

A Study of Learner's Mental Profile in Different Categories of Games

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Abstract: Adapting learning according to the learner's profile is an essential characteristic of Intelligent Tutoring Systems. Several studies have proposed different approaches to that aim. These methods are based mainly on the learner's individual traits, performances and emotions. However, few studies are interested to study the learner's behavior variation according to the nature and type of a presented task. In this paper, we have focused on the learner's mental profile based on electroencephalogram signals analysis and classification, in different cognitive games. These games are composed of three main categories (memory, concentration and reasoning) and organized according to a difficulty level varying from easiest to hardest. Primary results showed that learner's performance depend on the category of a game. Furthermore, some mental states (engagement and workload) are correlated with the cognitive game category.

Keywords: Memory cognitive games, Concentration cognitive games, reasoning cognitive games, EEG, engagement, workload.

1 Introduction

In Intelligent Tutoring Systems (ITS) adapting learning according to learner's profile is a fundamental criterion of intelligence. In fact, several researchers have suggested to spend more effort in defining a precise architecture of learner's profile and to adapt learning according to the different components of this profile [8, 9]. Indeed, defining a precise and a steady profile for a learner is very challenging for many reasons. Among these reasons, we all know that learning is a complex process. It can indeed be influenced by several factors; external factors related to the environment (interface quality, course organization, etc.) and internal factors related to the learner (current emotions while learning, learner's motivation, learner's engagement on a task, etc.). All these factors could have a direct influence on learner's performance and consequently learning success. Thus, many studies from different disciplines (artificial intelligence, human computer interaction, cognition and neuroscience) have focused on detecting and assessing users' mental profile based on different approaches, and more specifically electroencephalogram (EEG) signals analysis and classification [3, 4, 6]. The major part of these systems was based on two fundamental mental metrics, namely, mental

workload and mental engagement. *Mental workload* refers to the portion of operator information processing capacity or resource that is actually required to meet system demands [5]. *Mental engagement* is related to the level of mental vigilance, attention and alertness during the task. However, most of these approaches do take into consideration neither the brain specificities nor the type of cognitive tasks involved.

In this paper we aim to assess learner's mental states variation in different categories of a set of cognitive games that we developed. These mental states are issued from signals treatment and analysis provided by the B-alert software [1]. Thus, we formulate the following hypothesis: 1) we think that the type of a task has an impact on the learner's performance, 2) the type of a task has an influence on learner's mental states, showing more or less cognitive workload and engagement.

2 Related Work

To date several studies were conducted to detect, assess and predict learner's states evolution during interacting with e-learning environments which can influence learning. Among these states, we can quote learner's emotions, motivation, behavior, etc. For example, to detect if a student is engaged or not on a task, Beck [2] has built a student model which based on 3 parameters (response time, question difficulty and nature of answer (correct or not)). This model can trace learner's engagement by calculating a probability based on learner's previous performance and behavior. Besides, Johns and his colleagues [7] were used dichotomous Item Response Theory (IRT) models to estimate student's proficiency in answering multiple choice questions. These approaches are based mainly on learners' statistics while interacting with a system.

On other site, some researchers have considered data issued from certain physiological sensors, more specifically electroencephalogram (EEG), to detect learner's states of engagement and disengagement. For example, Pope [10] has developed an EEG engagement index based on brainwave band power spectral densities and applied in a closed-loop system to modulate task allocation. Performance improvement was reported using this engagement index for task allocation mode (manual or automated). This index has been even effective to detect learner's attention and vigilance in learning tasks [4]. Furthermore, Stevens and al [11] explored the feasibility of monitoring EEG indices of engagement and workload acquired and measured during performance of cognitive tests. Results showed an increase of engagement and workload during the encoding period of verbal and image learning and memory tests compared with the recognition period. They showed also that workload increased linearly with the level of difficulty. Moreover, Galan and Beal [6] evaluated positively the use of EEG for estimating attention and cognitive load (Workload) during math problems. They could be used for predicting learner's success or failure by a combination of engagement and workload measures established by Stevens and his colleagues.

In the same vein, we proposed in this work to adopt a sensor-based approach in order to detect learner's mental evolution in different categories of cognitive games. We also used the last two metrics proposed by Stevens and al [11] to track learner's mental states evolution. However, we think that these two metrics depend not only on the difficulty of a proposed task but also on the nature and the type of this task. For that aim and in order to prove this assumption, we developed a set of different categories of cognitive games. We conduct also an experiment to gather learner's EEG data. Our

main goal from this primary experiment is to study learner's mental evolution according to the nature of a proposed task based on statistics collected from our cognitive games categories and some learner's mental states (Essentially engagement and workload) established by B-Alert software [1]. In the following, we will describe briefly these cognitive games.

3 Cognitive Games Categories

We developed a set of 2D cognitive games for studying the learners' performances and brain behavior. This set contains three categories of games (*memory*, *concentration* and *reasoning*) and three difficulty levels (easy, medium and hard) presented in an ascending order. Each category includes two to three subcategories of different games. In what follows, we will present these games ordered by category name.

3.1 Memory

The following category is mainly based on the popular game of Digit Span. In this game, we familiarize the learner with a series of numbers and ask him to remember and type them afterwards. We implement two versions of this game: Forward Digit span (FDS) when it comes to typing the numbers retained in the same order in which they appeared on the screen and Backward Digit Span (BDS) when it comes to the typing numbers in order to reverse their apparition. Each version has 6 difficulty levels ordered from easiest (L1) to hardest (L6).

3.2 Concentration

This category contains two subcategories of concentration games: Feature Match and Rotations described below.

3.2.1 Feature Match (FM)

This game consists in identifying whether the two images appeared on the screen are identical or not according to their forms, numbers and colors. It has also six difficulty levels (ranging from L1 to L6) which vary in its geometrical number and forms (see figure 1).



Figure 1 Example of Feature Match for level 6

3.2.2 Rotations (RT)

This game is similar to the previous game. It has five difficulty levels which vary depending on the complexity of the image content (number of shapes). It consists in identifying whether two images match or not doing their rotations.

Reasoning

This category contains three sets of reasoning games: Arithmetic addition, Odd One Out, and Intuitive reasoning.

3.3.1 Arithmetic Addition (AA)

In this game, we kindly ask the player to add two variable numbers. Like any other game, this one has three levels of difficulty, where in each level we vary the number of digits to add going from 2 until 4.

3.3.2 Odd One Out (OO)

This game has three difficulty levels. For each difficulty level, it has a fixed series of images. Every series has a certain correspondence between images (color, form, number, etc.) and one odd one out which is different according to one or more characteristics (see figure 2). Thus, the player should identify each time the odd one out image.

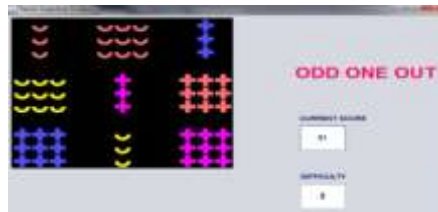


Figure 2 Example of Odd One Out game

3.3.3 Intuitive Reasoning (IR)

This game has three levels of difficulty (varying according a time constraint: unlimited, 1mn and 30s) and 15 series in total; where every level contains 5 series of exercises. Unlike other games, this game is based on the intuitive or analogical reasoning (see figure3).



Figure 3 Example of a series of intuitive reasoning game

4 Experiment

In order to study learners' mental states variation in different games category, twenty participants (9 women and 11 men, mean age=28, standard deviation=4.67) were in-

vited to play our cognitive games. This study is about 2 hours, which are mainly distributed into three steps: (1) Initially, we installed the B-Alert X10 headset on the participant, (2) The participant is invited to do 3 tasks of baseline defined by the manufacturers of this headset [14] to establish a classification of mental states, (3) the participant is finally invited to play our set of cognitive games which composed of 3 categories as described above.

During all the experiment, electroencephalogram (EEG) was recorded by using a Wi-Fi cap with a two linked mastoid references. 9 sensors (F3, Fz, F4, C3, Cz, C4, P3, Poz and P4) were placed on the participant's head using the international 10-20 system. EEG was sampled at a rate of 256 Hz and converted to Power spectral densities (Alpha, Beta, Theta and Sigma). EEG was processed by B-Alert software [18]. This software allows us to obtain a real time classification of certain mental states (sleep Onset, Distraction, Low engagement, High Engagement and High workload). From this set, we selected in this study Workload and Engagement states. Thus, we synchronized the EEG mental states of Engagement and Workload with all the categories of cognitive games developed.

5 Statistical Results

We recall that in this work, we want to consider to following points: (1) examine the learner's performance variation depending on the category of game, (2) Study the variations of mental states depending on the category of game.

5.1 Learners' performance and category of game

First, we computed for each category and for each game, the average of the players' scores, as well as their standard deviation (see table 1). The scores for each game set are calculated as follows: Each correct answer is worth 1 point and each response incorrect is 0. We, then calculated for each game the percentage of total score achieved in the game (TSG: Total Score in Game), as well as the percentage of total score achieved in the game category (TSGC: Total Score in Game category).

Table 1 Distribution of scores between games

Game Category	Mean (SD) of TSGC	Game Name	Mean (SD) of TSG
<i>Memory</i>	65.66 (2.46)	FDS	64.61 (3.14)
		BDS	67.64 (3.96)
<i>Concentration</i>	81.90 (1.35)	FM	82.20 (1.70)
		RT	81.32 (2.24)
<i>Reasoning</i>	58.14 (2.52)	AA	67.79 (4.47)
		OO	63.03 (5.85)
		RI	49.47 (2.97)

From this table, we can notice that the category of *concentration* has the best percentage of scores for all the players, as well as *Feature Match* game. However, *reasoning* category is ranked the last. This can be explained by the fact that the category of game could have an impact on player's performance. In fact, *concentration* games do not require much mental workload comparing to reasoning games that require a lot of

concentration, memory work, arithmetic calculation, etc. To confirm this hypothesis, we conducted a one way ANOVA test after checking the normal distribution of scores for each category (using SPSS Q-QPlot). This test allows us to obtain a very significant result ($F(2,477)=31.1, p=0.000^*$). So, we can assume that player's performance depends on the category of game.

5.2 Learner's mental profile and category of game

To analyze the relationship between mental states and game category, we used three one way ANOVA tests. For the mental state of workload, results are very significant ($F(2,224)=18.33, p=0.000^*$). Indeed, for the mental state of engagement, results are also significant ($F(2,224)=3.32, p=0.04^*$). Furthermore, we obtained an average correlation between workload and engagement states ($R=0.4, p=0.00^*$). So, we can conclude that workload and engagement states depend on game category. This result is very consistent since learner's concentration and mental activity increases according to the nature of proposed task; more the nature or category of the task is interesting, more he is engaged on the task. Moreover, more the learner is engaged on the task, more he tries to reason and learn, so his mental state of workload increases.

6 Conclusion

In the present study we have showed that both learner's performance and mental profile (which is composed of engagement and workload states) depend on the category of cognitive game involved. So, we can confirm that the type or the nature of a proposed task in learning has a significant impact on learner's mental states and consequently his performance. This finding leads us to take into consideration learner's cognitive capacity before proposing a task and then try to adapt learning depending to the evolution of some selected outputs issued from EEG signal. More specifically, our future work will focus on real time learner's adaptation according the learner's mental states variation and the type of a proposed task.

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