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An EEG-based Application for Real-Time Mental State Recognition in Adaptive e-Learning Environment

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***Abstract*—This paper presents the basics of non-invasive electroencephalogram (EEG)-based brain-computer interfaces (BCIs) and a system that could support the learning process in an e-learning environment. More specifically, we focus on the user's mental state and how this can be detected and captured using EEG in order to provide a positive user experience through appropriate adaptation. Mental state is a multidimensional term that includes among else relaxation and concentration, which, in this paper, are captured using a low-cost EEG device that the users wear throughout the interaction with the online environment. The accurate identification of these states is made with the aid of Machine Learning (ML) and enables notifications and proper adaptation to automatically match the detected mental state. Finally, the results from the user experience during the system usage are presented assuming 10 participants. The evaluation showed that such a system would provide a positive user experience.**

***Index Terms*—adaptive-interactive systems, e-learning, EEG, machine learning, brain-computer-interface, and mental state.**

I. Introduction

E-learning systems started to gain high popularity during the COVID-19 era when everything was forced to go online. Traditionally, e-learning systems were designed using the so-called "one-size-fits-all" approach [1]. The learning content and system functionality were the same for all students. However, this may be problematic for the learning process since each student has individual learning differences and needs. With the rise of adaptive systems, the learning content, presentation, navigation, or system functionality can be adapted based on the user's needs or preferences, keeping them motivated and maximising their learning performance and experience when using these online platforms and, thus, increase the learning outcomes [2].

Creating and maintaining a user model is necessary so that the system can adapt and be accomplished explicitly, or implicitly [3]. Learning is a cognitive process that relies on the student's current internal states like emotions, mental engagement, mental workload etc. Mental engagement is the level of someone's alertness and mental workload is the mental effort that is put into a task [4].

EEG is an accurate non-invasive physiological method to detect the human brain's electrical activity and estimate someone's mental state, with a temporal resolution of milliseconds [5]. The use of EEG in adaptive learning environments anticipates improved user experience, performance, or both. Despite the advantages of the EEG technique, the high cost and difficulties in setting up an EEG device restricted its use to medical purposes [6]. Nowadays, these devices are getting cheaper and more accessible and, therefore, are commercially used for games and neurofeedback. EEG devices are a popular solution for providing unobtrusive and continuous data about the users' mental states. Also, compared to other physiological sensors such as electrocardiographic activity (ECG), neural-based ones (EEG, fNIRS) are considered an even better choice. However, mental state elicitation is a complex task that needs expert knowledge in many different domains such as sensor technology, signal processing, neurophysiology, experimental psychology, systems design, engineering, and advanced ML algorithms.

The aim of this paper is to present the basic design and implementation principles of an EEG-based application whose functionality adapts based on the learner's mental state providing support and a positive user experience in e-learning environments. The mental state embraces attention/engagement, cognitive workload, affective state, mental fatigue, emotions, relaxation, concentration etc; we focus on concentration/relaxation. Based on previous research studies [7]–[9], we developed and tested a system that can efficiently model and detect the mental state of the user using physiological data acquired from an EEG device of 4 channels that the candidate learner wears while using the system.

The rest of the paper is organized as follows. Section II describes the fundamentals of EEG theory. Besides, in Section III, a description and analysis of the system components are made. In addition, in Section IV, we discuss the acquired results from the user experience. Finally, conclusions and future directions are outlined in Section V.

II. Fundamentals on EEG

The human brain is separated into three main parts: the cerebrum, the cerebellum and the brainstem. The cerebrum is the area that mainly controls high-level functions such as complex thinking. The cerebrum is divided into 4 main lobes, each with a different function. The frontal lobe is responsible for problem-solving, emotions, movement, and speech. The parietal lobe is related to problem-solving, pain and taste. The temporal lobe is responsible for hearing and memory, and finally, the occipital lobe relates to visual processing tasks. In the clinical and research settings, a standardized position of electrodes is used where electrode placement uses 10% or 20% inter-electrode distance from standard skull landmarks, such as nasion-inion (anterior-posterior plane) and left-right preauricular points (lateral plane). Also, depending on the lobes that they correspond to, these positions are prefixed with: F (Frontal), P (Parietal), O (Occipital), and T (Temporal). Besides, there is the C (Central) point that is named after the central sulcus. These names are followed by a number (Odd numbers: left hemisphere and even numbers: right hemisphere) [10].

EEG is a non-invasive method for measuring the electrical activity of human brain neurons detected by electrodes placed on the scalp. EEG activity is discriminated into spontaneous EEG and evoked potentials (EPs). In the EPs, brain activity is associated with a specific event (psychological or physical) [11]. Steady-state visual evoked potentials (SSVEPs) and P300 are two well-known examples of EPs. SSVEP is the brain activity measured at the occipital lobe when a visual stimulus like a flashing light is repeating itself at a specific frequency. The P300 is a positive potential detected 300ms after an odd stimulus is presented among regular ones (oddball paradigm) [12]. When an event occurs there are small voltage differences in the EEG signal that can be extracted by repeating the stimulus in a precise time-locked manner and averaging all the trials. This technique is called Event-Related Potentials (ERPs) [11]. In this study, we focused on spontaneous EEG as this is more relative to grasping a user's mental state.

EEG recording is usually contaminated by a non-brain signal, called "artifact" which has a higher amplitude and a different shape than that of a normal brain signal. This contamination should be carefully handled for acquiring a reliable signal for further analysis. The artifacts are categorized into physiological and non-physiological. Physiological artifacts may be caused by the heart pulse, breathing, sweating, blinking or eye movements in general, by muscle contractions like movement in general or tongue movement, talking or chewing [13]. Non-physiological artifacts may be caused by power line noise, a low battery of the EEG device, electrode or wire movements, wire connectivity issues or shortages, excess quantity or drying of the paste or gel. Finally, using specific electrodes for detecting eye or muscle movement and cardiac pulse further helps detect these physiological artifacts.

A. EEG Processing Pipeline

EEG-based BCIs translate the brain signals to desired commands or classes (in our case, mental states). This is a complex and difficult task and in order to do so, the signal must first be processed and analyzed with the help of ML leveraging the following sub-tasks: EEG signal acquisition, preprocessing, feature extraction/selection, training and classification [10].

Through the EEG recording device enough labelled raw EEG data for all desirable classes (concentration, relaxation) are acquired (signal acquisition). Then, EEG signals' preprocessing removes power line noise and artifacts in order to increase signal quality. This is usually done with filtering, data segmentation, removal of bad segments or more advanced techniques [14]. Signal filtering is done by applying low-pass, high-pass, band-pass or band-stop filters to the signal. Low/high pass filters keep the signal below/above a certain frequency and attenuate the rest of the signal. Bandpass/bandstop filters keep/attenuate the signal in a specific range of frequencies [15]. The most common filtering scenario is to apply a filter to remove frequencies below 0.1 Hz and then a filter for power line noise at 50/60 Hz. Notice that the application of a single low-pass of 30Hz may not be enough to efficiently filter the power line noise [14].

Another part of preprocessing is data segmentation. Data segmentation is a standard procedure in ERP experiments due to their nature. The continuous EEG recording must be separated into small segments called windows that start with the stimulus onset [15]. The artifacts' detection can be accomplished manually (offline) or automatically (online) by the system with various techniques such as Independent Component Analysis (ICA), Principal Component Analysis, Canonical Correlation Analysis (CCA), regression or filtering methods, etc [16]. ICA, due to its simplicity, is the most preferable and can detect eye blinks or muscle movements [14].

Preprocessing is followed by the EEG features extraction and selection process to obtain the so-called feature vector. The features may be derived in frequency, time domain or time-frequency domain and must be selected wisely as more features will lead to computational complexity [17]. Power Spectral Density (PSD) is the most frequent and important EEG feature. PSD captures the power distribution of the signal in the frequency domain [18]. The EEG signals are classified into five categories based on the frequency bands: δ (0.5–4 Hz), θ (4–8 Hz), α (8–13 Hz), β (13–30 Hz), and γ (>30 Hz). These bands are mostly investigated by researchers and their dominance depends on the task at hand [19]. In [9], the authors noted α, β and γ as appropriate for classifying relaxation/concentration mental states.

Machine Learning constitutes a useful tool for EEG tasks as well to train efficient classifiers for decoding information from high-dimensional EEG data and learning the appropriate mental class from a feature vector (supervised learning) [14]. Naive Bayes, k-NN, Random Forest (RF) and Support Vector Machine (SVM) are candidate models [20] for predicting the user's mental state. RF performs better than other models with large data [20]. Also, it works well on smaller datasets, due to its robustness to overfitting. SVM is the most frequent due to its simplicity and high generalization.

III. The System description: its components and architecture

A prototype web system (classified as a passive BCI) was developed to simulate an e-learning environment where users attend online lectures and consume learning content in general. This system could be a Massive Open Online Course (MOOC) or a system used by schools or universities to support or substitute their lectures. The presented system was designed to adapt its functionality based on the user's mental state using Muse 2, a low-cost EEG device.

More specifically, a status functionality has been developed. This is commonly used in online communication systems such as Skype, Slack etc, and indicates whether a user is available. Usually, this status is changed explicitly by the user among several other states ("Online, Busy, Away" etc) or implicitly by the system when the user is idle ("Away"). However, the "Busy" indication is a status that cannot be changed implicitly. In the current system, the status of the user is automatically changed based on his/her mental state. The selected mental states are "Relaxing" and "Concentrating" which correspond to "Available" and "Busy" states. Besides, these mental states are more easily detected using the selected EEG device.

A. User Interface and Functionalities

First, the user should register an account (username and password) and then log into the system with these credentials. The web application offers the following links: "Introduction, Device Tutorial, Prepare Device, Signal Quality, Train, Predict and Attributions". Also, the following functionalities are available: "Notifications, Connectivity, Settings, Logout and Status".

Initially, the user is instructed to go through the "Introduction" and read the instructions that are presented there. From there, the system guides the user to the next steps. At the "Device Tutorial", a video on how to wear the Muse device is presented. Then, at the "Prepare Device", the user is asked to turn on the device, wear and pair it with the system. When this is done successfully, the user moves on to the "Signal Quality" step, where the user can test how good the signal is for each of the 4 electrodes of the EEG device. If the signal quality is sufficient for all electrodes, the user is prompted to move on to the "Training" and "Prediction" steps. Specifically, for "Prepare Device" and "Signal Quality", the user is suggested to ask for extra guidance on how to wear the device and check its signal because this is the most important factor of the system's success. However, if needed, the user can also ask for extra guidance at any step.

The training procedure is the most important part of the system. Two types of tasks are presented in an alternated order for 1 minute and each one is expected to induce a specific mental state, "Relaxing" or "Concentrating". During the relaxing task, a picture (nature photos mostly) is presented and the user is asked to relax with eyes open while listening to a soothing music track with no lyrics. During the concentrating task, two consecutive shapes are presented asking the user to count how many circles/squares/rectangles are contained in the given shape. There are 6 sessions for each type of task with a total training time of 12 minutes. The music and shapes differ from each other.

In the prediction step, the user is asked to select one type of task of his/her preference to induce the mental state and test it. For this reason, both types of tasks are presented on the screen. If the user chooses to follow the relaxing task, then he/she can ignore the shape and try to relax with the relaxing photo and music. If the user chooses to follow the concentrating task, then he/she can mute the music. There are 4 prediction sessions lasting 30 seconds each. When each session ends the user's mental state is estimated and presented on the screen based on a subject-specific training set. Then, the adaptation takes place, and the user status changes automatically ("Available" or "Busy"). Feedback from the user is asked to check whether the prediction was correct or not. At the same time, at the "Available" status, all system notifications are enabled and at the "Busy" status, notifications are disabled. When all 4 prediction sessions end, the user is prompted to repeat the prediction phase to better validate the predictions. Additionally, if an error occurs at the training or prediction step, then the user can repeat the current step instead of repeating the whole procedure. When the prediction phase is completed the system thanks the user for his/her participation and the evaluation questionnaire is given.

Finally, at the "Settings" functionality, the user can change the EEG device between a test device and two versions of the Muse 2 device. The first version of Muse uses native Bluetooth connectivity and the second one needs a BLED112 USB dongle for Bluetooth Smart/Bluetooth Low Energy communication. The second one was selected by default. The test device was used only for development purposes.

B. System Analysis

User Interface was created so that it is user-friendly and supportive for the user-student. Each step was strictly organized into small steps to make the user feel secure and comfortable. The connectivity functionality is responsible for informing the user if there is any connectivity issue (such as an EEG device pairing issue, backend communication issue, or eeg-client communication issue). Without it, the user can't complete the training step successfully if an error occurs that would frustrate the user. "Notifications" functionality was developed in order to notify the user (who is in the "Available" state) with 3 basic events: the user logging into the system and the completion of the training and prediction phases. Note that these notifications are disabled at the Busy status. The

"Status" functionality emulates the "Busy" and "Available" cases of communication applications like Skype or Slack. In an e-learning system, this indicates if the user is concentrated on his/her task (e.g., studying). As for the EEG device, the Muse 2 headband was selected since it is an easy-to-use and low-cost device. Also, its availability in Europe renders it a quite popular choice in the field of BCI and this also contributes to having a large community, libraries and supporting content on the internet for this topic. Also, even though Muse 2 was the only device tested, the system has the potential to work with approximately 20 other EEG devices as well with a small change in the code, using the "Settings" functionality.

Furthermore, the participants were asked not to minimize their eye blinking, even though it is an artifact; the blink rate is associated with tasks of different levels of difficulty, and this can be actually exploited to successfully classify relaxation and concentration mental states [7]. Also, they were instructed to have their eyes open to avoid distressing and, since, in a real environment, they would not close their eyes while navigating through the system. During the prediction phase, the two tasks are presented side by side with a splitter in between. This was implemented to be controllable by users allowing them to select the mental state they wish. Generally, only functional adaptations were made in this system in order to be easily noticed and evaluated by the user.

C. System Architecture

The system contains 3 main components: a backend (runs on the server), a web-client (compiles at the server and runs on the client) and an eeg-client (runs on the client). The backend component is responsible for the communication between other components, namely, for saving the raw EEG data to the Database (MySQL), predicting the user's mental state and returning it to the user. For establishing communication between servers and clients, it is used WebAPI, a classic uni-directional Application Programming Interface (API) [21] and WebSockets, a very fast bi-directional communication protocol [22]. WebAPI is used for operations like saving or retrieving EEG data and WebSockets for operations like checking EEG connectivity, returning asynchronous error messages from the EEG device, starting/stopping the recording of the EEG data and so on.

The web-client contains the user interface, text, images, music tracks etc. The EEG client is a Python script that the user should run on his/her personal computer to establish a communication channel between the EEG device and the backend. This is responsible for fetching and sending the raw data from the EEG device to the backend when it is asked for. The EEG data is obtained using BrainFlow [23], a Python library that can fetch, parse and even analyze EEG/EMG/ECG data from a list of available devices using a unified API. The database saves all information unencrypted, such as the user's id, username, password, and email. This information is needed for the authentication mechanism (user register/login). All system-supported EEG devices are saved under the device table. The device id is necessary so that the brain-flow library can accurately recognize and connect to the device. Also, the name and the sampling rate of the device are stored.

The available mental states are assigned an id $\in$ {-1,0,1} and saved in table form where each id corresponds to the "Unknown, Relaxed, or Concentrated" state, respectively. These records are useful for internal code organization. User's EEG data for training and prediction are saved into tables that keep information about the block id, a unique id that references the EEG block and brainflow_id, an integer that is used internally by the brain-flow library. Moreover, the raw EEG numeric values for each electrode (EEG channel) are captured in the fields electrode_1, electrode_2, electrode_3, and electrode_4 and the field classification_class describes the mental state (-1, 0, 1) that is to be classified. Also, brainflow_unix_time is recorded and captures the timestamp of the recording in Unix format.

Figures 1, 2 show how the different subsystems interact during training and prediction processes, while the web-based system interface is presented in Figure 3. In the training phase, the web-client sends a request to the backend using WebSockets ("eeg-start-training"). The backend transfers this command to the eeg-client so that the device can start recording the raw EEG data and the web-client presents the relaxing/concentrating task to the user. When the task is completed, a new WebSocket event is emitted from the web-client ("eeg-stop-training") to the backend and then to the eeg-client so that the EEG device can stop its recording and send the raw data back to the backend ("send-eeg-data") and eventually be saved to the database. In the prediction phase, a similar process is executed and finally, the web-client sends a new request to the backend to get the prediction. The backend estimates the mental state from the saved raw EEG data and returns the result to the user. The mental state algorithm exploits BrainFlow's functions to apply a bandpass filter between 7 and 59 Hz and a bandstop one between 48 and 52Hz to remove the line noise. The PSD feature [24] is elicited for each EEG channel using Welch's method with a hamming windowing function. Then, the relative band power of α, β, and γ is calculated with a 1 Hz bandwidth [9] and 50% overlap. Eventually, the Random Forest is used to predict the mental class.

IV. System Evaluation

The system was evaluated based on the User Experience (UX), one of the most valuable factors of a product's/system's quality. UX captures the user's emotional and psychological responses that result from the product's use [25]. For this evaluation, 10 users participated voluntarily and used the system that was deployed on a local computer. Users were not asked to control their sleep or avoid caffeine or alcohol consumption. For each user, an account was created. Before using the system, the users were informed about the system's purpose, adaptive e-learning systems, EEG, and the tasks that they should perform; No demo was provided. Also, they were helped with preparing, wearing and signal quality checks (the last one was the most important part of the system to ensure a

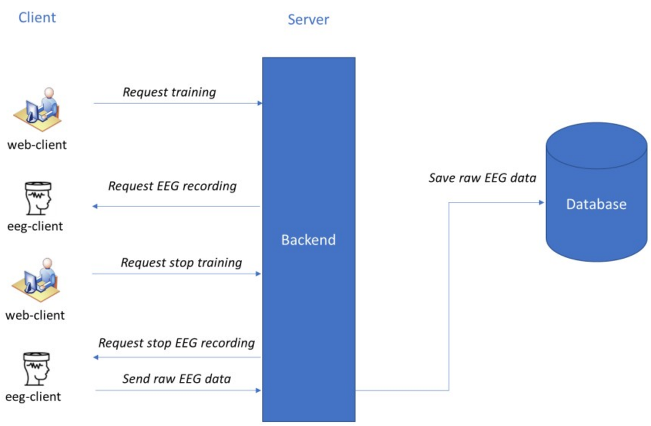

Fig. 1. Training flow.

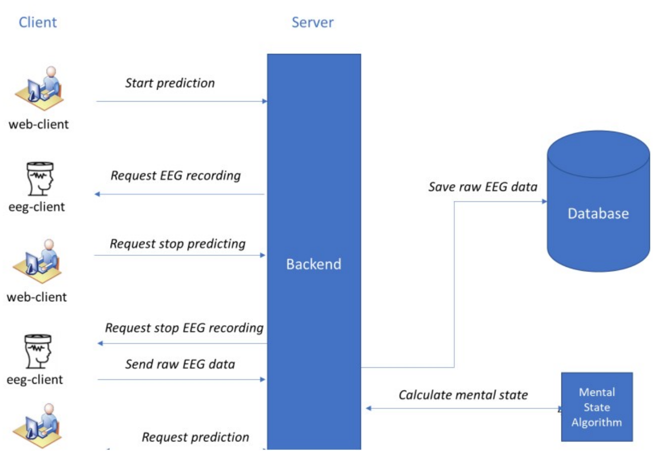

Fig. 2. Prediction flow.

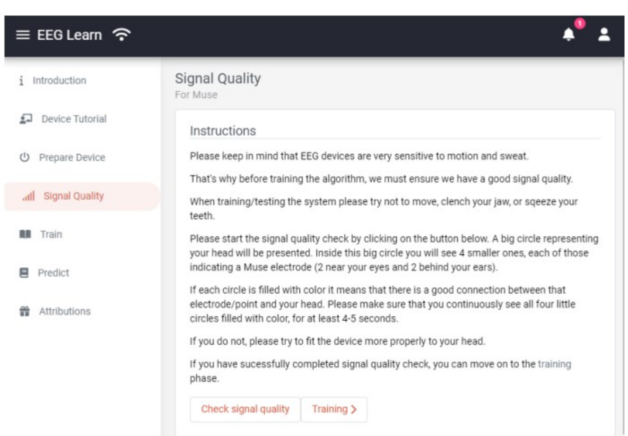

Fig. 3. User interface.

proper training and prediction phase). Furthermore, the users were asked to read the instructions – video, prepare and wear the EEG device, check its signal quality and finally, train and test the algorithm. When all tasks were completed, the user was asked to fill in a questionnaire

The first section of the questionnaire contained demographic questions such as age, gender, occupation etc. The second section included questions about the platform's functionalities to ensure that all aforementioned tasks were completed successfully. Finally, the third section contained the User Experience Questionnaire (UEQ), which is one of the most popular standardized questionnaires of UX [25]. It contains 26 questions in randomized order with 7-stage scales, starting from -3 (most negative) to +3 (most positive), with 0 being a neutral answer. It has good construct validity of scales and high-scale consistency [26]. UEQ measures UX in 6 different scales: Attractiveness, efficiency, perspicuity, dependability, stimulation, and novelty. Attractiveness is how pleasant the product is. Efficiency is how easily and fast the user accomplished the system's tasks. Perspicuity is how easy it is for the user to learn and understand the product. Dependability is how secure and predictable (in a positive sense) the product is felt. Stimulation is how interesting and motivating the product is. Finally, novelty is how creative and innovative the product is [26].

A. *User Experience Questionnaire Results*

The involved users spent ∼1 hour using and evaluating the system successfully. Six users were female and four were male. A bachelor's and master's degree had 70% and 30% of the users, correspondingly. Also, 30% of them had a degree in Computer Science, 20% of them had a medical-related degree, 20% of them had a degree in engineering, 10% of them had an education-related degree, 10% of them had a degree in economics, and 10% of them was in other area. Almost all users (90%) had a full-time job, and one user (10%) had retired. 80% of the users were married, and only 10% of them had children. All users were familiar with technology, and 80% of them were using wearable devices. Half of the users use e-learning platforms frequently, 30% of them not so frequently, while 20% of them have never used e-learning platforms. Besides, only 30% of the users were already familiar with the EEG concept. All users considered that the system instructions were complete (90% strongly agreed, 10% agreed).

All users agreed that they successfully checked signal quality (80% strongly agreed, 20% agreed) and completed the training and prediction phase (90% strongly agreed, 10% agreed). 40% of the users highly agreed that the predictions made by the system were accurate. 30% of the users simply agreed to that as well. 20% of them were neutral and 10% of them disagreed about the predictions' accuracy. Most of the users found that the adaptations of the system would be practical in a real environment (60% strongly agreed, 30% agreed), and 10% of them find them impractical. Most of the users found the EEG device comfortable (50% strongly agreed, 30% agreed) while 20% of the users disagreed. Finally, most of the users claimed that they would use a system like the one created in this study (40% strongly agreed, 40% agreed) and 20% of them were neutral about this.

All items received only positive responses on average. Attractiveness was the scale that received the highest score (2,66), followed by perspicuity (2,57), stimulation (2,45), efficiency (2,35), dependability (2,3), and novelty (2,17). These scales can also be grouped into pragmatic quality which is task-related (perspicuity, efficiency, dependability) and hedonic quality (stimulation, novelty). Based on these qualities, attractiveness scored 2,67, pragmatic quality was 2,41 and hedonic quality was 2,31.

V. Conclusions

In this study, an adaptive e-learning application was developed and evaluated. A popular and low-cost EEG device was used as it can implicitly grasp the user's current mental state and provide useful system adaptations that could support the user's learning. The system used an efficient, attractive, and friendly environment leading to an overall positive user experience. In the future, it is expected that the cost of EEG devices will be even lower. Also, with technology advancements, the EEG devices' limitations, such as synchronization issues when using multiple sources-devices and artifacts handling, could be optimally tackled, making the usage of such devices common and trivial. Adaptive e-learning systems with implicit adaptations that can make use of such devices are expected to provide a huge advantage to learners and support their learning by achieving as much personalization as possible.

Finally, in an extended version of the system, our aim is to take into account the cognitive style of the users (e.g., classifying them as Field-Dependent/Independent) [27] in order to further improve the system's adaption to the special cognitive profile of the user.

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