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Predicting Learners' Performance Using EEG and Eye Tracking Features

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Abstract

In this paper, we aim to predict students' learning performance by combining two-modality sensing variables, namely eye tracking that monitors learners' eye movements and electroencephalography (EEG) that measures learners' cerebral activity. Our long-term goal is to use both data to provide appropriate adaptive assistance for students to enhance their learning experience and optimize their performance. An experimental study was conducted in order to collet gaze data and brainwave signals of fifteen students during an interaction with a virtual learning environment. Different classification algorithms were used to discriminate between two groups of learners: students who successfully resolve the problem-solving tasks and students who do not. Experimental results demonstrated that the K-Nearest Neighbor classifier achieved good accuracy when combining both eye movement and EEG features compared to using solely eye movement or EEG.

Introduction

In recent years, there has been a rising interest in computer-based learning environments in using different indicators to monitor students' experience and learning performance. In fact, understanding students' behaviour is of primary interest since it allows learning systems to adapt help strategies accordingly. In this context, it is important to constantly assess the learners' cognitive states.

The use of sensing technology has proven its effectiveness as they provide reliable indicators about the students' behaviour within educational environments (Ben Khedher et al. 2019; Jraidi et al. 2013; Jraidi and Frasson 2013). Different physiological sensors are being used such as heart rate (AL-Ayash et al. 2016; Le et al. 2018), galvanic skin response (Noroozi et al. 2018; Nourbakhsh et al. 2012), body posture (D'Mello et al. 2012; Grafsgaard et al. 2013), facial expressions (Sawyer et al. 2017; Whitehill et al. 2011), etc. Among all existing technologies, eye tracking (ET) and electroencephalography are increasingly being used since they provide valuable quantitative and objective information regarding both the learners' visual behavior and brain activity (Ben Khedher et al. 2017a, 2018a; Berka et al. 2007; Chaouachi et al. 2010).

EEG has been shown to be a predictor of learners' mental state while interacting with computer-based learning environments. Moreover, researches have shown that students' mental states affect their cognitive process and thus their learning performance. Therefore, it is fundamental for intelligent tutoring systems to identify learners' states particularly negative states in order to develop appropriate interventions. For instance, engagement (Huang et al. 2014), frustration (Heraz et al. 2007), workload (Berka et al. 2007; Chaouachi et al. 2010) and confusion (H. Wang et al. 2013) are among the most common observed states that can be detected using EEG during a learning process.

In the same context, eye movements are also closely linked to human cognition. Indeed, eye tracking have become widely used in educational environments this last decade, since it provides effective clues to educators that may help them assess students' learning experience in an effort to enhance learning materials. Eye movements are the most common data sources that eye tracking researchers analyze to make inferences about cognitive and attentional processes. Several eye movement features can be employed to assess leaners' attention namely, fixations (Ben Khedher et al. 2017b, 2018b; Scheiter et al. 2018; F. Wang et al. 2018), saccades (Lallé et al. 2018) and pupillary responses (Toker et al. 2017).

The objective of the current study is to investigate whether combining EEG and eye tracking sensing modalities can improve predict students' learning performance. In particular, the goal is to use both kind of features in the context of problem solving to discriminate between successful and non-successful learners.

The rest of the paper is organized as follows: section 2 outlines some related works, section 3 describe the experimental protocol as well as the data preparation process. Section 4 discusses the obtained results and finally section 5 presents a conclusion and future works.

Related Works

Many researchers are paying a particular attention to multimodal sensor based approaches in order to provide a more robust assessment model. In fact, using different sensors provides an added value and may help overcome the issues faced when using a single modality. This multimodal sensors-based approach is used in different research domains to explore users' behaviour (Arroyo et al. 2009; Brouwer et al. 2017; Jraidi et al. 2014; Lobo et al. 2016; Scharinger et al. 2015; Slanzi et al. 2017). For instance, Slanzi and his colleagues used three different sensors namely, eye tracking, pupil dilation and EEG to analyze users' behaviour when performing a web search in order to predict click intentions. Results demonstrated that fixations with clicks had greater pupil size than fixations without clicks. In the work of Brouwer et al. (2017), EEG and eye tracking technique were used as data sources during a visual search task. The authors used fixation duration and pupil size to explore whether the user fixated a target (i.e an interesting point within the environment) is fixated or not.

Merging different data sources is also widely used in learning environments (Harley et al. 2015; López-Gil et al. 2016; Lu et al. 2015; Rodrigue et al. 2015; Shen et al. 2009). For instance, Harley and his colleagues (2015) used facial expression, self-reports and electrodermal activity (EDA) for emotion recognition. Results indicated high agreement between facial expressions and self-report suggesting that these two modalities are reliable indicators of learners' emotions. However, low agreement was found in terms of EDA. Muldner and Burleson (2015) used EEG, eye tracking and skin conductance to differentiate between high and low creativity students (Muldner and Burleson 2015). Similarly in (Kruger et al. 2013), the authors measured cognitive load by means of pupil dilation, EEG and self-reports. They reported significant correlations between cognitive load and pupil dilation and EEG, respectively. For instance, negative emotional states are correlated with higher cognitive load.

Although the previously stated works used several sensors to assess learners' cognitive behavior, they are not generally combining features from all sensors. Each channel is correlated in an isolated way to the target variable. In this work, we propose to combine EEG and eye tracking to assess students' learning performance during a problem-solving task. We used different features from both modalities and investigate whether the combination of several modalities can outperform a single modality.

Experimental Study

In this experiment, we recorded the eye movements and cerebral activity of novice medicine students as they were interacting with our learning environment Amnesia and solving clinical cases. For that purpose we used eye tracking and encephalography (EEG) techniques to extract respectively two fixation-based metrics and two brain indexes as presented in figure 2.

Apparatus

For the eye movement recording, a commercial eye tracker (Tobii Tx300) with a sampling rate of 300 Hz was used. Participants were seated in front of a 23-inch computer monitor (1920 x 1080 resolution) that integrates the infrared sensors and the camera. The monitor, on which the stimuli was displayed, was placed at a distance of 65 cm approximately from the participants' eyes. Free head movements were allowed during the experiment.

For the recording of the EEG signals, we used the Emotiv EPOC neuroheadset with a 128 Hz sampling frequency. The headset contains 16 electrodes placed according to the 10-20 international standard (Klem et al. 1999) as shown in figure 1. Fourteen electrodes representing different brain regions (O1, O2, P7, P8, T7, T8, C5, FC6, F3, F4, F7, F8, AF3 and AF4) and two more reference electrodes corresponding to the P3 and P4 regions called respectively, Driven Right Leg (DRL) and Common Mode Sense (CMS).

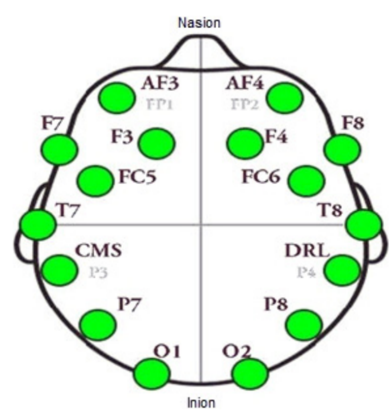

Figure 1. Emotiv EPOCs eletrodes positioning.

Participants

We collected data from fifteen undergraduate students recruited at the medicine department. Participants were between 20 to 27 years (*M* =21.8, *SD* =2.73).

Protocol

The first step for the participant is to sign a consent form that explains the material and the course of the experiment.

Then, an introductory scene was shown as well as a reminder of the game's objectives. After, we outfitted the participant with the EPOC headset and placed him in front of the eye tracker. Finally, a standard 9-point calibration was performed to evaluate the measured gaze point quality. All participants in the experiment passed the calibration phase successfully.

Upon the end of the setup process, the recording session begins by displaying the serious game to the participants. When playing, the learner resolved six different medical cases. For each medical case, the participants were instructed to identify the correct diagnosis and the appropriate treatment. They had to consider a series of observations such as patients' demographic information, symptoms and antecedents. For each diagnosis, the students were given different response alternatives and they had up to three attempts to find out the correct answer. They could also collect additional clinical data such as analyses and antecedents until reaching the right diagnosis. Once the diagnosis is established, the students had also up to three attempts to find out the adequate treatment and after three errors made either in the diagnosis or the treatment, the game is over.

The players had 30-45mn of time to interact with the whole game. Once they resolved all cases or the game was over, the learners filled a post-game questionnaire related to the game design and usability.

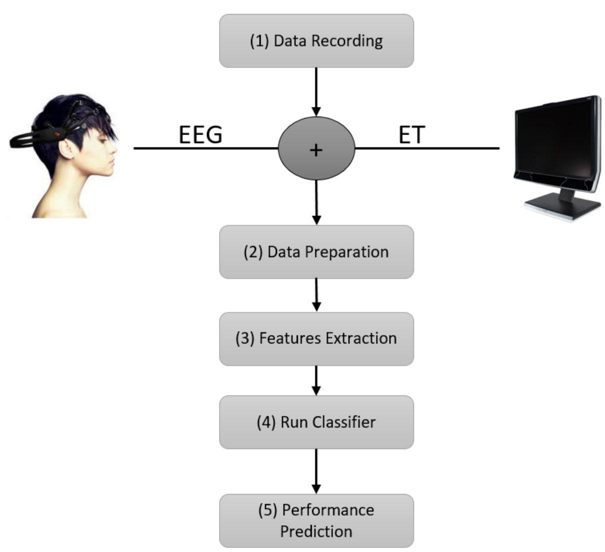

Figure 2. General representation of the predictive model

Data Preparation

Eye Movement's Recording

We used iMotions 5.2 software for data analysis and features extraction. The biometric Attention Tool integrates an eye tracking platform for visual attention detection that offers a high quality data acquisition and analysis.

In each medical case, we divided the interface into different regions as to perform detailed analyses according to different areas of interest (AOI). Six specific regions were defined representing six task-relevant regions within the resolution environment, as presented in figure 3: Information (*I*), Antecedents (*A*), Symptoms (*S*), Analyses (*N*), Diagnosis (*D*) and Treatment (*T*). The *I* are of interest contains the demographic information of the patient (e.g. first name, age, weight, etc.). The *A* area includes the previous diseases that the patient could have had. All the symptoms related to the specific disease are represented in the *S* area. In the *N* region, we show additional clinical data such as heart rate and blood pressure. In the *D* region, we present different diagnosis alternatives among which the student has to pick out the correct illness. Finally, in the *T* area we show different treatment alternatives among which the student has to choose the adequate ones.

From eye movement recordings, two features were extracted namely; *fixation duration* and *number of revisits*. Fixation duration represents how long the participant maintains fixating each area of interest. Number of revisits represents how many times the participant re-fixate the AOI.

Mental States' Recording

In this study, two brain indexes namely, mental engagement and mental workload, were extracted using the methodology of (Chaouachi et al. 2015). The engagement index was computed by establishing a ratio between the three EEG frequency bands θ (4-8 Hz), α (8-13 Hz) and β (13-22 Hz) as follows:

$$\textit{Engagement index} = \beta / \theta + \alpha$$

For each participant, the three frequency bands were transformed by multiplying 1-second of the EEG signal by a Hamming window and applying a Fast Fourier Transform. Then θ, α and β values were summed to obtain a combined value over all the 14 regions. Finally, a 40-second mobile window was used to reduce the fluctuation of the obtained engagement index. For instance, the value of the index at time t represents the total average of the ratios computed on a period of 40-second preceding t.

Unlike the engagement index, for the mental workload measurement, there is no a standard index directly extracted from the EEG signals. For that purpose, the authors built a predictive mental workload model for each participant based on two phases namely, training phase and learning phase. In the first one, brainwave signals of the participants were recorded as they were resolving some cognitive tasks. Then, from the obtained data, EEG features were extracted and used as inputs in the model to derive a mental workload index as output. Then, the second phase was used to validate whether the workload index computed in the training phase

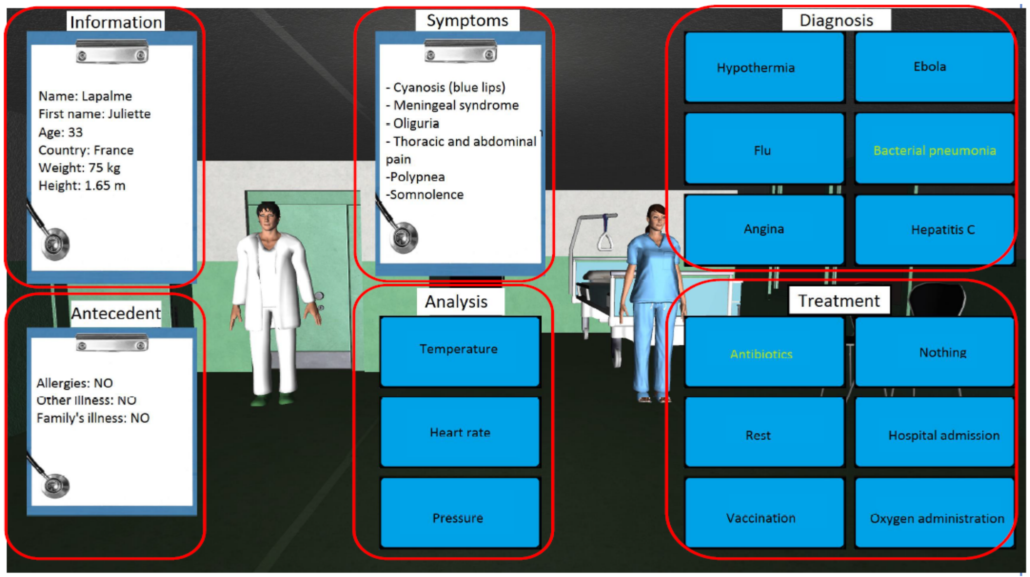

Figure 3. The six areas of interest in all the medical cases.

was able to assess the evolution of students' learning experience. For more details about the procedure, please refer to (Chaouachi et al. 2015).

In order to assess the learner's mental behavior, a slope of each index is computed using the least squared error function of the index's values in each medical case. For the engagement index, if the slope value is positive, then the learner is considered as mentally engaged. Otherwise, the learner is considered as mentally disengaged. For the workload index, if the slope value is between - 0.03 and + 0.03, than the workload is considered as positive. Otherwise, if the slope value is above 0.03, the learner is considered as overloaded, and if the slope is below -0.03 the learner is considered as underloaded. Thus, the learner's mental state is considered positive, if he is mentally engaged and neither overloaded nor underloaded; otherwise, it is considered negative.

Results and Discussion

In this experiment, we combined Eye Movement (EM) and EEG features to predict learners' performance by discriminating between two groups of learners (group 1: success and group 2: failure). Fifteen features were extracted that describe learners' visual and cerebral activity namely, mental engagement, mental workload, mental state, fixation duration (in each AOI) and time to first fixation (in each AOI). Then, for classification, we used 6 different classifiers namely Naïve Bayes, Multilayer Perceptron, Binary Logistic Regression, K-Nearest Neighbor, Decision Tree, and Random Forest. We used *k*-fold cross validation technique for prediction performance. We run the classifiers with different values of *k* and we obtained higher accuracies with k=7.

The classifier with the highest accuracy is the K-Nearest Neighbor (KNN) generated using the *IBk* algorithm, followed by Multilayer Perceptron (MP). We run also a baseline classifier that predicts the class that has the most observations in the training dataset (Success in our case). From table 1, we reported the highest accuracy rates in all cases for the KNN classifier compared to MP and baseline suggesting that using a fusion between EEG and eye movement features, we were able to identify successfully the learners who may need assistance to resolve the medical cases.

Table 1. Classifier accuracy results

	IBk	MP	Baseline
Success	83%	76%	85%
Failure	45%	27%	9%
Overall	75%	65%	69%

Furthermore, we built two other classifiers using in the first one only features that are linked to learners' eye movement and in the second classifier only features that describe learners' mental states in order to assess whether the performance achieved by combining the two modality is better than using a single modality. For EM-based features, the IBk classifier achieved 65.38% accuracy. One can say that it is a high performance, however, the recall evaluation metric was very low (0.182). The same trend was observed for EEG-based features, where the IBk classifier was only able to predict the most likely class (group 1: success) showing that both modalities were note able to identify the group of learners who failed in the cases' resolution.

As presented in table 2, the combination of EEG and eye tracking has shown the highest prediction rate in terms of the second class. We can also notice from the table that using only EEG-based features, the classifier fails to recognize the negative class (i.e. failure). These findings clearly show that using both types of features EM and EEG can improve prediction performance to discriminate between two groups of learners.

These findings confirm that a prediction model can be built based on a combination of features from two modalities such as fixation duration and mental state. We suggest that our multimodal sensor-based approach can be used to effectively predict learners' performance during an interaction with a learning environment.

Table 2. Classifier accuracy results per modality

	EEG	ET	EEG and ET
Success	100%	78%	83%
Failure	0%	18%	45%
Overall	79%	58%	75%

Conclusion

In this paper we have presented a two-modality sensor-based approach to automatically predict students' performance using eye movements and electrophysiological activity. Our objective was to investigate whether combining both features can efficiently discriminate between two groups of learners: students who successfully resolved the different medical cases and students who do not.

We conducted an experiment in which novice medicine students interacted with the Amnesia serious game and resolved clinical cases. An EEG headset and an eye tracking device were used to record learners' brainwave signals and eye movements respectively. Different classifiers were used to predict students' performance: 75% of accuracy was achieved. Results demonstrated that the combination of electrophysiological and eye tracking sensors produced better performance than the use of a single sensor. As future work, we are planning to use this predictive model in real time in order to predict learners' performance trend and develop early help strategies accordingly to enhance their learning experience.

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