Motivational Strategies to Support Engagement of Learners in Serious Games

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Abstract: The use of Video Games as learning tool is becoming increasingly widespread. Indeed, these games are well known as educational games or serious games. They mainly aim at providing to the learner an interactive, motivational and educational environment at the same time. In order to better study the necessary characteristics for the development of an effective serious game (both motivational and educational), we evaluated the physiological responses of participants during their interaction with our serious game, called HeapMotiv. We essentially measured a physiological index of engagement through an EEG wifi headset and studied the evolution of this index with the different missions and motivational strategies of HeapMotiv. Focusing on the gaming aspects, the analysis of this engagement index behavior showed the significant impact of motivational strategies on skills acquisition and motivational experience. An agent-based architecture is proposed as a methodological basis for serious games conception.

1 INTRODUCTION

The success of Computer-Based Education (CBE) over the past decades, established a trend towards the development of new engaging, immersive and effective environment. In this context, the development of Serious Games (SGs) intended to train and educate learners within an enjoyable and challenging environment represents a new attractive approach for technology-mediated learning (Garris et al. 2002, Prensky, 2001, Johnson et al. 2008).

However, like in the other CBE systems, the interaction in SGs can be entertaining and motivating for the learners, or annoying and frustrating (Malone et Lepper 1987). SGs should support learners during interaction for instance with motivational strategies such as actions (or tactics) suitable to scaffold learners' motivation towards tasks and goals. Resulting learning would be easier, faster, more enjoyable, more self-directed, and more effective. What is really surprising is that very few studies concern motivational strategies.

From a conceptual point of view, aligning learning and fun may be a difficult challenge for the designers. Prioritizing playful aspects over learning content in order to motivate and engage learners, risks to make them more focused on the gameplay and less concentrated on the learning content. However, a game design which is based on intensive learning phases, can be in contradiction with learners' expectations and may rapidly annoy them (Gunter et al. 2006). Thus, striking an appropriate balance between a right learning mode and entertaining aspects in the game constitutes an important challenge for designing effective SGs. Hence, the assessment of learners' experience with SGs may be a key factor in the success (or failure) of such systems, as it will allow the designers to improve and adjust adequately the game.

Moreover, the idea of supporting SGs with motivational strategies can also be a promising target for SGs designers. These strategies are based on the idea of giving learners more control in adapting and adjusting the pace and the game components to their skill level. The aim of these strategies is to enhance SGs' capabilities to maintain learners in an appropriate level of engagement and motivation (derbali et al. 2012, Huang et al. 2010). Nonetheless, measuring the impact and effectiveness of such interventions can also be an important task for the SGs designers.

To that end, we propose a sensor-based approach using an electroencephalogram device (EEG) to analyze the behavior and the engagement of learners

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while interacting with a SG which embeds motivational strategies. We define a computed engagement index able to identify trends in learners' behavior. The objective of this research is twofold: first we investigate whether the physiological engagement index is effective to provide valuable information about learners' behavior. Second, we study the impact of SGs design and motivational strategy on learners' motivation and engagement.

The organization of the paper is as follows: the first section presents previous works in similar fields. The second section presents our SG environment. In the third section, we present the details of the experimental procedure. Finally, the fourth presents the results and a discussion about the impact of our findings in the field of SGs design.

2 PREVIOUS WORK

Recently, a large body of research was directed towards improving learners' experience and interaction in learning environments. Affective and social dimensions were considered in these environments to provide learners with intelligent and adaptive interaction (Picard et al. 2001, D'Mello et al. 2009). These approaches were either based on empirical observations and studies of learners' behavior or on correlation between physiological cues and interaction data. They have been used to feed different models aimed to improve the learning environment design by giving real-time adaptive interaction or adjustments according to learners' states.

Various ranges of sensors and devices, such as skin conductance, heart rate, electromyogram, camera and respiration, combined with machine learning models were generally used to build up sensor-based models capable of detecting learners' reactions. They also support educative content with appropriate interventions (Conati 2002, Predinger et Ishizuka 2005).

From a motivational standpoint, the review of literature demonstrates that several tools and frameworks for motivational assessment and support were provided for learning environments (Boyer et al. 2008, Vincente and Pain 2002, Rebolledo et al. 2011, Johnson et al. 2005, Ryan et al. 2006). For example, games appeared as the most appropriate tool to motivate people (Whitton 2007, Tychsen et al. 2008). Besides, millions of people are captivated by games. They spend their time and money to play. Therefore, the potential for combining games and learning becomes ever more significant. Many experimental studies state that computer games can provide new ways of learning (Coles et al. 2007). In fact, they show that educational games or serious games are capable of helping players to learn. Johnson and colleagues (2005) reported that the designers of educational games employ a range of artificial intelligence techniques, (controlling the behavior of non-player characters, providing performance feedback, etc.) to promote long-term user engagement and motivation (Johnson et al. 2005). Ryan and colleagues (2006) stated that the motivational pull of computer games is attributed to the combination of optimal challenge and informational feedback (Ryan et al. 2006). However, few studies tackled to what extent these strategies impacted learner's motivation or the way they impacted learner's objectively. In the present work, we propose to assess learner's engagement using an engagement index measure (*EEG mental Engagement Index*) combined with subjective self-reporting estimation of motivation, to analyze how learners reacted to motivational strategies. For that we developed a game in which it was possible to assess learner's reactions in different missions without and with motivational strategies.

3 MOTIVATIONAL STRATEGIES AND HEAPMOTIV

3.1 ARCS Model and Motivational Strategies

In his ARCS model (Keller 2010), John Keller used existing research on psychological motivation to identify four categories of motivation: Attention, Relevance, Confidence, and Satisfaction. Keller's model has been used in learning, training and games (Gunter et al. 2006, Dempsey et Johnson 1998). Therefore, it is of particular interest in our study. Keller also, defines four different motivational strategies associated to each category of his ARCS model (Keller 2010): Attention getting strategies, Relevance producing strategies, Confidence building strategies, and Satisfaction generating strategies. These theoretical strategies tend to (1) find the right balance between consistency and novelty; (2) find out which tactics to use and how to adjust them for the learners; (3) build relevance in the instruction by connecting it to the learners' backgrounds, interests, and goals; enhance learners' confidence by allowing them to control some situations; etc.

In this paper, we use the ARCS model as a basis to implement different motivational strategies in our game HeapMotiv as described hereafter, more precisely in the second version of the game, HeapMotivV2. For example, an **Attention getting strategy** is based on submitting challenges as time and errors constraints: (1) a time constraint for each level of difficulty: unlimited, 90 seconds, and 45 seconds for easy, normal, and hard level respectively, and (2) wild cards representing the number of accepted errors committed by the player: unlimited, 3 wild cards, and 1 wild card for easy, normal, and hard level respectively. **A Relevance producing strategy** has been designed before the beginning of each mission by presenting an instructional video to explain and inform learners of the main goal of the mission and its relation to the binary heap data structure. Then, this version of HeapMotiv integrates a **Confidence building strategy** which allows learners to control the level of each mission (easy, normal, and hard) and to possibly repeat the mission with the same or a different level (at most six trials). Finally, a virtual companion "Sinbad" applies a **Satisfaction generating strategy** by providing feedback on learners' performance when they find a way out of the labyrinth and meet "Sinbad". A detailed description of these motivational strategies is contained in (Derbali et al. 2013).

3.2 HeapMotiv

For the purpose of experimentations we have built HeapMotiv; a serious game intended to teach binary heap data structure. This SG is a 3D-labyrinth that has many routes with only one path that leads to the final destination (Fig. 1). Along the paths of the labyrinth, several information signs are placed to help the learners to find the correct destination. Learners have to play different 2D missions aiming to entertain and educate them about some basic concepts of binary heap, before obtaining information signs.

In order to study the impact of motivational strategies, we have implemented two versions of this game: HeapMotivV1 and HeapMotivV2, which are intended respectively to control group (CTR) and experiment group (EXP) during the experiment. In HeapMotivV1, players interact with the game without introducing the motivational strategies. However, in HeapMotivV2, the game have been reproduced based on the ARCS model (Keller 2010), and incorporated mostly some motivational strategies as described in the previous section.

In its current implementation, HeapMotiv is

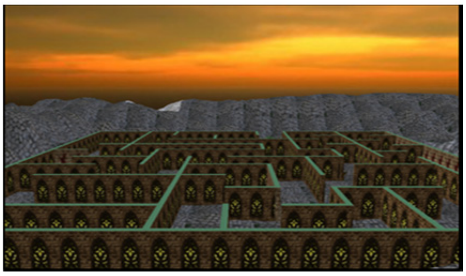

Figure 1: HeapMotiv environment.

composed of three missions: the first two missions (Tetris and Shoot) are designed to build a binary heap and maintain the heap property, whereas the third mission (Sort) is designed to show basic operations for a binary heap (insertion and deletion) and the heap-sort algorithm. An overview of these missions is presented in figures 2, 3 and 4.

Tetris is based on traditional Tetris game. A learner has to move nodes during their falling using the arrows to fill a binary tree without violating the heap property. In the first version HeapMotivV1, Tetris is over when the tree is completely filled. In the second version HeapMotivV2, players are penalized (time constraint or loss of wild cards) when they make mistakes and Tetris may be over without filling the whole tree.

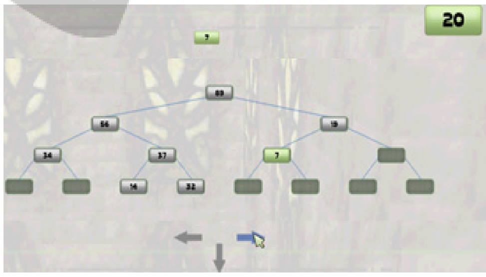

Figure 2: Tetris mission.

Shoot is based on shooter games. A learner has to spot violations of shape and heap properties, and then has to fix these violations by shooting misplaced nodes. Shoot is over when all errors are detected or balls are exhausted. In addition, the mobility of nodes is an additional constraint in HeapMotiV2.

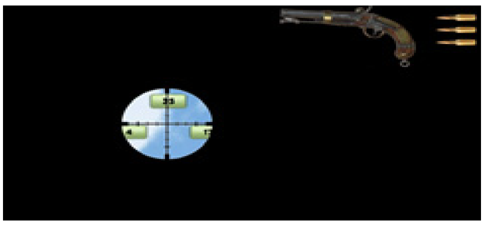

Figure 3: Shoot mission.

Sort begins by building a binary heap out of the data set, and then removing the largest item and placing it at the end of the partially sorted array. It is a comparison-based sorting algorithm to create a sorted array. Sort mission involves the discovery of rules to insert and delete a node correctly.

Figure 4: Sort mission.

4 EXPERIMENT

An experimental protocol was established where participants were invited to play our serious game HeapMotiv. Following the signature of a written consent form, each participant was placed in front of the computer monitor to play HeapMotiv. During the experiment, the participant was equipped with an EEG headset. EEG recordings were adopted using the multi-channel wireless portable device, called EMOTIV EPOC. This device is a high resolution, neurone-signal acquisition and processing wireless neuroheadset. It produces a reliable and valid EEG data collected from 14 channels, each based on saline sensors. The EEG monitoring using this device is as accurate as other conventional EEG systems (Stytsenko et al. 2011).

In the interest of measuring the learner's engagement index from his brainwaves and studying the evolution of these measures in different situations of HeapMotiv game, a baseline was computed before starting the game. This technique consists of calculating the average of all the EEG channels during a fixed period of time (5 minutes). 10 pre-test and 10 post-test quizzes about general knowledge of the binary tree and the heap data structure were also administered to compare learners' performance regarding the knowledge presented in HeapMotiv. The pre-test and post-test questions were different and balanced. Besides, an Instructional Materials Motivational Survey (IMMS) and a Self-Report Engagement (SRE) were administrated after each mission to assess learner's motivation and engagement, respectively. IMMS is derived from four categories of ARCS model of motivation (Keller 1987). An illustration of the experimental process is shown in the following Figure.

Figure 5: Experimental protocol.

As mentioned previously, EMOTIV can record 14 EEG channels based on the International 10-20 locations (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4). The EEG recordings were then managed in real-time by an EEG-capture tool developed in our lab using the EMOTIV software development kit. The developed tool provided temporal measurements of the user's signals and collected data was pre-processed and synchronized with HeapMotiv log file. An artefact rejection technique based on a threshold on epoch power was employed in the capture software to remove noise and data contaminated from body-movement or eye blinks. EEG data were decomposed into 1-second length segment overlapped by 0.5 second. The resulting segments were multiplied by a Hamming window function to decrease spectral leakage. A real-time Fast-Fourier-Transform (FFT) was used to extract 1-Hz bin power data segment for each EEG site location.

4.1 Computing EEG Engagement Index

In this study we used an EEG engagement index developed by Pope and colleagues at NASA (Pop et al. 1995). This index showed a great reliability in switching between piloting mode. It was also, used as criteria for adaptive and automated task allocation (Chaouachi et al. 2010). In assessing users' engagement within educational context, this index showed to provide an efficient assessment of learners' mental vigilance and cognitive attention (W et al. 2010). This index uses three EEG bands: Theta (4–8 Hz), Alpha (8–13 Hz) and Beta (13–22 Hz). It has the following equation:

$$r = \beta / (\alpha + \theta) \quad (1)$$

To compute this index, we proceeded as follows. First, we applied a Fast Fourier Transformation to convert the EEG signal from each active site into a power spectrum. Then, we produced the EEG bands by summing Bin powers (the estimated power over 1 Hz) together with respect to each band. Next, we mean the sum of band power computed from each measured scalp site. Finally, we obtain the *EEG mental engagement index* at instant T by applying a moving average technique. This technique consists of averaging each engagement index within a 40 seconds sliding window preceding instant T. This procedure was repeated every 2s and a new 40s sliding window were used to update the index.

4.2 Participant's Repartition

A total of 20 participants (8 females and 12 males) were invited to play our SG HeapMotiv. The sample mean age was 24.8 ± 5.94 years. Participants were recruited from the University of Montreal and had no prior knowledge about heap data structure. Participants were randomly distributed to the control group (CTR: n=10, HeapMotivV1), or to the experimental group (EXP: n=10, HeapMotivV2).

5 STATISTICAL RESULTS

5.1 Motivation and Learning

A paired sample t-test was conducted to compare the reported motivational scores in the experimental and control groups. Results showed a significant difference in the motivational scores reported by the participants in the experimental group (EXP: M=61.86, SD=7.01) and the control group (CTR: M=51.1, SD=8.39); t(18)=-3.115, p=0.006. The previous result highlights the positive impact of the motivational strategies embedded in HeapMotivV2 on the subjective measure of motivation of the experimental group by comparison with learners in the control group who did not benefit from the motivational strategies in HeapMotivV1.

A paired sample t-test was also conducted to compare learners' scores in the pre-test and the post-test. There was a significant difference between all learners in the pre-test (M=9.5, SD=3.1) and the post-test (M=13.1, SD=3.6); t(38)=-3.335, p=0.02. After playing and finishing the game, the number of correct answers is significantly higher. This result evidences that learners can improve their knowledge even in a complex field (i.e. heap data structure). Although a paired sample t-test result was not significant between the correct answers of the two groups (EXP: M=14.2, SD=2.2; CTR: M=12, SD=4.61; t(18)=-1.36, p=n.s.), participants of the EXP group have, in general, outperformed those of CTR group. The addition of motivational strategies in HeapMotivV2 could explain the considerable increase of the number of correct answers after finishing the game.

5.2 EEG Engagement Index Evaluation

Next, we conducted statistical tests to study the behavior of the computed EEG engagement index with regard to self-reported engagement and ARCS motivation. A positive significant correlation (r=0.54, p=0.03) was found between learners' self-reported engagement and the respective mean EEG engagement index. This preliminary result confirmed that the measure of engagement used in this experiment can reflect reliably the learners' perception of *their own engagemen*t during the game. In addition, the correlation run between the self-reported engagement and the motivational scores reported after each mission has been significant (Tetris: r=0.743, p=0.000; Shoot: r=0.446, p=0.049; Sort: r=0.488, p=0.029). However, non-significant correlation was found between the motivational scores and the EEG physiological measures. This result is not very surprising as the relationship between motivational state and mental engagement is complex and difficult to estimate by the learners themselves. We can however extract a clear trend, as we will detail hereafter with the measures obtained from the EEG.

5.3 Learners' Engagement and Motivational Strategies

Figures 6 (a), (b), and (c) depict the behavior of EEG engagement index of two learners of different groups. According to respective performance scores obtained we distinguish a mean player in the CTR group and a mean player in the EXP group. We show their respective engagement index for the Tetris mission (Fig. 6(a)), the shoot mission (Fig. 6(b)), and the Sort mission (Fig. 6(c)). A closer look to the figure shows that the EEG engagement index of EXP player is clearly above the baseline value throughout all missions. This result confirms also our first goal which was validating such an index for assessing learners' performance progression. The following finding confirms also, the positive impact of motivational strategies when comparing an average player in the EXP group to an average player in the CTR group.

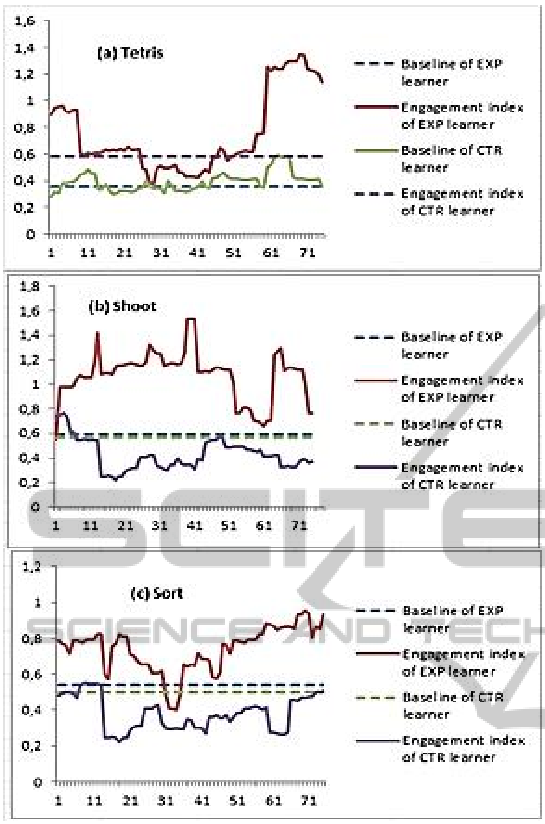

Figure 6: Engagement index (solid line) and Baseline values (dashed line) for EXP learner and CTR learner while trying Tetris (a), shoot (b) and sort (c).

For each one of the three missions, we compared the difference of learners' engagement index behavior in the two groups. The learner's average engagement index was extracted and the difference between this value and the corresponding learner's baseline was computed. Results of an independent samples t-test showed that, for each mission, the difference between the engagement index and the baseline was significantly higher in the EXP group: Tetris ($t(18)=-2.262$, $p=0.036$), Shoot ($t(18)=-2.819$, $p=0.011$) and Sort ($t(18)=-2.496$, $p=0.023$).

This result highlights the significant impact of the motivational strategies on the objective measure of engagement which seems to enhance learners' mental alertness and vigilance. However, a general decrease in engagement index differentiates in the last mission (we can see this trend in Figure 6(c)).

Our research aims at determining the role of motivational strategies in supporting learners' motivation and engagement through the different missions. As a matter of fact, the three missions of

Table 1: Mean (Standard Deviation) of the difference between the engagement index and the baseline for all the learners.

Mission	Group	
	CTR	EXP
Tetris	0.08 (0.2)	0.27 (0.15)
Shoot	0.03 (0.14)	0.28 (0.22)
Sort	0.02 (0.17)	0.17 (0.06)

HeapMotiv were designed differently: Tetris and Shoot missions had playful aspects which are theoretically and intrinsically attractive for the player. However, the Sort mission had non-game-like characters and involved more reflection effort. It also, required a certain level to master previous educative content. Repeated ANOVA measures determined that average engagement index differed statistically and significantly between the three mission for both groups ($F(2, 38) = 3.35$, $p=0.042$). Post hoc tests using the Bonferroni correction revealed that learners' engagement index was slightly but, not significantly reduced between the Tetris and Shoot mission (M=0.54, SD=0.17 vs. M=0.53, SD= 0.19, respectively, p=n.s). However, Sort mission reduced significantly the engagement index (M=0.44, SD=0.02, p=0.013) from the first two missions. This result highlights the fact that the game missions' design might have affected the learners' engagement. The variation of the index showed that it had significantly higher value with game-like missions and lower value in the last mission. In terms of motivational strategies, participants of EXP group have been more engaged than those of CTR group during Sort mission. Used strategies seemed to have then, a slight role in maintaining learners' engagement when playful aspects are almost inexistent.

In the next section we discuss the implication of our findings in a more generic methodology to build SGs using an Agents-Based architecture.

6 AGENT-BASED SERIOUS GAMES

Our above results showed that motivational strategies have a positive impact not only in supporting overall motivation and engagement, but also, in attaining high performance during the third mission. Indeed, players of EXP group performed better than those of CTR group when they played Sort mission. The design of serious games is complex and expensive. It involves a lot of resources: humans, techniques, funds, ergonomics, gameplay, etc. However, special attention should be given to aspects which trigger motivation and engagement of the player. Motivational strategies are essential, and in order to benefit from strategies which can not only dynamically adapt to the game but also improve themselves, it is useful to have a structure of agents.

Agents provide a flexible framework for SGs design. Agents can be used to respond quickly and autonomously to variable game situations according to the learner, and trigger appropriate strategy. They can also learn from the behavior of the learner and complete or improve existing strategies. The following architecture (Figure 7) shows the role of each component.

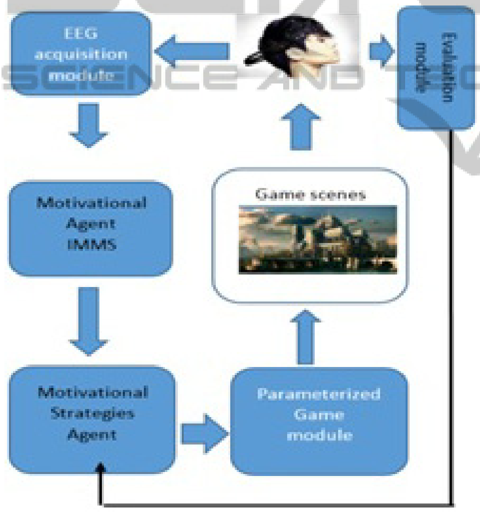

Figure 7: Motivational agent.

- The *EEG acquisition module* is in charge to measure the different brainwaves and extract the engagement index. It includes also personal information about the player (age, level of dexterity, historic)
- The *motivational strategies agent* contains a variety of parameterized strategies associated with information provided by EEG. Each strategy is evaluated and weighted according to the degree of performance obtained by the learner after the interaction with the game. The agent computes also a type of learner associated with the strategy.
- The *parameterized game module* consists of different characteristics of a game such as environments (scenes), artefacts, periods of reactions, difficulty level, re-initialization procedures. It selects the environment (game scenes) to be presented to the learner according to the selected motivational strategy.
- The *motivational agent* receives the engagement index from the EEG module and selects an adequate strategy. The selection integrates the IMMS evaluation and the self-report questionnaire (cf section 4).
- The *evaluation module* is in charge to control the evolution of learner's performance resulting from a given strategy. The weight of the motivational strategy is updated after analysis of this performance.

The advantage of this framework is that the motivational strategies can be improved with the time and also multiple new strategies can be introduced to complete the efficiency of SGs.

7 CONCLUSIONS

This paper introduced a new assessment metric for learners' engagement in SGs. Results obtained from an experimental study, showed promising results in assessing learners' engagement and motivation. Deeper analysis of our results showcased also, the importance of motivational strategies to enhance learning outcomes and to support the lack of playful aspects in some tasks of our SG, which impacts learners' engagement. Our future work will involve measuring the impact of SGs design as well as, players' profile on the cognitive reasoning level. Further detailed strategies will also, be considered to distinguish motivational factors and situations in our SG that support learners' performance.

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