New Perspectives in e-Learning: EEG-Based Modelling of Human Cognition Individual Differences

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Abstract. Learning is the process of acquiring knowledge, skills and values, through lifelong education. Learning abilities are affected by the subject's cognitive skills showing how they think, process information, pay attention and remember things. The dynamic nature of a human's mental state usually impacts the aforementioned structural characteristics of human cognition, hindering learning performance as well. Nowadays, technological advances in Brain-Computer Interface (BCI) systems, in combination with advanced processing methods, have paved the way for the highly accurate capturing of human brain activity, helping to decode cognitive and mental status to adapt the learning process. This paper aims to present the first research outcomes of a study in progress. More specifically, the main proposition lies in extending the basic functionalities of our electroencephalography (EEG)-based e-learning prototype system to deliver personalized solutions by taking into account the individual cognitive differences of the learners. Some primary findings are showcased that investigate the potential association of cognitive style with the power spectral features of brain activity in a specific context where the subjects execute a visual task. It is anticipated that the real-time recognition of the learner's cognitive style will help educators adapt and advance the learning process.

Keywords: brain-computer interfaces · e-learning systems · EEG · cognitive style

1 Introduction

Several human cognitive theories and models [17] have been conceived determining internal fundamental mechanisms of human cognition when a subject interacts with the external environment in a specific context executing a task. Human cognition is multi-factorial and spans into elementary

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cognitive factors of the human mind such as the speed of processing, perception, attention and working memory capacity [4,23] and high-level cognitive factors such as cognitive styles (e.g., Verbal/Imager, Wholist/Analyst also known as Field-Dependent/Independent) [6,11,20], which suggest that individuals have differences in the way they process, analyze, comprehend, store and retrieve information.

The convoluted nature of human cognition unveils the importance of combining cognitive science with information technology, which has evolved so far separately [33], underscoring the interdisciplinary nature of the research. Besides, the recent advances in EEG-based sensing techniques of brain activity and low-cost recording devices, and Artificial Intelligence (AI) have further promoted and supported the development of intelligent and adaptive EEG-based applications [25] for several interfaces, such as mobile, augmented, virtual and mixed reality devices, [22,30]. It is expected that the synergy of cognitive science with AI will further promote the functionalities of existing and forthcoming information systems and smart devices by providing a multitude of computing capabilities and services leveraging EEG device(s) in various human-computer-interaction (HCI) scenarios [16].

Capitalizing on recent literature [8] on enhancing students' performance in e-learning, more than half of the studies employed eye-tracking devices focusing on eye movements and fewer works exploited (non-invasive) EEG for measuring brain activity. Integrating BCI systems with advanced processing methods is pivotal in educational technology. More specifically, by harnessing real-time brain activity data, educators can tailor learning experiences to individual cognitive styles, optimizing learning outcomes. Here, showcasing a forward-thinking approach to pedagogy, we aim to enhance our existing EEG-based prototype system by incorporating knowledge that could allow, in real-time, to consider the users' high-level cognitive factors e.g., cognitive style, and use this data as personalization and adaptation features.

The main contribution of this work is an analysis of raw EEG data processed to acquire spectral features to quantify high-level Field-Dependent (FD) and Field-Independent (FI) aspects of the human mind [28]. It is a work in progress. In the next period, this analysis will be further extended, helping to comprehend how we could make a personalized cognition-aware prototype system to provide new perspectives and opportunities in e-learning based on the learners' cognitive styles.

As per the structure of the paper, Sect. 2 presents background knowledge from an EEG perspective. Also, some key points of our EEG-based prototype system are mentioned in Sect. 3. In Sect. 4, some primary results are showcased by exploiting EEG data acquired in a visual task, to understand the association of individual differences (cognitive style) and brain signal frequency-domain features. Finally, Sect. 5 summarizes the current paper.

2 Background on EEG

The human brain area is divided into the cerebrum, cerebellum and brainstem. The cerebrum subarea mainly controls high-level functions (e.g., complex thinking) and is separated into four main lobes, each related to different functions. The frontal lobe is responsible for problem-solving, emotions, movement, and speech. The parietal lobe is also involved in problem-solving, pain and taste. The temporal lobe is responsible for hearing and memory, while the occipital lobe relates to visual processing tasks.

EEG is a non-invasive technique for capturing the brainiac activity detected by electrodes arranged to the scalp according to the standardized 10/20 international system. Each electrode is identified with the capital letters F (Frontal), P (Parietal), O (Occipital), T (Temporal) and C (Central) [29] corresponding to the brain lobe in which they are located followed by a number; odd numbers in the left hemisphere and even in the right one. For analyzing EEG biosignals activity, five frequency bands are mainly studied. In Table 1, a summary of EEG waves, frequency bands, brainiac regions and related activity is demonstrated.

Table 1. EEG waves properties [29,31]

Wave	Band Hz)	Lobe	Activity
$\boldsymbol{\delta}$	0.1–3	frontal (adults), posterior (children) wave of high amplitude	dreamless sleep, unconsciousness
$\boldsymbol{\theta}$	4–7	Fz to Cz (frontal midline)	idling, response reaction, dreaming, imagining, larger in meditative concentration, cognitive processes
$\boldsymbol{\alpha}$	8–12	both hemispheres, P, O, C at rest	relaxation, resting eyes closed, visual processing activity over the O
$\boldsymbol{\beta}$	13–29	F, P, O	resting state with eyes closed thinking, reception, transmission, processing, integration, concentration
$\boldsymbol{\gamma}$	30–100	somatosensory cortex region	two senses combined, object recognition, short memory matching.

EEG activity is classified into spontaneous EEG and evoked potentials (EPs). In the EPs, brain activity is associated with the event (psychological or physical) [15] and includes Steady-state visual evoked potentials (SSVEPs) and P300. SSVEP is measured at the occipital (O) lobe when a visual stimulus is repeating itself at a specific frequency. The P300 is a positive event-related potential detected 300ms after an odd stimulus is presented among regular ones [21]. In this study, we focused on spontaneous EEG as this is more relative to grasping a user's cognitive and mental state.

Non-brain signals, called artifacts usually corrupt the EEG signal data. Such signals are discerned from the brain source signals as they differ in shape and amplitude (higher). The contaminated brain signals should be properly cleaned to obtain a reliable signal for analysis. The artifacts are categorized into physiological and non-physiological [2]:

– Physiological: heart pulse, breathing, sweating, or eye movements (e.g. blinking), muscle contractions (such as movement in general or tongue movement), talking, chewing [14].
– Non-physiological: power line noise, electrode or wire movements, excess quantity or drying of the paste or gel.

Dedicated electrodes can detect eye movements and cardiac pulse; this helps detect these artifacts as independent signals without applying any processing technique for extracting them from the brain signals.

3 A Brief Overview of the EEG-Based Prototype

A prototype web system belonging to passive BCI was developed [2] to simulate an e-learning environment where learners attend online lectures or consume learning content and the users' mental state is monitored and captured in real-time using an EEG device. Such a system can be leveraged during Massive Open Online Courses (MOOCs) or used by schools or universities to support the learning process. A low-cost EEG device was used as it can implicitly grasp the user's current mental state to identify if the student is concentrated or relaxed.

In a learning environment, such a system could employ a different EEG device with different capabilities and therefore support the educational process by measuring, apart from concentration/relaxation, other aspects of the mental state such as the students' confusion level [27] during (online) lectures, attention levels, cognitive workload, etc., when students try to solve complex problems. Indeed, the latest advances in BCI systems and EEG-based signal sensing technologies and devices allow for gathering sufficient data to continuously monitor humans' mental and cognitive state [5].

The system has been designed and developed following the principles of cognitive science, EEG and signal processing. Our purpose is to enhance its functionality by making it adaptable to advanced cognitive traits of the human brain and, specifically, the users' differences - cognitive style when interacting with an interface for executing tasks [13] delivering personalized solutions.

In the following, we present two key subsystems, their functionalities and potential approaches for processing and modelling human cognition assuming objective EEG measures, thus developing a credible human cognition-centred system.

3.1 Preprocessing

Acquiring enough raw data through an EEG recording device (signal acquisition), signals' preprocessing [26] is applied to increase signals' quality by removing power line noise through appropriate filtering techniques, artifacts and/or bad segments [12].

Filtering: For EEG signals filtering, a band-pass filter was considered to keep data in specific frequency bands $\alpha, \beta, \gamma, \delta, \theta$ [19]. Also, notch filtering was deemed to remove power line noise at 50/60 Hz [12].

Artifacts Removal: The most common methods for artifact removal [10] are Canonical Correlation Analysis (CCA), Artifact Subspace Reconstruction (ASR) [1] and Independent Component Analysis (ICA) [3]. CCA is a statistical approach applied as a Blind Source Separation (BSS) technique that removes muscle contamination using EEG data recordings and a temporally delayed copy of them [9]. ASR is a real-time component-based technique for rejecting large-variance components. ICA is a time-efficient [24] and simple technique, and thus, the most preferable; it decouples mixed signals into their various components, and in EEG is used for separating brain data from "noisy" components, i.e. muscle and blink artifacts [12]. Currently, the system considers the ICA method for handling artifacts but we aim to incorporate more efficient methods.

3.2 Individual Differences Modelling Based on Power Spectral Density

Generally, the definition of a cognition model may be based on the extraction and selection of appropriate EEG features in the frequency domain, time domain or time-frequency domain [26,34]. Power Spectral Density (PSD) is the most frequent and important EEG feature. PSD captures the power distribution of the signal in the frequency domain [32] focusing on five basic frequency bands: δ (0.1–3 Hz), θ (4–7 Hz), α (8–12 Hz), β (13–29 Hz), and low γ (30–42 Hz). In clinical and research settings, these bands are associated with different mental and cognitive states; their dominance may differentiate among the four main lobes F, C, P, and O [31], and depends on the task at hand [7]. Therefore, the next section will focus on understanding whether PSD features can be used to capture the cognitive differences among individuals.

4 Data Analysis

To understand the mechanisms involved in capturing the activity of the human brain when a visual task is performed and to find out potential differences according to the cognitive style of each individual, we chose to experiment with a dataset obtained in the context of the Picture-Gesture Authentication task, that the subjects executed while their EEG signals were recorded. The subjects were undergraduate students from the polytechnic and the primary education departments. Their age was in the range of 21 to 27. Also, there were 2 males and 2 females. The brain activity throughout the execution of the task was captured by a BioSemi EEG recording device of 32 electrodes, placed according to the international 10–20 system, at a sampling frequency of 2048 Hz, with a 24-bit resolution. The recorded data was down-sampled to 512 Hz to reduce the data size.

Also, for the subjects, it was known in advance their cognitive style as they had executed the Group Embedded Figures Test (GEFT) [18], categorizing them as Field Dependent-Field Independent (FD-FI). A limitation of this data is the number of subjects; it consisted of only one FD and three FI subjects.

The acquired raw EEG signals of the subjects were processed offline (namely, preprocessing with Butterworth bandpass filter, powerline noise elimination with notch filtering at 50 Hz and the ICA method for artifacts handling (identification and removal). In the following, to extract the average band power feature, an FIR digital filter with a Kaiser window was designed for all interested frequency bands ($\delta, \theta, \alpha, \beta, \gamma$), and the average normalized power was estimated per spatial channel of brain areas. Figure 1 illustrates the key steps of EEG signal processing.

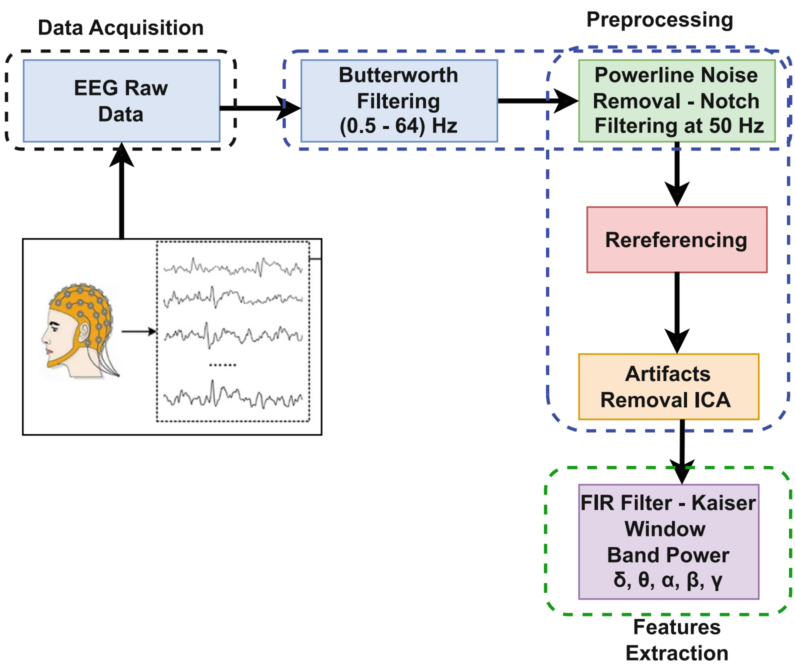

Fig. 1. Overview of EEG signals acquisition during the visual task, data preprocessing and features extraction.

Our analysis started with the hypothesis that there was a significant difference between FDs-FIs in the average power of EEG signals throughout the subjects' interaction with the application by trying to log in via a graphical password. In Tables 2, 3, we present the average values of the aforementioned feature of the channels located in frontal F(FP1, FP2, F7, F8, F3, F4, Fz), central C(FC1, FC2, FC5, FC6, C3, C4, Cz), parietal P(CP1, CP2, CP5, CP6, P7, P8, P3, P4, Pz) and occipital O(O1, O2, Oz, PO3, PO4) areas of the human scalp. In this activity, the participants tried to remember and apply the graphical password, so their activity was associated with the "login" phase of the application. The first results indicated small scale differences among FD-FI subjects which are reflected in the average power of the EEG time series data of the spatial channels. In particular, from the specific measurements, it was estimated that the average power of FI was approximately 1.3 times the average power of FD. Also, from our findings, it was observed that beta waves in the Optical and Parietal areas presented the highest average power. The outcomes are justified by the fact that beta waves in these areas are prominent during states of thinking, learning, concentration and problem-solving.

Table 2. Average normalized power at δ, θ, α and β, γ bands per cortical area F, C, P, O for FD.

	β	α	θ	δ	γ
Frontal	0.1973	0.1489	0.1349	0.1290	0.0644
Central	0.2718	0.1968	0.1770	0.1686	0.1047
Parietal	0.3346	0.2433	0.2190	0.2087	0.1246
Occipital	0.3443	0.2559	0.2311	0.2207	0.1133

Table 3. Average normalized power at $\gamma, \delta, \theta, \alpha$ and β bands per cortical area F, C, P, O for FIs.

	β	α	θ	δ	γ
Frontal	0.2555	0.1929	0.1748	0.1671	0.0837
Central	0.3531	0.2557	0.2300	0.2191	0.1359
Parietal	0.4348	0.3162	0.2846	0.2712	0.1623
Occipital	0.4470	0.3323	0.3002	0.2886	0.1469

5 Conclusions

In conclusion, in the context of this paper, motivated by the need to enhance students' cognitive performance in online learning, basic research concepts and principles for human cognition modelling with EEG are discussed. Cognitive

Psychology is the cornerstone for the conceptualization of a cognition-centered system while signal processing focuses on the elicitation of EEG features to quantify individual differences reflected in students' cognitive style. The findings presented in this study primarily have a qualitative nature; Although this primary investigation shows small differences in the average power of EEG signals between the FD and FI while executing the visual task, statistical analysis could not be performed with a limited number of subjects. Therefore, our prospects rely on performing inferential statistical analysis to validate hidden effects and identify crucial factors correlating individual differences with brain signal patterns. The first outcomes indicated that EEG is a candidate measure to quantify individual cognitive differences that could be used to train future e-learning systems to provide personalization. While there are challenges ahead, including the need for further validation and refinement of the proposed methods for concrete modelling of complex human cognition, the paper's insights have the potential to contribute to future developments in the field.

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