On Modeling, evaluating and increasing players' satisfaction quantitatively: steps towards a taxonomy

Mariela Nogueira[1], Carlos Cotta[2], and Antonio J. Fernández-Leiva[2]

[1] University of Informatics Sciences, La Habana, Cuba
mnogueira@uci.cu
[2] University of Málaga, Málaga, Spain
{ccottap,afdez}@lcc.uma.es

Abstract. This paper shows the results of a review about modeling, evaluating and increasing players' satisfaction in computer games. The paper starts discussing the main stages of development of *quantitative* solutions, and then it tries to propose a taxonomy that represents the most common trends. In the first part of this paper we take as base some approaches that were already described in the literature for quantitatively capturing and increasing the real-time entertainment value in computer games. In a second part we analyze the stage in which the game's environment is adapted in response to player needs, and the main trends on this theme are discussed.

Keywords: player satisfaction, player modeling, adaptive game, taxonomy

1 Introduction

Most of the games' genres assume as an important goal the entertainment of the players, which can be different for distinct player (e.g., players may not enjoy the same challenges). If the preferences of the player could be modeled, we might be able to adapt the gameplay to each player [1] and try to increase players' satisfaction during the play. The IEEE Task Force on Player Satisfaction Modeling [2] was created with the primary focus on the use of Computational Intelligence for modeling and optimizing the player's perceived satisfaction during gameplay, and grouped many of the most relevant events and results on this topic.

In [1], a new taxonomy is defined about the player modeling, in which models are distinguished according to their purpose: satisfaction, knowledge, position and strategy. Some of the most common models' applications can be: the classification of players according to their skills or preferences; the training of bots to simulate human's behavior [3]; the analysis of physical and emotional states of the player, and the prediction of behaviors, among others. For the specific topic of modeling focused on measuring the level of player satisfaction two main trends were categorized in [4]. One of them approaches the subject from a *qualitative* point of view, closer to psychology, whereas the another proposes alternatives to measure fun *quantitatively.*

With respect to *qualitative* approaches, we can mention a number of works that can be considered pioneer; for instance, the theory of the intrinsic motivation of Thomas W. Malone [5] or the theory of Flow defined by Czikszentmihalyi [6]. Also, a very influential work is the adaptation of this latter theory to the game's field (made by Penelope Sweetser and Peta Wyeth in [7]), and also the contributions in the understanding of the entertainment in games proposed by Lazzaro [8] and Calleja [9]. The research on qualitative approaches is often useful in conceptualization of a modeling process, because some of them allow the classification of different types of players, their preferences, and trends in behavior [10]. In this aspect, two interesting studies were addressed in [11] and [12], both works focused on identifying behaviors that distinguish the human players from the bots, in the game of *Pong* and in a strategy game respectively.

All these works based on the qualitative approach have limitations that decrease the robustness of the result, since most of the studies are based on empirical observations or linear correlations established between the provided information in the player's profile and reported emotions [13].

On the other hand, quantitative contributions are focused on the attempt to formally model the behavior of the player based on her preferences, skills, emotions, and other elements that influence the decision-making process. These models are then used in conjunction with the online information that is being received from the user, to define a measure of the level of fun that the player is obtaining in the game.

The work presented here focuses on the quantitative approach and tries to identify the main stages of development of quantitative solutions with the aim of easing the definition of a taxonomy that represents the most common trends used in each of them.

This paper is organized as follows. Section 2 shows a taxonomy which includes the main trends in the process of modeling and quantifying player's satisfaction. In the third section we analyze the stage in which the game's environment is adapted in response to player's needs, and we discuss a taxonomy for this theme. Finally, Section 4 provides some conclusions and gives some indications for future work.

2 Players' satisfaction approaches

It is not an easy task to determine the satisfaction an activity causes to a person, since the mechanisms to manage the human emotional states are complex. Many factors influence a change in mood, and seeking for a generality is not simple because each person has her own characteristics as well as particular preferences. In the following we discuss different attempts to formally model the fun that a player obtains during the game; this analysis allows to identify the fundamental stages of this process and distinguishes taxonomies between most used trends. Each of them is explained below.

2.1 Selection of relevant information

This task represents a basic process that should be done as initial stage; its goal is to identify the elements that will influence the amount of players' fun; to do so, researchers usually base their analysis on the qualitative studies mentioned in the introduction. It is thus necessary to have a broad knowledge of the game functions in order to establish a direct projection of the psychological elements in real variables (that are assumed to be measurable) to describe the behavior of the user.

The information obtained in this process can be classified according to its nature under different points of views: for example, *offline* and *online* [14], *observational* and *in-game* [15], and *subjective*, *objective* and *gameplay-based*, [16]. In general all of them can be summarized in three categories with respect to the nature of the information: *reported*, *in-game*, and *sensorial*.

Reported Information. It represents the information that is requested directly from the user, for example, when the player has to create a game-profile, or answer a questionnaire designed to know her predilections (for instance, [16] proposed to adapt the game not only to the skills of players, but also to their preferences. To do so, a model of the player experience can be created from the answers provided by the player, after a gameplay session, to specifically designed preference questionnaires). The main goal is to identify the player via her preferences. The reliability of the information collected is completely dependent on the consistency of the responses provided by the players. This information is usually employed to validate players' models. Also [17] proposed the use of questionnaires that should be filled by the players to measure their satisfaction.

In-game information. It comprises the data that are generated and processed within the game engine (and during the game); this task usually involves the gathering of numerical data describing players' performance. For example, in a combat game, we may consider kill counts, death counts, and use of sophisticated weapons.

Sensorial information. Here, physical sensing of the player during play is obtained from one or more specialized devices; it is representative of emotional reactions in players. Sensors measure players' attributes including: galvanic skin response, facial reactions, heart-rate, and temperature, among others. The objective here is to increase the amount of information that can be obtained during a game session and that can be complementary to that obtained as in-game information (in the sense explained above). By doing so the game designer can have more arguments to manage fun in the game with more assurance, and might try the adaptation of the play to the player, with the goal for instance to improve her 'immersion' in the game [9].

In fact, the design of game interfaces is nowadays one of the most interesting topics in game development and there is a growing tendency to use multi-sensory (e.g., visual, auditory and haptic) interfaces to broaden the game experience (i.e., sensation) of the player. Precisely [18] analyzed if *by displaying different information to different senses, it is possible to increase the amount of information available to players and so assist their performance*; in general, the conclusions obtained in this analysis shown that players had improved not only 'immersion' but also 'confidence' and 'satisfaction' when additional sensory cues were included.

2.2 Capture players' fun

In this stage the aim is to determine how the value of fun can be defined. Two main approaches, explained by Yannakakis and Hallam in [19], are usually considered., and in this section we try to refine their classifications. The first one proposes to find an scalar value of fun, and the second focuses in the creation of a model which defines the relation between variables and entertainment's level (i.e., a model of players' fun).

2.2.1 Scalar value of fun. This approach proposes the empirical definition of a mathematical formula to quantify players' fun, according to their behavior. This way allows a fast path to know the player's status during the game, and further to employ this information for assisting her with the aim of increasing her entertainment. An example of this approach is described in [19] where a quantitative metric of the *interestingness* of opponent behaviors is designed on the basis of qualitative considerations of what is enjoyable in predator/prey games. A mathematical formulation of those considerations, based upon observable data that are taken into account during game sesions, is derived. This metric is validated successfully when it is compared with the human notion of entertainment in the context of the well-known *Pac-Man* computer game [19].

2.2.2 Model of players' fun. Here it is necessary to quantify the variables that influence the fun in order to have notion of its evolution in every moment of the game; these values will be use as inputs to the model construction process. The main difference with the previous approach is that the relationships between variables and the level of entertainment will be defined through machine learning techniques. We can mention here the two main approaches that have been proposed in the literature and that are discussed below:

Empirical evaluation
In this case the model is obtained from any metaheuristics algorithm (or soft computing technique in general), and the objective function defined to guide the optimization process is derived from the author's appreciation. An example of this approach was presented in [20] where authors consider that some change in the rules of the game *Commons Game* would make it much more exciting, in this way, game players are modeled with Artificial Neural Networks (ANNs). The weights of the neural network based model are evolved by a multi-Objective evolutionary algorithm [21]. In order to evaluate each individual they defined two objective functions: the variance of the total number of each card chosen in each game run, and the efficiency of played cards, respectively.

Relative evaluation
This variant has been the most widely used in the literature. Here, the metric that guides the process of models' optimization is directly based on the results that the learning mechanism shows, and this represents precisely the primary distinction with the approach previously discussed where the metric is defined by authors. The basic process is carried out by a training of models that is followed by a supervised approach, so that one can identify when a generated model is correct. Then, the function is defined on the basis of analyzing the balance between correct and incorrect models, which depends on the effectiveness of the learning's mechanism. For example, in [22] an artificial neural network (ANN) representing the user's preference model is constructed using a preference learning approach in which a fully-connected ANN of fixed topology is evolved by a generational genetic algorithm which uses a fitness function that measures the difference between the preferences of entertainment (treported by a group of children) and the output value of fun returned by the model. Another instance than can be catalogued in this category was presented in [23]; here the authors do not use neuronal techniques but a different linear model obtained with Linear Discriminant Analysis; this model follows a supervised approach in search of a correlation between physiological features and the reported subject enjoyment. Also, [17] proposed a combination of ANNs with the technique of *preference learning* to assist in the prediction of player preferences; here players are requested to explicitly report their preferences on variants of the game via questionnaires, and computational models are built on the preference data.

3 Game's adjustment

This will be the final stage of an attempt to optimize the players's satisfaction. After having obtained the models that identify the player, and having a measure of her entertainment, it is the moment to use that information and adapt or adjust the game to the characteristics of the user with the aim of providing a personalized match according to her preferences, resulting in an entertaining experience that at the same time meets her expectations.

The processes of modeling and satisfaction evaluation are closely related to the implemented adjustment mechanism. The indicators that were considered for the evaluation of satisfaction must match up with the adjustable elements of the game, in a way that manipulating them will influence the level of satisfaction. Some of these elements could be: aesthetic aspects, auxiliary contents that can serve as a guide to the player, the drama, the level of difficulty of the terrain and opponents, among others; but selection of these elements is not a trivial task; this is precisely the goal of Procedural Content Generation for games [24] that represents one of the most exciting lines of research inside the community of computational intelligence applied to videogames. Moreover, it is also true that it is not clear the impact of game difficulty and player performance on game enjoyment. This was precisely the analysis conducted in [25] although the authors could not give concrete conclusions.

From the conceptualization of the game, the script and the design should be developed with a generic approach that allows the flexibility in each game be adaptable to the wide range of preferences imposed by any group of users. The previous issue is also important to reduce the probability that the new game variants might be not well accepted. For example: causing a dramatic change in the rules might frustrate the player, or conducting the game towards unknown status, which is indeed possible when machine learning techniques are used.

With regard to the scope of the game settings we can categorize two approaches that comprise many works described in the literature and that are discussed in the following.

3.1 Circumstantial adjustment

Let's call the first one *circumstantial adjustment* which embraces only the action of changing the specific game elements according to the needs of the player; for example, the difficulty of the opponents - i.e., the game artificial intelligence (AI) - is often decreased because we have previously identified that the level of challenge goes beyond the users' skills. This approach focuses on managing the elements that will directly influence the level of satisfaction of the player. The change it will cause to the game is something particular to that play, which do not lead to a persistent change in the player's model, or in the decision making rules, because online learning don't occurred.

A successful application of this approach can be found in the experiment described in [26] and [22] where the aim was to increase, in real time, the satisfaction of the player in a game with physiological devices. Here, the authors, starting from collected data from several studies conducted with children, constructed a model of the user preferences using ANNs which proved to have a high precision. They implemented a mechanism of adaptation which allows to customize the game to the individual needs of each user. The logic of the used game was based on well-established rules, which allowed the authors to identify the specific parameters that handled the level of challenge and curiosity of the player, and to obtain an adaptive version of the game turned out to be preferred by the majority of users in the validation tests.

3.2 Constructive adjustment

This approach refers to the *constructive adjustment*, and the difference with the approach previously mentioned is that here not only the elements that determine the level of entertainment vary but also a transformation (or reconstruction) in the operation of the AI mechanism is carried out as a result of the online learning; an example of this transformation could be to adapt the game strategy that rules the decision-making of the *non-player characters* (NPCs); another example might be to vary the model that identifies the player taking into account the information is being received online (i.e., during the game session).

In [14], this latter issue is called *dynamic modeling* and has a corrective nature because the player's skill (as the game progresses) tends to improve and thus the player progressively polished her technique as part of her own adaptation, and these changes have a direct impact on her preferences. This line of research represents a very interesting field that promises to get a more reliable representation of the human player preferences.

The *constructive* approach offers advantages over the circumstantial one as regards the customization of models with the use of machine learning techniques but it is also more complex to implement; as a consequence we cannot affirm that one is better or worse than the another. In the following we discuss some examples where good results were obtained with this approach.

In a recent proposal made in [27] an evolutionary algorithm to adapt the AI strategy governing the opponent army not controlled by the player (in a strategy game in real time) to the ability of each player is developed; the objective was to catch the interest of the player in every game with the hope of increasing, as a result, her satisfaction. The idea is developed in two processes: the first one takes place during the game execution and consists of extracting a formal model to imitate the behavior of the player (i.e., the way that the player plays and the decisions that she takes during the game); in the second step authors try to generate automatically, through an evolutionary algorithm, an optimized AI adequate to the player's level (i.e., player's skill) in correspondence with the model previously obtained. These two processes are repeated indefinitely during the game, the first one is conducted on-line during the game whereas the second one is executed in-between games. The interesting fact of this proposal is that the AI level depends specifically on the player and is adapted to her with the aim of increasing player's satisfaction by engaging the player to play the game again.

Another example of the application of this paradigm is debated in [14], where authors described a framework for dealing with this issue and providing more adaptable games, and in particular approaches for dealing with two particularly current issues: that of monitoring the effectiveness of adaptation through affective and statistical computing approaches, and the dynamic remodeling of players based on ideas from *concept drift*. This article also discussed the use of ANN with supervised and non-supervised learning which are feasible to implement similar applications.

3.3 Who makes the adjustment?

In the majority of the works that have been focused in the topic of the adaptive games, the adjustment is started by the own game, as part of the software's adaptation, without the player noticing that this is happening, as we have seen in the examples previously analyzed. In this case we can name *auto-adaptation* to this approach. Nevertheless, the attempt of personalizing the game can be seen from another perspective where the player is the protagonist of managing the adjustable elements of the game. This seems to be evident, but it marks a difference from the design of the game. It is thus a question of giving the player at all time the control so that she can plan her own way towards the satisfaction. Let us say they are games with *controllable adaptation*.

An illustrative example of *controllable adaptation* in games is proposed by Jenova Chen in [28] as an implementation of the Theory of Flow from Czikszentmihalyi. Here, the author uses the concept of Dynamic Adjustment of the Difficulty. His aim was to design an adaptive game that would show the user the way to her zone of flow. One of the games implemented for this design was *Flow* and proved to have a great acceptance. In *Flow* the players use the cursor to sail, simulating an organism inside a virtual biosphere, where they can eat other organisms, evolve, and advance. Twenty levels were designed; every level introduces new creatures that symbolize new challenges. Unlike the traditional games in which the player finishes a level and advances progressively towards upper levels, *Flow* offers to the user the total control of the progress in the game. In every moment of the game the player is continuously being informed about the possible organisms that she can eat, and according to her choice she will be able to advance towards top levels or to return to a lower one. The fact of offering the total control on the difficulty of the game, allows the own managing of the balance among the challenges and the skills which at the same time control the immersion in the zone of flow. Doing so, Czikszentmihalyi makes possible that a very simple game become *adaptive* to every player, without getting into the intrinsic complications that have the processes of modeling and auto adjustment previously analyzed.

4 Conclusions

Nowadays, increasing player's satisfaction in (video)games is an exciting (and sometimes a very hard to achieve) challenge. This paper has discussed a number of different approaches that try to intensify the diversion of the player from a quantitative point of view, and can be considered a first (and preliminary) attempt to extract a taxonomy of this issue.

Most of the proposed approaches whose primary objective leads to increment quantitatively player's satisfaction can be catalogued in two main categories: one that tries to quantify user's entertainment in a game, and another which focuses in adapting the game in response to player's needs. Several proffers have been proposed in both themes, and some of them have been validated and shown interesting results.

However, as the investigation continues, there are several open research questions, and further attempts will be developed for obtaining more accurately models that represent player's preferences, more complete metrics of entertainment, and more powerful adaptation mechanisms to personalize the games. For these reasons, any proposal of taxonomy, will be temporal, and should be extended in a near future. Future work will be focused on enriching this initial taxonomy, refining its classifications and embracing other aspects of the *modeling and increasing player satisfaction* issue.

Acknowledgements This work is partially supported by Spanish MICINN under project ANYSELF (TIN2011-28627-C04-01), and by Junta de Andalucía under project TIC-6083.

References

1. Machado, M., Fantini, E., Chaimowicz, L.: Player modeling: Towards a common taxonomy. In: Computer Games (CGAMES), 16th International Conference on. (July 2011) 50 –57
2. Official wiki of IEEE Task Force on Player Satisfaction Modeling: `http://gameai.itu.dk/psm`. 2011
3. Fernández-Leiva, A.J., Barragán, J.L.O.: Decision tree-based algorithms for implementing Bot AI in UT2004. In Ferrández, J.M., Álvarez, J.R., de la Paz, F., Toledo, F.J., eds.: 4th International Work-Conference on the Interplay Between Natural and Artificial Computation (IWINAC 2011, Part I). Volume 6686 of Lecture Notes in Computer Science., La Palma, Canary Islands, Spain, Springer (2011) 383–392
4. Yannakakis, G.: How to model and augment player satisfaction: A review. In: Proceedings of the 1st Workshop on Child, Computer and Interaction, WOCCI'08, ACM Press (2008)
5. Malone, T.: What makes things fun to learn? Heuristics for designing instructional computer games. In: Proceedings of the 3rd ACM SIGSMALL symposium and the first SIGPC symposium on small systems. Volume 162., ACM (1980) 162–169
6. Czikszentmihalyi, M.: Flow: The psychology of optimal experience. New York: Harper & Row (1990)
7. Sweetser, P., Wyeth, P.: Gameflow: a model for evaluating player enjoyment in games. Computers in Entertainment 3(3) (2005) 3–3
8. Lazzaro, N.: Why we play games: Four keys to more emotion without story. Technical report, XEODesign, Inc. (2005)
9. Calleja, G.: Revising immersion: A conceptual model for the analysis of digital game involvement. In Akira, B., ed.: Situated Play: Proceedings of the 2007 Digital Games Research Association Conference, Tokyo, The University of Tokyo (September 2007) 83–90
10. Aarseth, E.: Playing research: Methodological approaches to game analysis. In: Digital Games Research Conference 2003, University of Utrecht, The Netherlands. (November 2003)
11. Livingstone, D.: Turing's test and believable ai in games. Computers in Entertainment 4(1) (2006)
12. Hagelbäck, J., Johansson, S.J.: A study on human like characteristics in real time strategy games. [29] 139–145
13. Yannakakis, G., Togelius, J.: Tutorial on measuring and optimizing player satisfaction. In: Computational Intelligence and Games, 2008. CIG '08. IEEE Symposium On, IEEE Press (dec. 2008) xiv –xvi
14. Charles, D., Black, M.: Dynamic player modeling: A framework for player-centered digital games. In Mehdi, Q., Gough, N., Natkin, S., Al-Dabass, D., eds.: Proc. of 5th Game-on International Conference on Computer Games: Artificial Intelligence, Design and Education, CGAIDE'2004, University of Wolverhampton School of Computing (2004) 29–35
15. Cowley, B., Charles, D., Black, M., Hickey, R.: Using decision theory for player analysis in pacman. In: Proceedings of SAB'06 Workshop on Adaptive Approaches

for Optimizing Player Satisfaction in Computer and Physical Games, Rome, Italy (2006) 41–50
16. Yannakakis, G.N., Togelius, J.: Experience-driven procedural content generation. T. Affective Computing 2(3) (2011) 147–161
17. Martínez, H.P., Hullett, K., Yannakakis, G.N.: Extending neuro-evolutionary preference learning through player modeling. [29] 313–320
18. Nesbitt, K.V., Hoskens, I.: Multi-sensory game interface improves player satisfaction but not performance. In: Proceedings of the ninth Conference on Australasian User Interface. AUIC '08, Darlinghurst, Australia, Australian Computer Society, Inc. (2008) 13–18
19. Yannakakis, G.N., Hallam, J.: Capturing player enjoyment in computer games. In Baba, N., Jain, L.C., Handa, H., eds.: Advanced Intelligent Paradigms in Computer Games. Volume 71 of Studies in Computational Intelligence. Springer (2007) 175–201
20. Baba, N., Handa, H., Kusaka, M., Takeda, M., Yoshihara, Y., Kogawa, K.: Utilization of evolutionary algorithms for making commons game much more exciting. In Setchi, R., Jordanov, I., Howlett, R., Jain, L., eds.: Knowledge-Based and Intelligent Information and Engineering Systems. Volume 6278 of Lecture Notes in Computer Science. Springer Berlin / Heidelberg (2010) 555–561
21. Coello, C.A.C.: Evolutionary multi-objective optimization: Current state and future challenges. In Nedjah, N., de Macedo Mourelle, L., Abraham, A., Köppen, M., eds.: 5th International Conference on Hybrid Intelligent Systems (HIS 2005), Rio de Janeiro, Brazil, IEEE Computer Society (2005) 5
22. Yannakakis, G.N., Hallam, J.: Real-time game adaptation for optimizing player satisfaction. IEEE Trans. Comput. Intellig. and AI in Games **1**(2) (2009) 121–133
23. Tognetti, S., Garbarino, M., Bonarini, A., Matteucci, M.: Modeling enjoyment preference from physiological responses in a car racing game. [29] 321–328
24. Togelius, J., Yannakakis, G.N., Stanley, K.O., Browne, C.: Search-based procedural content generation: A taxonomy and survey. IEEE Trans. Comput. Intellig. and AI in Games **3**(3) (2011) 172–186
25. Klimmt, C., Blake, C., Hefner, D., Vorderer, P., Roth, C.: Player performance, satisfaction, and video game enjoyment. In Natkin, S., Dupire, J., eds.: Entertainment Computing ICEC 2009. Volume 5709 of Lecture Notes in Computer Science. Springer Berlin / Heidelberg (2009) 1–12
26. Yannakakis, G.N., Hallam, J.: Real-time adaptation of augmented-reality games for optimizing player satisfaction. In Hingston, P., Barone, L., eds.: 2008 IEEE Symposium on Computational Intelligence and Games (CIG 2008), Perth, Australia, IEEE (2008) 103–110
27. García, J.A., Cotta, C., Fernández-Leiva, A.J.: Design of emergent and adaptive virtual players in a war rts game. In Ferrández, J.M., Álvarez, J.R., de la Paz, F., Toledo, F.J., eds.: 4th International Work-Conference on the Interplay Between Natural and Artificial Computation (IWINAC 2011, Part I). Volume 6686 of Lecture Notes in Computer Science., La Palma, Canary Islands, Spain, Springer (2011) 372–382
28. Chen, J.: Flow in games (and everything else). Commun. ACM 50(4) (2007) 31–34
29. Yannakakis, G.N., Togelius, J., eds.: Proceedings of the 2010 IEEE Conference on Computational Intelligence and Games, CIG 2010, Copenhagen, Denmark, 18-21 August, 2010. In Yannakakis, G.N., Togelius, J., eds.: CIG, IEEE (2010)