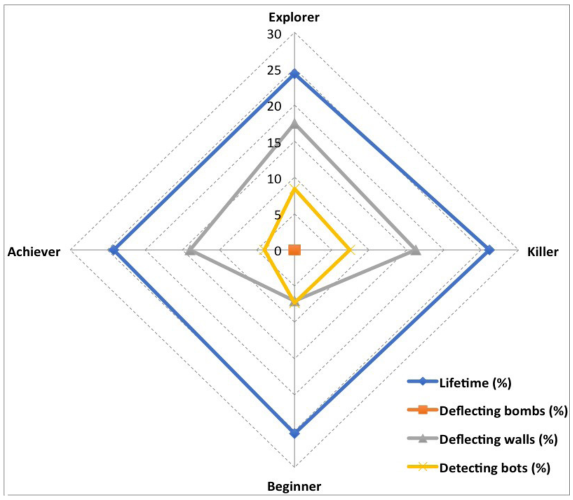
This section presents the analysis of different bot types (killer, achiever, explorer and beginner), their behavior against other enemy bots and a dynamic scenario within a battle arena. In this context, different aspects were analyzed from the data gathered already mentioned in section III and, considering shooter games, the player type that had a lower number of deaths is a success case expected. However, as important as the analysis of the deaths in battle is the identification of results from the specificities defined in the FSMs of each bot type.

4.1 Bots Performance and Game Balance

The 100 rounds of battle generated 35,800 data entries. Considerable differences are not expected between player types about the number of raycasting, since the rays are constantly traced with each rendering cycle, independent of the player type. Although the number of raycastings did not have expressive variations among the bot types, the killer had the lower number of deaths (Figure 3(a)). Counting the total deaths from each profile, explorer has 209 (30%), killer 91 (13%), beginner 197 (28%), and achiever 203 (29%). The killer's deaths are about 50% smaller than the other types. Considering the type of killer player and the scenario used in the experiment, although this bot is one of the types that has the FSM with less variability (Figure 2(a)), his aggressive focus is a factor that makes it more competitive, especially in an arena.



(a)



(b)

Figure 3. Bots performance. (a) Number of raycasting, shoots and death for each bot type. (b) Values for lifetime and time spent to deflect bombs, wall and detect bots.

Related to the lifetime and time spent to deflect bombs, walls and bots, the results can be observed in the Figure 3(b). It is noticed that the lifetimes are similar to the bots, but with difference for the times related to deflect walls, where the beginner had the worst performance. On the other hand, the achiever had the worst result related to detect bots. The bombs deflection time is so low in relation to the total lifetime of each bot that it becomes irrelevant to the behavior analysis.

Considering the number of times each bot took a specific behavior, Figure 4 shows the relationship between survival and death.

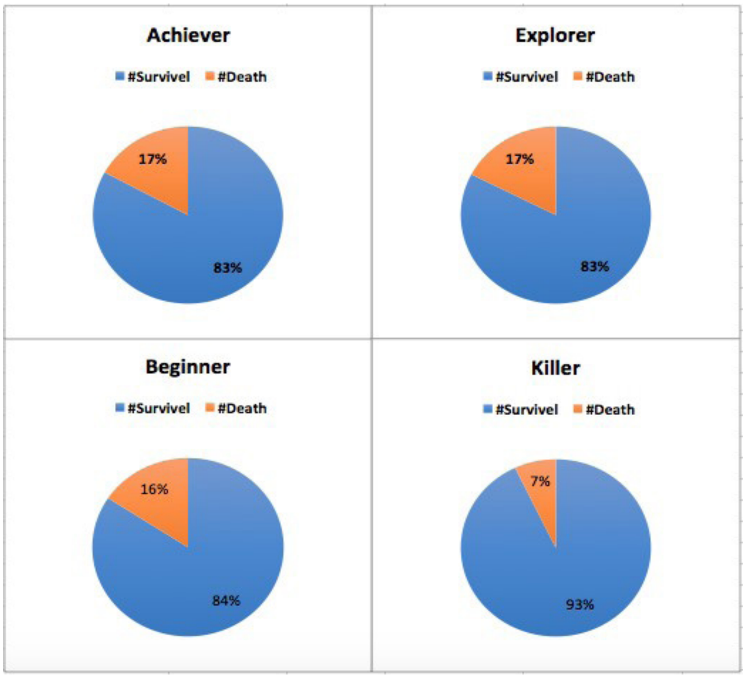


Figure 4. Survival x deaths.

The Figure 5, in turn, shows the relationship between shots and death. From the collected data, the killer died a smaller number of times and was the most shot firing, although part of those shots was not against bots. Analyzing the difference between shots fired at bots, the killer hit approximately 5% more than other bots. Thus, it is possible to infer in this experiment that the shots not fired directly at robots impacted performance, which may be related to the context of the environment.

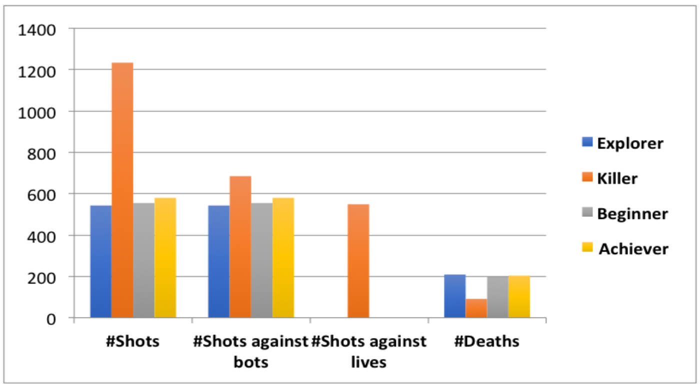


Figure 5. Number of total shots fired by bot, shots against bots and lives and deaths.

The best performance achieved by the killer is consistent with the players' typology adopted for this work (BARTLE, 1996). Analyzing the context of an arena, it is not surprising that there is a tendency for someone with aggressive behavior to potentially have a better outcome. This reality may vary according to the context of the game in which the agents will be acting.

One of the basic premises for developing a consistent game is the balance (SCHELL, 2011). In general, a balance between different elements is necessary so that a dominant strategy does not occur, in which some gameplay elements are not used because they are always inferior (ROGERS, 2010) (SCHELL, 2011).

Eventually, balancing for equity between agents may not be the goal. For example, it is possible that one agent is more efficient than another in order to enter different levels of difficulty at different points in the game. In other cases, a balance can be sought. In the case of the context of the arena used in this work, adopting a criterion of progressive difficulty, one possibility would be that the bots adopting the killer behavior were inserted in the game later than others.

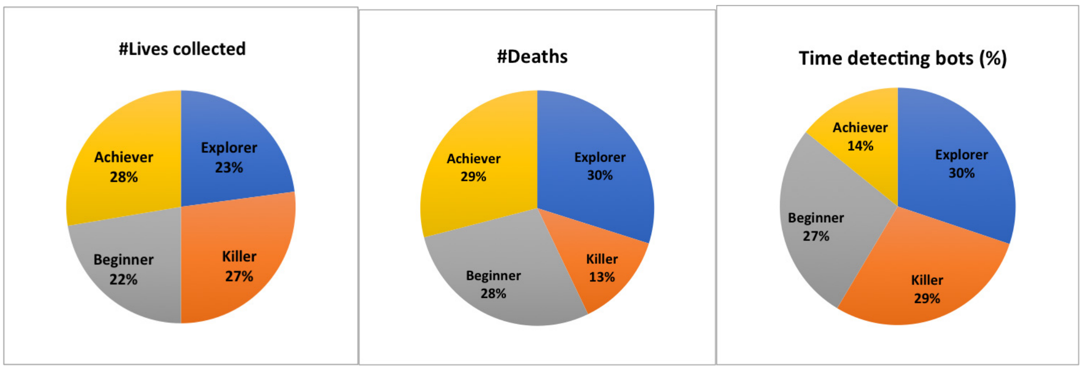
In the next subsection, the relation between the environment and the increasing of the efficiency impact of some types of bots behavior are discussed.

4.2 Agents and Environment Balance

Considering the definition of non-deliberative agents (CASAL; GODO; SIERRA, 2011) (EHLERT; ROTHKRANTZ, 2001), the balancing between the efficiency of the bots and the stimuli generated by the environment are relevant. These stimuli are related to four main elements: wall and bombs deflection, bot detection and lives collection.

Regarding the lives collection, the achiever performs this action intentionally, from the detection of lives by raycasting. The killer, explorer, and beginner collect lives involuntarily by colliding with them while focusing on another action. However, the number of lives collected are similar as can be seen in the Figure 6. Although is not the focus of the killer, explorer and beginner, they have collected a considerable number of lives. On the other hand, the achiever could not reduce his number of deaths despite being the bot who collected most lives. In relation to bot detection, there were no substantial differences between explorer, killer and beginner.

As described in the achiever FSM (Figure 2(d)), one of the states of this player type is focused on collecting lives. Although potentially an advantage, the collection of lives is also a state that makes the agent more vulnerable to attacks from enemies, especially in an open arena like the experiment. Again, the environment is a factor that may be the differential in this context, determining how exposed the bots are.



(a) (b) (c)

Figure 6.:Total number of lives collected by bots.

Related to deflect wall, as shown in the Figure 3(b), the killer and the explorer obtained the greatest interaction with the environment. However, considering the detection and deviation of bombs, the values are insignificant when compared to the other actions for which the bots have dedicated their life time: a little more than around 1% of lifetime for killer and almost 0,5% for achiever.

As noted in the FSM of the achiever player type (Figure 2(d)), there is a state focused on deflecting bombs (S5). Although not having a specific state for this action, the killer achieved better results in relation to the achiever. The killer states machine (Figure 2(a)) has as one of its basic movements the circular walk (S1), which was determinant to do not collide with more bombs. This factor was not intentional in the implementation and achieve an unexpected result about deflecting bombs.

Unlike using the environment criterion, balancing can be achieved by directly modifying the behavior of the bots or even the benefit that collectible items such as life provide, for example. Compared with the typology (BARTLE, 1996) used as a concept for the bots, it is coherent that the achiever, even exploring the possibilities of interaction, does not get the best results as the killer in an open arena. Thus, analyzing these data, it is observed a tendency that the interaction with the environment realized by killer is determinant for the number of victories such as the aggressiveness of their behavior.

4.3 Accuracy Against Enemies

The accuracy related to the confrontation of the enemies in the context of the open arena used in this work is related to two types of data collected: detection of bots and shots fired against bots. This subsection seeks to analyze this relationship between shots fired and death numbers of each bot type.

As mentioned earlier, the killer was the bot that accumulated the lowest number of deaths, around 50% less than the other types (Figures 4 and 6(b)). In relation to bot detection, there were no substantial differences between explorer, killer and beginner (Figure 3(b) and 6(c)). The achiever, however, showed less detection times than other profiles, reaching about 50% less than the explorer. The achiever is strongly focused on interacting with collectible objects, his focus is not overly combative, which leads to less precision considering the enemy detection aspect. In addition, achiever is the only type of player that avoids contact with nearby bots, as shown in state S4 of their FSM (Figure 2(d)).

If accuracy in detecting enemies is a determining factor, perhaps the nature of the achiever in collecting lives and regaining their integrity contributes to its not having bad results. In addition, the detection of other bots is not the only factor to be considered, but also what occurs from this detection.

Observing the accuracy of the shots fired at other bots, the killer had the highest score, followed by achiever, beginner and explorer (Figures 5 and 7). The difference between the detection of bots and shots in bots is disproportionate in the case of the achiever, once he had the bots detection lower but, on the other hand, was the second bot (behind killer) that fired more times against bots. Besides, killer had approximately 50% fewer deaths even having only about 10% more shots against robots than the other profiles Again, the environment factor should be considered and, as previously shown (Figure 7) the killer's total shot is higher than the other profiles, which may have contributed for the result.

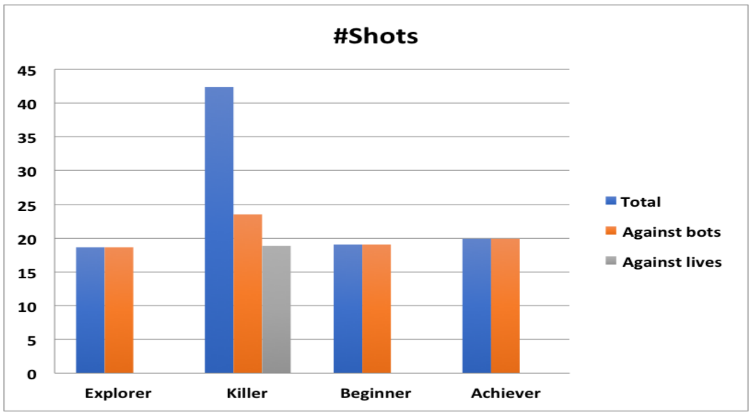


Figure 7.Total shots x shots against bots x shots against lives.

Finally, the difference in the shots fired between explorer, beginner and achiever does not show too many variations, as well as their respective death rates. The accuracy of the shots tends to be more determinant than the detection of bots, although the detection leads to strategic actions like to deflect of near enemies, as observed in the achiever. To determine the impact of actions, it is important to observe the rules and characteristics of the game: if short range shots have more damage than long shots, the state of shunting of nearby agents could be more impacting to the achiever and decrease their death rate. Thus, a higher correlation between detection accuracy and death rates could occur.

4.4 Lifetime and Efficiency

During the experiment, the bots cast a ray every rendering cycle of the game, then is possible to observe the correspondence between the lifetime and the number of raycasting (Figure 8). The bot that presented the longest lifetime and the largest number of raycasting was the killer followed, respectively, by the beginner, achiever and explorer being that they do not have significant variation values.

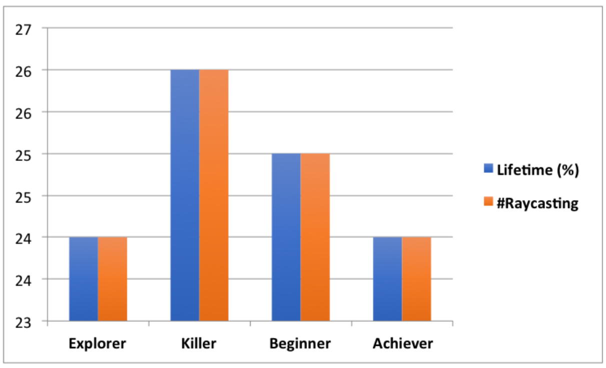


Figure 8.Lifetime and number of raycasting of each bots types.

In the experiment performed in this work, it is evident the difference of each bot behavior. There are specific actions for the different players types based on the Bartle's typology. As previously discussed, the achiever is the only one who deliberately moves to collect lives, which makes their behavior unique. Only the killer has a circular movement in the walking state, among other singularities. It is this diversity that makes the variabilities analyzed in the experiment emerge. On the other hand, even with differences, all bots types end up being competitive, and this is what is expected by the nature of the application in an arena.

Still, it is necessary to define clear criteria about what is a bot's effectiveness in a game. In this experiment, effectiveness can be considered as staying alive in the arena for longer and/or to present the lower number of the death, both results related to the killer behavior. However, as stated in section 4, seeking overall efficiency is not always related to the best results in a game, but rather contributes to achieving what is designed, which often means presenting behaviors that can be considered flawed, such as the action of the explorer, a bot type that tries to collect bombs and has a greater tendency to suffer damages caused by these.

As observed in the experiment carried out in this work, the lifetime is not directly related to what is considered efficiency. For example, if one type of behavior adopted by the bots is stealthier and more defensive, it may take longer for this bot to be eliminated. Still, that does not mean he is a competitive agent and have assertiveness to eliminate opponents. However, it is important to note that the competitiveness criterion of this application is strongly related to the combativeness. Although some strategic actions are adopted, they do not have many possibilities for variation.

The bot efficiency cannot be considered equal in different contexts within diverse games. In the experiment performed, there are no bots that collaborate in restoring the integrity of other bots, just as there are no bots with greater defensive capacity and that could strategically act as a line of defense for allies. The insertion of these two types of agents would change the interpretation of efficiency. In the case of these two possible agents, the ability to shoot other bots would not be an indicator of efficiency.

For bots that collaborate on restoring the integrity of other bots, indicating the amount of health retrieved would be a positive indicator. In case the bot acts as a line of defense for the allies, the amount of damage suffered by the enemy shots would also be reliving as well as the life time. In the implementation of this experiment, there is a delay of 10 seconds between the shots performed, so shooting at the right time can be considered strategic. If there was a bot with the characteristic of protecting other bots, possibly a strategic action of the shooters would be to save shots for when the weaker enemies were exposed. This context would make the life of the bot protector a strong indicator of efficiency.

The singularity of each game requires unique criteria and rules for defining what is efficiency and how to make it balanced. In this experiment, protection elements could be added in the scenario for some variations of player types to protect themselves better, as well as to increase the recovery value of agents' integrity when collecting lives, generating a greater balance. Another possibility would be to reduce the damage by shots, considering that the killer has an expressive advantage for firing more, but without presenting a substantially superior assertiveness against agents comparing to the other profiles.

5 I CONCLUSIONS

Shooter games have a combative nature and are characterized by fast action and tactical level of players and bots which should be able to perform their tasks in short time. Generally, in these games' genre, bots have the same level of skill and follow specific rules, related to move around in an environment, avoid obstacles, aim, shoot, pick up items, run among other actions. For implementation of bots basic behaviors, techniques of AI are employed highlighting those based on FSM related to verification of environment and decision making.

Currently, there are few works that investigate the desirable behavior of bots in shooter games (see the section II) that, beyond the tactical level, must present more realism, showing believable behaviors but without increase the complexity of these. Thus, this work presented a proposal of revisiting the Bartle's player type in order to promote the bots believability related to decision time, aggressiveness, number of tactics, and aiming skill.

Then, four bots type were proposed related to shooter games: the beginner, the achiever, the killer, and the explorer. In order to do that, four well-based FSM were proposed, related to a battle scenario definitions and rules. However, after the experiments results, it is noticed that it is not possible to design bots, regardless of whether they are based on Bartle's typology or on another model, if the game context is not considered. Each game has singularities in its implementations and rules (ROGERS, 2010) (SCHELL, 2011). Thus, the behavior of the agents must be a support for the game, respecting the defined rules, and the behavior data gathered analysis can contribute to the refinement and balancing of the game.

In the context of the presented experiment, an efficient killer performance is natural. Possibly, in an environment where item collection was extremely critical to performance, the achiever and the explorer could get better results. However, it was not expected that the killer had an interaction with the environment as efficient as the other types, and even superior to the achiever, designed to have this focus. Thus, the agents design must emerge through experimentation besides different scenarios. In this work the environment as an open arena was decisive to results.

As future works, this work should be extended to include studies related to deep reinforcement learning to increase the specificity of each bot behavior proposed.

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