Evaluation Between Humans and Affective NPC in Digital Gaming Scenario

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Abstract— the scenario of affective computing has expanded into different areas, demonstrating its applicability in various fields and specific scenarios. The area of digital games, in particular serious games, is one of the areas that can benefit from the use of affective computing, especially when used in artificial intelligence agents, also defined as NPC (Non-Player Character) simulating human affective aspects such as personality, emotion and mood. Many advances have been made for combining affective computing and serious games. However, since games present a direct interaction with the user, they require more attention to one important factor: the fun factor provided by the game. This paper aims at evaluating the fun factor of a game by experiencing a memory game that makes use of affective agent as a NPC opponent. The results in this paper demonstrate significant advances in the ability to simulate affective NPC agent in games toward modifying the way in which players analyze a current NPC and mainly at the level of pleasure dueling it.

Keywords— affective computing; NPC; digital games; artificial intelligence;

I. Introduction

The digital games market is very promising. Every day new games are developed in the quest to meet the great demand of the entertainment market. Games are divided into several groups according to their characteristics, each one of them aims to cater to the tastes, pleasures and entertainment desires of its players. Analyzing a game as a commercial product you can map certain features that make one game a greater success than others. Among them, the most common is how much the players enjoy the game, what is the amount and duration of the player's pleasure, as defined by Mendes [1] as fun to play, or just "fun". Even serious games do not have a different goal in building systems that are fun to users, in order to reach beyond some specific purpose, able to provide moments of pleasure. Among many features that make the game, the interaction between human and agents in the format NPC (Non-Player Character), game characters that are not controlled by the players is one of the most important in the fun factor. Measuring the pleasure of playing a game, as highlighted by Adams and Dormans [2], when a game is too predictable, normally it is not much fun, because the point of view of the player's choices and his decisions does not have much effect on the final result. When players feel that the decisions they make during the game or even the growth achieved in the game do not change the results, they tend to become quickly frustrated. However, serious games which involve the growth and decision making of the player must have a certain level of unpredictability provided by an artificial intelligence to make it more fun [2]. Unpredictability in games is different from randomness, since it does not produce random results, but have their decisions similar to those decisions and actions performed by humans, due to the amount of unpredictable differences [3]. According to Adams and Dormans [2] There are two general ways to produce sets with unpredictable characteristics: when choices are made by more than one player and when the game has a complex set of rules of operation.

In games where the choices are made by the players tend to be unpredictable; it is very noticeable in games like MMOG (Massively Multiplayer Online Game) where many players interact online, allowing endless possibilities of clashes, challenges and goals, many of it are created by the players themselves. Due to players produce their own movement in the game, compared to NPC the level of predictability of the opponent is bigger in the first case, which makes this scenario currently very attractive to players. In the second case, when the game has a set of complex rules, as usually happens in serious games that are simulations of human aspects, they seek levels of unpredictability in its complexity, making the player unable to map the behavior of the NPC, at least in the long term, as in a chess game. Make complex games are likely to become more unpredictable in the actions of NPC simulating the second to the first case as highlighted Abt [4], Bergeron [5], Michael and Chen [6], is an task extremely difficult, complex and really explored in works of serious games. However, its success that makes games more unpredictable similar to how humans are so, and consequently producing funnier games [1].

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This paper works on the development of the second case, to develop agents in the NPC format, which can assign the architecture complexity of the game in order to reduce the predictability of their actions. According to Russell et al. [7] an agent can be considered an entity that perceives its environment through sensors and acts through actuators. Affective computing, independent of the application scenario games allows, among other things, the creation of agents "computationally" affective. Affective agents are created so that they can infer, interpret, model and/or simulate aspects of human computer in an attempt to reduce the existing gap between the computational decision making and human decision-making. Thus, making it more compelling to human perception and therefore improving fundamental human-computer interaction in games [8].

Applying knowledge to produce affective NPC in the digital games area, moves to the direction of simulating human behavior in a NPC, which can be considered as an evolution in an attempt to stimulate, improve and therefore increase levels of interaction the man-machine interface, and consequently decrease the predictability in serious games, where humans interact with an NPC. The study proposed in this paper extends the work of Sales et al. [9] held in which the construction of an architecture for emotional NPC solely for the scenario of digital games, and the simulator developed for testing the behavior of the architecture. Despite extending another research, this paper has different and directly importance in the applicability of the use of architecture in the digital gaming market, as it seeks to test, quantify and evaluate how the fun factor behaves using as a criterion for measuring the predictability of actions of NPC from the point of view of the players.

Evaluate the fun factor is complex and requires the interaction with humans. Therefore, the interaction of humans was conducted in a modified memory game from the research of Sales et al. [10] in which allowed the interaction between humans against NPC (and humans against humans), as show in the Fig. 1. The memory game was chosen to simulate the reality, like serious games do too. Therefore, even the memory game not being a game that fits as a serious game, the benefits found in simulating an affective NPC can be used in both, especially the fun factor as alerted by Bergeron [5], often not being awarded due attention in serious game.

The tests were intended to measure the variability needed for specific game scenario used, allowing inferences as to increase the fun factor in the perception of the users during testing. The results obtained in this paper indicate a strong applicability of the architecture developed by Sales et al. [9] towards producing games that are able to display variability in scenarios that seek to restrict the reality, as in serious games, which indicates viability in the production of serious games simulating the behavior of humans while being fun.

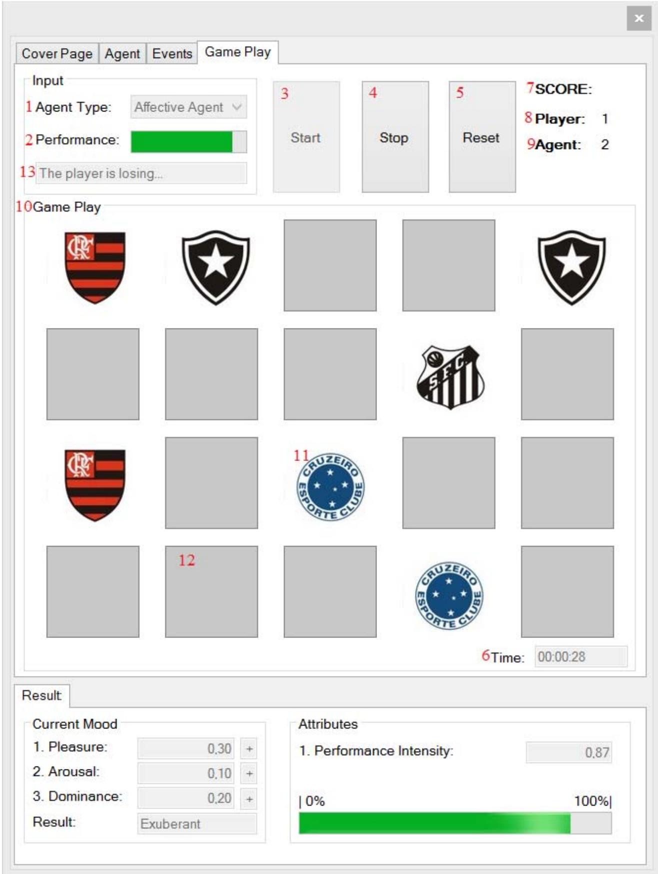

Fig. 1. Modified memory game test

This paper is structured as follow: the second section presents related works, the third section presents the techniques and activities planned and used in the test, the fourth section presents how the tests happened and the fifth section presents the results found in testing. Finally, the sixth section presents the conclusions of the results we achieved this paper.

II. Related Work

In this section we describe some of the work related to this Paper. Due to the characteristics of the contribution of these works were equally divided in two groups: the first group is the works that supported, or otherwise are similar at some point in this research, and thus contributed to its evolution. Even the research of this study is not exhaustive, which can cover important work that contributed in the construction of this paper. The second group is about the works that gave rise this paper, since it involves an extension of other studies published and together constitute a research that works on the evolution of agents in artificial intelligence applied to game features with affective scene.

Among the first group, stands out tests developed in BotPrize prize [11], carried the team (UT^2) University of Texas at Austin in which managed the deed of being approved in a test with characteristics similar to the reasoning of the Turing test [12]. In those tests, the agent created convinced the judges that it was more humane than half of the people against whom competed, with the scenario used a virtual world of

Unreal Tournament 2004 ™, a famous shooter game (FPS - first person shooter). The virtual agent created by the researchers / players participated in a tournament with humans and agents, with the goal of the game was to score points and eliminate opponents, each player in addition to the testing had appointed a special weapon as a weapon of judgment, in which opponents scored as human or NPC depending on the evaluation of behavior. The agent created had a rate of 52% of humanity [11]. Besides the derivation cited the work of Alan Turing himself [12] relates to the development of this paper. In summary, the Turing test seeks to test the ability of an agent to display intelligent behavior similar to a human being, presenting compelling behavior. The implementation of the Turing test synthesis consists of a person "A" is communicating with another "B" using a computer, both using natural language. The first person "A" communicates with a third computational agent "C" also using natural language. All involved are separated and the first person "A" does not know who is a real person and who is a machine, so the test is the perception of the person "A" who is a person and who is a computational agent. Clearly the tests developed by BotPrize [11], distorts the original proposal of the Turing test as the test of this paper also does. However, the central idea of all three is the same, get the perception of a sample of human about an interaction with computational agents.

Among the second group of works, architecture developed by Sales et al. [9] named MANPC aims to be engaged in NPC games that simulate the real world and are therefore plausible simulation of affective behavior consistent to the expected human. Subsequently Sales et al. [10] Tests conducted on the use of MANPC a full memory game, named "Memory Game Test". In that second paper the results covered analysis of the values of attributes before and after the use of MANPC module, demonstrating the viability of the different behavior of the NPC currently used, and compare and position the different levels of affective NPC behavior between extreme types of agents, perfect agent (agent that seeks to maximize their own chances of winning) and random agent (agent that has totally random behavior). The paper developed here extends the work presented by Sales et al. [10]. To understand the functioning of the affective NPC, you need to examine how it behaves in the game. All the time, emotional NPC uses strategies that can maximize its chances of winning in direct proportion to the cognitive components related to the calculated performance. So it tries to write information about the pieces opened by him and the pieces opened by the opponent, using the direct proportion of the cognitive components attention and perception respectively, as well as the position of pieces in the game. When opening a piece, the agent always tries to check on your memory if there are combinations using the direct proportion to the cognitive component memory. If there is any, the agent always prioritizes, if is not, the agent opens a new piece. With the information of the new piece, the agent attempts to fetch combination with one of the already opened parts using direct proportion as the cognitive component planning, and this prioritizes this new combination. If there is not combination, the agent opens a new piece randomly from the group of unknown pieces.

III. METHODOLOGY

This paper evaluates a new criterion in the game of memory used, this being the result of behavior with human characteristics by the affective NPC, from the point of view of humans. For understanding what validate this test seeks to answer three questions and make some inferences from this:

- (Q1) What percentage of players playing against an affective NPC believes to be playing against a real person?
- (Q2) What is the level of difficulty perceived by the player in a match against the affective NPC?
- (Q3) What is the level of fun perceived by the player in a match against the affective NPC?

The goal of the human validation test is using a similar scenario with the Turing test, test the level of conviction affective NPC compared to other agents used, in the point of view of real players. In practice, the test presented here to search using a random sample of people, who know the rules of the game of memory, and agents heuristics (affective, random and perfect), answers questions (Q1, Q2 and Q3) in a similar scenario used in the Turing test.

In the first step of convincing human validation tests, each player must play once against each of the other human players in a completely observable environment. In the second step of the test, players are placed individually in separate locations, where new items were administered. About new games, is explained that the opponent may be faced: one of the humans who have played, or a perfect agent, or a random agent, or an agent with the emotions (affective NPC), and it is explained what are the characteristics and behavior of each of these agents. At the end of each game, the user respond what opponent (human, affective, perfect or random) he believes have played, what level of difficulty throughout the game and the level of fun factor given to the match.

The questions are answered by a survey, obtaining characteristics, actions and opinions about a certain group of people, which is indicated as representative of a target population through a survey instrument, in case a questionnaire, according to the studies of Pinsonneault and Kraemer [13]. Following the research proposed by Pinsonneault and Kraemer, use the classification is descriptive purpose, which is to identify situations, events, attitudes or opinions are manifest in a given population, describing the distribution of a phenomenon evident in the population. In this kind of phenomena the hypothesis is not causal, but it's intended to check if the perception of the facts is not in accordance with the reality. In the classification of moments given by Sampieri et al. [14] regarding data collection, research can be classified as cross-cutting, since the data collection occurs in a moment, intending to describe and analyze the status of one or more variables at a given time. As sample has characteristics is the definition of Jean et al. [15] which defines it as a non-probabilistic as happens following some criteria, and not all individuals of the population has an equal chance of being selected. Among the classification performed by Yin et al. [16] the non-probabilistic survey of this paper happens by type for convenience, since participants are chosen because they are available. Regarding sample size, there is much discussion (Fink, [17]; Moscarola, [18]; Jean et al. [15]) about the ideal size for a non-probability sampling to achieve accurate and reliable results. In this study we adopted the view of Moscarola [18] where the author presents a simplified reading of this theme with the law of large numbers, which states with less than 30 sample observations has as much chance of finding a wrong or outdated value to a value approaching reality. As for the instrument used in conducting the survey, a questionnaire was developed formulated from the reference and practical guide developed by Fink [19] with suggestions of adherence to the context of the questions, the advice to offer open and closed questions, the choices of measures inherent in responses among others. Finally, in relation to measurements, these have validity for measuring correctly what was proposed, given the requirement of internal validity condition for the application of the tests in users physically separated environments. So that the communication does not influence the results, as well limiting the sample of 50 observations in the classification of external validity that meets the requirements of the law of large numbers without the performance and dedication of those involved in the questionnaire responses are affected by the course of time, as the aspects considered by Campbell and Stanley [20].

The division of tests into two parts happens in making the most accurate and practical evaluation. In the first step the players interact with each other in the quest to map the characteristics and performance of their opponents, making it similar to what happens when two players play some sort of game over a player and somehow hold some knowledge of the way another act in the game. In the second step the main objective is to verify the existence of some confusion in the perception of affective NPC in view of the player.

IV. Experimenting Affective NPC in The Memory Game

Conducting the tests occurred on the date of October 24, 2013, where five individuals were invited to participate in the process, which is divided into:

A. Pre-test:

The pre-test took place with the preparation of the environment. The tests involved five individuals, five machines with memory game installed at five environments physically separated, three sets of physical memory, five people to help on the tests and 50 printed forms. With the 08:00AM start, the goals and dynamics of the tests were presented to participants.

B. Alpha step:

The alpha phase began at 08:11AM, shortly after completion of the pre-test; individuals were named and matched against each other using a physical memory game, the results of these matches are in TABLE I.

TABLE I. Alpha step – Confrontation between humans

A vs B		Player B				
		H1	**H2**	**H3**	**H4**	**H5**
Player A	**H1**		H1	H3	H4	H1
	H2			H3	H4	H5
	H3				H3	H5
	H4					H5

The TABLE I. presents the confrontations between players and their results, for example, player H1 (Human 1) confronted H2 (Human 2) and won, however also confronted H3 (Human 3) and lost.

C. Beta step:

The start of the beta step occurred with the end of the alpha step (at 09:18AM), where each of the five players was accompanied to separate rooms to start the dynamics with the memory game on the computer. Altogether forty-one matches were performed, producing a total of fifty questionnaires as described in TABLE II.

TABLE II. beta step – Agents vs. humans

A vs B		Player B				
		H1	**H2**	**H3**	**H4**	**H5**
Player A	**H1 - human 1**		H1		H4	H1
	H2 - human 2			H2	H2	H5
	H3 - human 3				H3	H3
	H4 - human 4					H5
	Perfect agent		A. A.	A. A.	A. A.	A. A.
	A. A. (Fear)	H1		H3	H4	
	A. A. (Remorse)	H1	A. A.		H4	H5
	A. A. (Pride)	A. A.	A. A.	A. A.		H5
	A. A. (Shame)	H1	A. A.	H3	H4	
	Random agent	H1		H3		H5
	A. A. (Joy)	A. A.	A. A.		A. A.	A. A.
	A. A. (Love)	A. A.		H3	A. A.	
	A. A. (Anguish)		H2	H3		H5

Because the numbers of possible tests were randomly selected by seven of twenty two types of emotions defined by Ortony et al. [21] used in MANPC architecture, being selected emotions: fear, remorse, pride, shame, joy, love and anguish. Besides the five human participants, also the perfect agent and random agent were included in TABLE I. cells in gray, represents duels that did not occur, and the cells have met the victorious player, for example, the player H1 (Human 1) did not play against NPC with affective emotion of anguish (A. A. Anguish), but played with NPC with affective emotion of love (A. A. love) and lost.

V. ANALYSIS OF RESULTS

The analysis stage of the data structured information in order to make inferences in particular the data obtained from the questionnaires. With the tabulation of data by questionnaire responses obtained by some inferences can be synthesized, among them the TABLE III. it presents the inferences made by players when asked (Q1) which opponent the player believed to be facing:

TABLE III. DATA ANALYSIS – OPPONENT PERCEIVED

Player	Opponent	Error			
		Per.	Rand.	Affec.	Hum.
H1	H2	-	-	-	0
H1	H4	-	-	-	0
H1	H5	-	-	-	1
H1	A. A. (Fear)	-	-	1	-
H1	A. A. (Remorse)	-	-	1	-
H1	A. A. (Pride)	-	-	1	-
H1	A. A. (Shame)	-	-	1	-
H1	Random agent	-	0	-	-
H1	A. A. (Joy)	-	-	0	-
H1	A. A. (Love)	-	-	1	-
H2	H1	-	-	-	0
H2	H3	-	-	-	0
H2	H4	-	-	-	1
H2	H5	-	-	-	0
H2	Perfect agent	0	-	-	-
H2	A. A. (Remorse)	-	-	1	-
H2	A. A. (Pride)	-	-	0	-
H2	A. A. (Shame)	-	-	1	-
H2	A. A. (Joy)	-	-	1	-
H2	A. A. (Anguish)	-	-	1	-
H3	H2	-	-	-	0
H3	H4	-	-	-	0
H3	H5	-	-	-	1
H3	Perfect agent	0	-	-	-
H3	A. A. (Fear)	-	-	0	-
H3	A. A. (Pride)	-	-	1	-
H3	A. A. (Shame)	-	-	1	-
H3	Random agent	-	0	-	-
H3	A. A. (Love)	-	-	1	-
H3	A. A. (Anguish)	-	-	1	-
H4	H1	-	-	-	0
H4	H2	-	-	-	0
H4	H3	-	-	-	1
H4	H5	-	-	-	0
H4	Perfect agent	0	-	-	-
H4	A. A. (Fear)	-	-	1	-
H4	A. A. (Remorse)	-	-	1	-
H4	A. A. (Shame)	-	-	0	-
H4	A. A. (Joy)	-	-	1	-
H4	A. A. (Love)	-	-	1	-
H5	H1	-	-	-	0
H5	H2	-	-	-	0
H5	H3	-	-	-	0
H5	H4	-	-	-	1
H5	Perfect agent	0	-	-	-
H5	A. A. (Remorse)	-	-	1	-
H5	A. A. (Pride)	-	-	1	-
H5	Random agent	-	0	-	-
H5	A. A. (Joy)	-	-	1	-
H5	A. A. (Anguish)	-	-	1	-

The reading of the data, is made by the interpretation of the errors represented by the value 1 (one) and hits represented by the value 0 (zero), for example in the first row of data (second row of the table) the player H1 (Human 1) confront the opponent H2 (Human 2) and records 0 in Error column in affirming that he believed playing against a human. From the fifty responses, 66% of players did not hit which player with whom they were playing, which leads to an initial and superficial idea that indicate that among agents created could confuse players.

Grouping the NPC independent of affective emotion tied, we have four types of possible opponents of the player error: affective NPC, human, perfect agent and random agent. The total of fifty tests on all the tests that were carried out against the perfect agent and random agent, the player was able to identify who was playing; there were 0% errors in both cases. With this result it is assumed that both agents exhibit extreme characteristics, favoring so the player can rationally identify which agent is playing. With this data we can infer that both the random agent as the perfect agent are not suitable for games that seek to present a compelling expected behavior of a human being because they are easily identifiable.

However, when playing against humans, the player got a percentage of only 28% of errors, demonstrating that the player could easily interpret if it playing with a human. To infer that players could identify who were playing with a human in most cases, it is fair to assume that players were able to easily identify a non-human, and this proven by the previous two inferences. Therefore, when confronting the player with an affective NPC, as this is not a human, it was expected that this would tend to result of perfect and random agents, near or towards 0% errors. Although what happened was the extreme opposite, playing against the affective NPC in 84% of cases the person was wrong and did not identify to be playing against the player in question, and of those approximately 80% out of 84% of the errors were considering playing against a real person.

With data and evaluation of the question (Q1) is possible to assume that affective NPC can confuse the player in a scenario in which other humans are participating, demonstrating a level of simulation games in which adds value to simulate human emotions. The analysis of data from the answer to question (Q2) on the relationship of the level of difficulty in each game is present in the TABLE IV.

TABLE IV. DATA ANALYSIS – LEVEL OF DIFFICULTY PERCEIVED

Player	Opponent	1	2	3	4	5
H1	H2	0	0	1	0	0
H1	H4	0	0	0	1	0
H1	H5	0	0	1	0	0
H1	A. A. (Fear)	0	0	1	0	0
H1	A. A. (Remorse)	0	0	1	0	0
H1	A. A. (Pride)	0	0	0	1	0
H1	A. A. (Shame)	0	0	1	0	0
H1	Random agent	1	0	0	0	0
H1	A. A. (Joy)	0	0	1	0	0
H1	A. A. (Love)	0	0	0	0	1
H2	H1	0	0	1	0	0
H2	H3	1	0	0	0	0
H2	H4	1	0	0	0	0
H2	H5	0	0	0	1	0
H2	Perfect agent	0	0	0	0	1
H2	A. A. (Remorse)	0	0	0	1	0
H2	A. A. (Pride)	0	1	0	0	0
H2	A. A. (Shame)	0	1	0	0	0
H2	A. A. (Joy)	0	0	1	0	0
H2	A. A. (Anguish)	1	0	0	0	0
H3	H2	0	0	0	0	1
H3	H4	0	0	1	0	0
H3	H5	0	0	1	0	0
H3	Perfect agent	0	0	0	0	1
H3	A. A. (Fear)	0	0	1	0	0
H3	A. A. (Pride)	0	0	0	1	0
H3	A. A. (Shame)	0	0	0	1	0
H3	Random agent	0	1	0	0	0
H3	A. A. (Love)	0	0	0	0	1
H3	A. A. (Anguish)	0	0	1	0	0
H4	H1	0	0	0	0	1
H4	H2	0	0	0	1	0
H4	H3	0	0	0	1	0
H4	H5	0	0	0	1	0
H4	Perfect agent	0	0	0	0	1
H4	A. A. (Fear)	0	0	0	1	0
H4	A. A. (Remorse)	0	0	1	0	0
H4	A. A. (Shame)	0	0	1	0	0
H4	A. A. (Joy)	0	0	1	0	0
H4	A. A. (Love)	0	0	0	0	1
H5	H1	0	0	0	1	0
H5	H2	0	0	1	0	0
H5	H3	0	0	1	0	0
H5	H4	1	0	0	0	0
H5	Perfect agent	0	0	0	0	1
H5	A. A. (Remorse)	1	0	0	0	0
H5	A. A. (Pride)	0	0	0	1	0
H5	Random agent	0	1	0	0	0
H5	A. A. (Joy)	0	0	1	0	0
H5	A. A. (Anguish)	0	0	1	0	0

Reading the data is made by interpreting the indices of 1 through 5, where 1 is “very easy” and 5 it is “very difficult”. In TABLE IV. cells represented by the value one (1) indicates that the player has selected certain level and the representation of the value 0 (zero) means that he did not select, for example in the first row of data (second row of the TABLE IV.) we have the player H1 (Human 1) confront the opponent H2 (Human 2) and having chosen the level 3, which is “neither easy or difficult”. In accounting data on the difficulty level, there is a tendency to centralization of data at an intermediate level (3), with a slight tendency to higher levels of difficulty. Trying to compare the vision of how players understand the level of difficulty of the analyzed human and the difficulty level of the affective NPC, Fig. 2 shows a graphical comparison of the two series. For graphical comparison, some inferences can be made in both directions. In respect to the curvature of the two series, both are very similar, the highest values occur at the same level (3) and the lowest values (2) too, other levels also have low percentage differences.

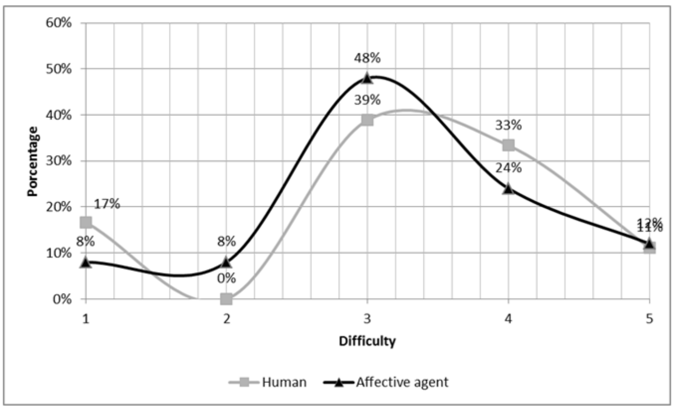

Fig. 2. Comparison between human and affective NPC

According to the distribution of the sample was conducted with random people, and just random emotions to be applied in affective NPC were chosen, we tend to believe that the aspect of difficulty of the game in question was very close to the level of difficulty expected humans. The TABLE V. presents the analysis of data from the answer to question (Q3) on the level of frustration/fun in each game:

TABLE V. DATA ANALYSIS – LEVEL OF FRUSTRATION/FUN PERCEIVED

Player	Opponent	1	2	3	4	5
H1	H2	0	0	0	1	0
H1	H4	0	0	0	0	1
H1	H5	0	0	0	1	0
H1	A. A. (Fear)	0	0	0	1	0
H1	A. A. (Remorse)	0	0	0	0	1
H1	A. A. (Pride)	0	0	0	1	0
H1	A. A. (Shame)	0	0	1	0	0
H1	Random agent	0	1	0	0	0
H1	A. A. (Joy)	0	0	0	1	0
H1	A. A. (Love)	0	0	0	0	1
H2	H1	0	0	0	1	0
H2	H3	0	0	0	0	1
H2	H4	0	0	0	0	1
H2	H5	0	0	0	1	0
H2	Perfect agent	0	1	0	0	0
H2	A. A. (Remorse)	0	0	0	1	0
H2	A. A. (Pride)	0	0	0	1	0
H2	A. A. (Shame)	0	0	1	0	0
H2	A. A. (Joy)	0	0	0	1	0
H2	A. A. (Anguish)	0	0	1	0	0
H3	H2	0	0	0	1	0
H3	H4	0	0	0	0	1
H3	H5	0	0	0	1	0
H3	Perfect agent	1	0	0	0	0
H3	A. A. (Fear)	0	0	0	1	0
H3	A. A. (Pride)	0	0	0	1	0
H3	A. A. (Shame)	0	0	0	1	0
H3	Random agent	0	0	1	0	0
H3	A. A. (Love)	0	0	0	1	0
H3	A. A. (Anguish)	0	0	0	0	1
H4	H1	0	0	0	1	0
H4	H2	0	0	0	1	0
H4	H3	0	0	0	0	1
H4	H5	0	0	0	1	0
H4	Perfect agent	1	0	0	0	0
H4	A. A. (Fear)	0	0	0	1	0
H4	A. A. (Remorse)	0	0	0	1	0
H4	A. A. (Shame)	0	0	1	0	0
H4	A. A. (Joy)	0	0	1	0	0
H4	A. A. (Love)	0	0	0	1	0
H5	H1	0	0	0	1	0
H5	H2	0	0	0	1	0
H5	H3	0	0	0	1	0
H5	H4	0	0	1	0	0
H5	Perfect agent	0	1	0	0	0
H5	A. A. (Remorse)	0	0	1	0	0
H5	A. A. (Pride)	0	0	0	1	0
H5	Random agent	1	0	0	0	0
H5	A. A. (Joy)	0	0	0	1	0
H5	A. A. (Anguish)	0	0	0	1	0

The Reading of the data is done by the interpretation of levels 1-5, where 1 is very frustrating and 5 is very funny. In TABLE V. cells represented by the value one (1) indicates that the player has selected certain level and the representation of the value 0 (zero) means that he did not select, for example in the first row of data (second row of the TABLE V.) we have the player H1 (Human 1) confront the opponent H2 (Human 2) having chosen the level 4 for the match, which is classified as "funny". The Fig. 3 shows the comparison between the isolated human indices percentages, affective NPC and overall NPC. Analyzing the graph generated, human and affective NPC had only positive categorization of "fun/frustration" with greater distribution in the "fun" level, with values of 67% for human and 64% for affective NPC.

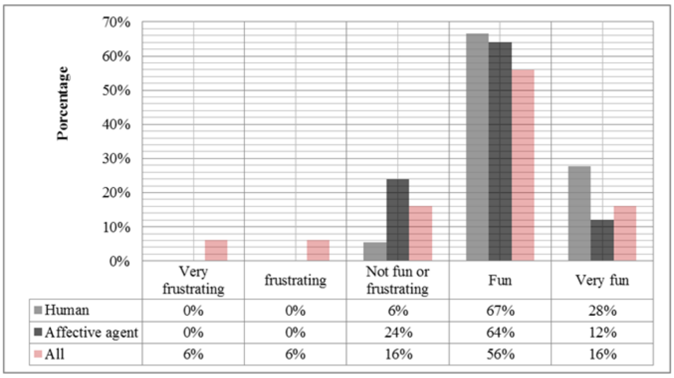

Fig. 3. Comparison of the fun/frustration

The difference that occurs between human and affective NPC are differences in quantity allocated to the index of "fun" and the tendency of data. While present in the data distribution of the human curvature distribution tends to become "Very fun" (28% versus 6% on your opposite side) in affective NPC tending to the opposite happens in "Not fun or frustrating" (24% against 12%). The evaluation of this fact makes sense from the standpoint that affective NPC tries not overcome the human in question "fun", so variations are expected as presented, however it should be noted the similar distribution and centralization at the same level “fun” (4), and can therefore infer that the affective NPC can simulate emotional aspects built near a human, who can manage the sense of fun to another human.

VI. Conclusions

This paper is an evolution regarding to the use of affective agents in a digital game scenario. Implementing autonomous affective agents based on emotions could modify the computer decision-making process on the NPC agent. However providing affective agents lifelike in games do not guarantee funnier games... In this paper, we brought some evidence of online games, where people tend to prefer to play against other people. In addition, we proposed a similar approach using a NPC affective agent. It is experimented based on a “kind of” Turing test for the evaluation of the fun factor when you make use of NPC affective agent instead of human.

In our results, we observed that 84% of users when they played against an affective NPC agent, they believed to be playing against another type of agent, and in 80 % of these errors claimed to be playing against a human. This result indicates that the affective NPC agent can be charged as a human in the scenario presented.

Another important result was the comparison between the curvatures of the series that find some difficulty in affective NPC agent and against humans, both being very similar at all levels. The final results also showed the level of fun or frustration among comparative matches against humans and against affective NPC agent, where the results focused on the same tracks and very closes values.

From the results shown in this paper, two points are worth mentioning: (i) this research strengthens the use of affective NPC agent in serious games in which proves that they can generate, in certain scenarios, unpredictability in agents and, consequently, increase the fun factor; (ii) we also add the possibilities of building lifelike agents based on their convincing behavior because of the affective computing.

Our work brings promising results for the game industry that includes also the serious game area.

As a future work we might improve our affective NPC agent with other affective aspects, such as Emotional Contagion and conformity, or some affective aggregation strategies for groups [21].

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