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Towards User Enjoyment: An Algorithm for Enhancement of Flow and Engagement in Virtual Reality Video Games

Andrés Mitre Ortiz, Héctor Cardona Reyes, Jaime Muñoz Arteaga

Center for Research in Mathematics, Human-Centered Computing Lab, Mexico

{andres.mitre, hector.cardona}@cimat.mx, jaime.munoz@edu.uaa.mx

Abstract. Although there is a broad work to enhance flow and engagement of User Experience (UX) in video games, they tend to generalize the technique used for every player, this leads to undesired user experience and negative outcomes. In addition, these works lack immersion and they generalized users preferences when applied to video games. To overcome this issue, we proposed a Q-learning algorithm that adjusts the game to proper challenges and skills of every single user. Hence, we intensify immersion by introducing the algorithm in a Virtual Reality (VR) video game, a practical case is presented to demonstrate the approach.

Keywords: flow, Q-learning, engagement, virtual reality, video games.

1 Introduction

Recent studies in User Experience (UX) has been applied to multiple applications [12, 7, 6], as in video games, researchers use diverse techniques to evaluate user experiences [33, 29] in terms of flow [8], these studies are evaluated with different methods, such as interviews [33], Experience Sampling Method (ESM) [29, 10] and questionnaires [18], being ESM the most used in the literature.

Video games are frequently considered a pleasurable and rewarding activity [15, 21], as well as improving interest in a method that keep users at the limit of their performance. They are considered a deeply engaging activity due to UX, such as presence, immersion, flow, psychological absorption and dissociation [20]. Video games has been considered for multiple applications, in a systematic review of computer games, Boyle et al. [5] stated that games for Science, Technology, Engineering and Maths (STEM) with a learning purpose, had a knowledge acquisition outcome [12], on the other hand, entertainment games addressed affective, cognitive and physiological states, e.g. exercise [23], stimuli [7] and life quality [6]. In contrast, Virtual reality (VR) is an emerging technology that contributes to the presence and telepresence [18] that refers to the sense of being in an environment, this technology is widely applied to different fields, such as entertainment [19], education [22] and health [25].

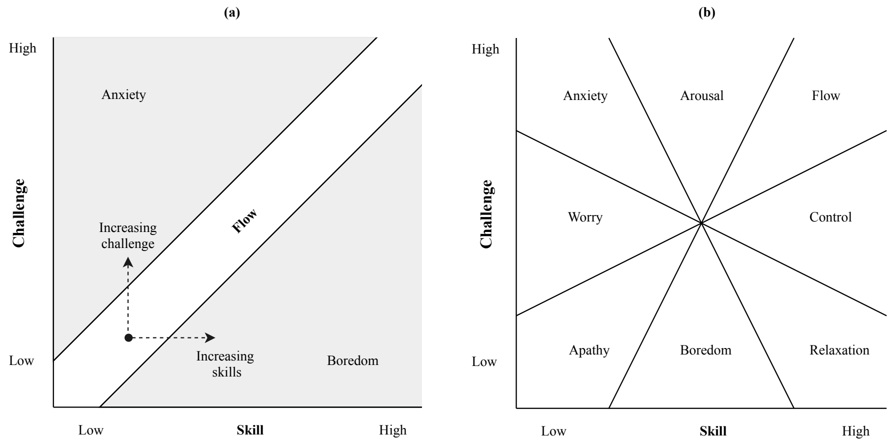

Fig. 1. Flow channels. (a) Flow channel from Csikszentmihalyi, 1990 (b) Adapted from Csikszentmihalyi, 1997, figure represents, four combinations of high/low skills and high/low challenges, representing a state equilibrium or unbalanced.

Ryan et al. [27] demonstrated that virtual worlds had considered human interaction in virtual worlds in an attempt to relate it to player satisfaction. Their survey experiments demonstrate that perceived in-game autonomy and competence are associated with game enjoyment.

Csikszentmihalyi describes flow as a process of optimal experience, where people under certain activity, put their abilities to their limit, by focused concentration and elevated enjoyment [8, 9]. Hamari [13], describes engagement in flow experiences as a reflection of complete absorption in a challenging activity, with the occurrence of elevated concentration, interest and enjoyment without any distraction. Schiefel et al. [28] reports that concentration is related to meaningful learning, interest reflects elemental motivation and stimulates users to continue the activity.

Flow experience relies on skills and challenges induced by an activity, where anxiety is evocated when the challenges are higher than user skills, and boredom is presence present when challenges are below user skills. According to the literature, if challenges of the activity are raised, the goal is to improve the player skills in order to enter a state of flow or optimal experience (see figure 1).

As algorithms enhance flow and engagement in video games approaches target to improve UX, they generalize UX for every user. This paper proposes a technique that does not generalize UX and targets to personal in Virtual Reality video games. In the next section, we introduce related works within flow and engagement in video games, in section 3 the proposal is presented and section 4 describes the conclusion and future work.

Table 1. Literature review of flow control in video games.

Author	Flow	Engagement	Technique	Evaluation	Control	Experiment	Game
Yannakakis Georgios N, et al. [38]	-	-	ANN	Survey	Physical	Children	Bug-smasher
Gustavo Andrade, et al. [2]	-	-	Reinforcement Learning (RL)	Statistical analysis	Fight actions	Simulation	Knock'em [3]
Hunicke Robin, et al. [16]	•	•	DDA	Not mentioned	Fight and defense actions	Simulation	Half-Life
Pieter Spronck, et al. [31]	-	-	ML: Dynamic Scripting	Simulation	Tactic of human gameplay	Simulation	Combat team game
Ibáñez-Martínez, Jesús, et al. [17]	•	•	DDA	None	Game parameters	Novel strategy	Tennis video game
Yannakakis Georgios N, et al. [37]	•	-	Feedforward NN and fuzzy-NN	Statistical analysis	Metric for real-time entertainment	People	Pacman and Bug-smasher
Vicencio-Moreira, Rodrigo, et al. [35]	-	-	Player-balancing techniques	Statistical analysis	Game mechanics	People	Mega Robot Shootout
Bian Dayi, et al. [4]	-	•	ML: Random Forest	Statistical analysis	Difficulty level	People	Virtual driving task
Mirna Paula Silva, et al. [30]	•	-	DDA	Statistical analysis	Difficulty level	Simulation	MOBA (DotA)
Simone Amico [1]	•	•	DDA	Statistical analysis	Difficulty level	People	VR Game

2 Related Works

The review of the state of art in the analysis of flow from video games is extensive, most of the work, focus on the characteristics of the game or the stimuli of the outcome experience, either being in flow, anxiety or boredom.

Multiple studies in video games are focused to increase UX with different techniques such as gamification [14], matchmaking systems, adaptive physics, Dynamic Difficulty Adjustment (DDA) [16, 17, 30], Neural Networks (NN) [38], Machine Learning (ML) [4] and Reinforcement Learning (RL) [2]. Although the literature is broad, a minority of papers focus in flow and engagement. According to our knowledge, only one work in the literature focused to enhance flow in Virtual Reality video games [1].

Simone adjusted the game based on performance DDA (users score), affective DDA using Galvanic Skin Sensor —Galvanic Skin Response (GSR) is a physiological signal that stimuli through emotions—, and a mixed performance-affective DDA. Results showed that performance DDA led to easy game-play for users, affective DDA led to difficult levels, but the mix of both of them led to the best results. The paper stated that it did not find a significant difference between participants who had experience in VR, and participants who did not. Table 1 shows a summary of related works that are applied to video games environments.

Although multiple works to enhance UX in video games exist, there are some drawbacks that authors do not consider such as:

- Most of the work focus on Dynamic Difficulty Adjustment (DDA), this limits only to different type of levels.
- Related works based on flow theory generalize the flow channel. They improve the flow according to challenges proportional to users' skills, or an average from a group of participants, assuming that every user or player has the same preferences, instead of personalized flow channels for every single player.

– Do not implement their applications in virtual worlds environment, this leads to an absence of deep engagement.
– Do not implement Machine Learning techniques, they instead adjust video game settings based on DDA and ETM.

Based on these drawbacks, and to solve these problems and ensure a flow experience for every user, this paper proposes a technique to enhance flow in VR video games in a personal way, according to user preferences with a Reinforcement Learning algorithm.

3 Proposal

The work proposes a Reinforcement Learning (RL) algorithm. Sutton et al. [32] stated that RL maps situations to actions to maximize a numerical reward signal, "the learner is not told which actions to take, but instead must discover which actions yield the most reward by trying them". This framework is usually defined in terms of the Markov Decision Processes (MDP), where an agent learns and take decisions inside an environment at each sequence of discrete-time steps, $t = 0, 1, 2, 3, ...$ At each time step t, the agents takes an action from a finite set of $states(s)$ of the environment $S_t \in S$ and on that selects an *action*, $A_t \in A(s)$, reaching a new state (s) and receives a reward, $R(s, a, s')$. MDPs maximize a long-term performance criterion, which represents the expected value of future rewards, the agents try to learn the optimal policy π. The policy maps from perceived states of the environment to actions to be taken in the current state.

3.1 Q-learning Algorithm

Q learning is a model-free incremental learning algorithm which optimizes sequential decision-making problems [36]. Q-learning has been applied to diverse problems in control systems, gaming and robotics [26]. Q-learning consists of iteratively computing values for the action-value function:

$$Q(s, a) \leftarrow Q(s, a) + \alpha[r + \gamma. V(s') - Q(s, a)]. \tag{1}$$

In eq. 1 $Q(s, a)$ is known as the action-value function, defined as the expected return from state s_n within an action (a). An optimal policy can be constructed starting from every state, $V(s') = max_a Q(s', a)$, where α is the learning rate and γ is a discount factor. Q learning differs from other Machine Learning algorithms since it does not require training data, the algorithm is able to find the optimal solution by iterating itself.

3.2 Input Variables

In the proposed approach, the agent controls the actions of the VR video game who is able to take actions at the end of every trial or level, the algorithm finds the parameters preferred by the user and take them into a state of flow. The followings definitions for the algorithm are:

1. *States:* according to Csikszentmihaly in Fig. 1 (b), the following states (s) are defined: anxiety, arousal, flow, worry, control, apathy, boredom and relaxation, creating a set of states:

$$S_t = \{s_0, s_1, s_2, ..., s_7\}. \tag{2}$$

2. *Actions:* to influence into users in an affective manner, we proceed to the literature to see how to affect the states of the user. According to Fassbender et al. [11] a study in a Reality Center found that participants were more engaged listening to instrumental background music while doing an activity, Tian et al. in [34] found that color scheme has a statistically significant effect on user preferences. To trigger immersion in VR, Rautaray et al. in [24] provided an analysis of the gesture recognition used in Human-Computer Interaction (HCI), based on this work, it is reliable to get the most affective gestures and applied them into a VR environment. According to the state of art, these variables have an affective effect on users, hence their experience while doing a certain activity can be changed or optimized. The set of actions is listed as:

   - A_0 : increase time,
   - A_1 : decrease time,
   - A_2 : mute background audio,
   - A_3 : play background audio,
   - A_4 : colorful graphics,
   - A_5 : gray-scale graphics,
   - A_6 : toggle gesture technique:

$$A_t = \{A_0, A_1, A_2, ..., A_6\}, \tag{3}$$

3. *External information:* user preferences are different for every player, an Experience Sampling Method (ESM) is included after an acquisition stage in order to get their preferences. Other information to the system which the states depend on are: user time, user score, audio status, color interface and technique used.

3.3 VR Video Game

Conforming to the input variables of the algorithm, a variety of VR video games can be developed since the input variables are suitable for every game, the variables can be easily modified. Hence the proposal can be applied to a broad genre of games such as arcade, educational, shooter, fighting, racing, Multiplayer Online Battle Arena (MOBA), sports and serious game. Figure 2 illustrates a general representation of the proposed system.

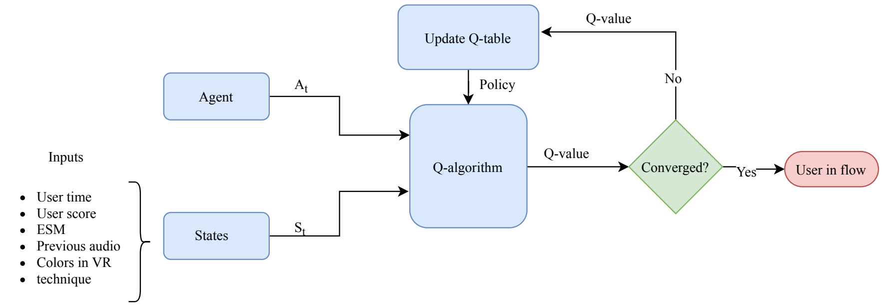

Fig. 2. General diagram of the system with the Q-learning algorithm.

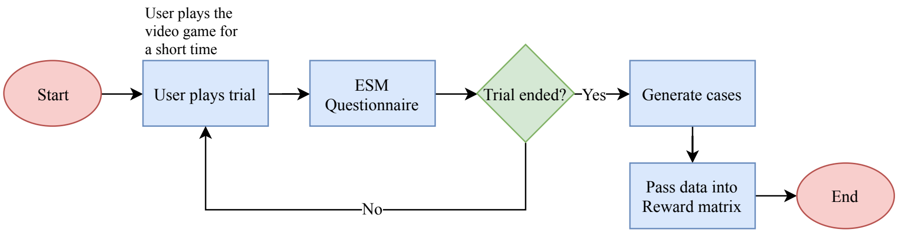

Fig. 3. Acquisition stage to get user preferences.

The Q-algorithm iterates after every trail and update the input parameters of the system, in every trail the algorithm will verify if the state of flow has been reached by the user —when Q-value has converged—, once it reach such as state, the algorithm finds the optimal policy that enhance the user experience.

In an example of a practical case, an user plays the video game for the first time, in order to get their preferences, an acquisition stage (Fig. 3) is required, this consist in generating different cases (preferences) in function of customized parameters of the video game (e.g. time, music background, interactive technique, etc). To get different cases, a trial of the video game is played for a short time, afterwards the cases are created —cases are a combination of parameters of the video game. These cases are considered as the input actions in the reward matrix for the Q-learning algorithm.

According to Fig. 3, flow state will be distant for every user, e.g. an user can prefer high challenges and low skills, in contrast another user can prefer high skills and low challenges. The algorithm will iterate until it converges, in other words when user loops in the state of flow.

4 Conclusion and Future Work

In this paper, a Q-learning algorithm to enhance flow and engagement in users in a personal manner while being in a VR video game is proposed, hence every policy that reaches the flow state will be different in function of the user. The proposal ensures that every user enjoys the game play.

Previous works improves user experience, ignoring the fact that every user has different preferences when playing video games, e.g. there may be users that prefer a higher levels of challenge that leads into difficult matches, in the other hand, there may be users that will enjoy easier matches. Another drawback in the literature is that most of the used techniques are applied to 2D video games, these outcomes into less engagement in contrast to VR video games.

As a future work, we plan to test the proposed algorithm, a group of participants will be tested during a 1 week with several trails. Statistical analysis will be used to evaluate the results as well as an Experience Sampling Method (ESM). Some failures could come from usability: video game is not property designed, experiment: environment circumstances, process and validation can result to undesired outcomes, User Experience: consistency, predictability, visual representations and customizability are factors that need consideration in order to avoid problem. According to our knowledge, the presented paper is the first work to implement Reinforcement Learning algorithm to enhance user flow and engagement in VR video game.

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