Using EEG Signal to Analyze IS Decision Making Cognitive Processes

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Abstract In this paper, we demonstrate how electroencephalograph (EEG) signals can be used to analyze people's mental states while engaging in cognitive processes during IS decision-making. We design an experiment in which participants are required to complete several cognitive tasks with various cognitive demands and under various stress levels. We collect their EEG signals as they perform the tasks and analyze those signals to infer their mental state (e.g., relaxation level and stress level) based on their EEG signal power.

Keywords EEG · Decision making · Signal processing · Cognitive process

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1 Introduction

In this paper, we investigate the properties of EEG signals when people engage in cognitive processes during Information Systems (IS) decision-making. Decision-making is fundamental to most human behaviors [1], and can be classified into four categories: intuitive, empirical, heuristic and rational. Among them, rational decision-making is more easily defined and explained with cognitive psychology, and will be the focus of this paper. Rational decision-making is a method where the brain develops a criterion of functions representing potential choices and processing available information to find the good choice among others [1]. The two subcategories for rational decisions are static and dynamic. Static decisions are made based on statistically viable information such as loss and gain, cost–benefit, practicality and functionality. Dynamic decisions are based on alternatives, present situation and past knowledge of similar situations. In this paper, we focus on the EEG signals analysis of rational decision-making.

This paper discusses how rational decision-making can be analyzed with help from EEG (electroencephalogram) signal power variance generated by humans who are making those decisions. EEG has been traditionally used as a diagnostic application for diseases such as Epilepsy [2], and more recently has become a popular tool for NeuroIS studies (e.g., [3, 4]), and decision-making research (e.g., [5, 6]). In this paper, we measure and analyze the EEG signals from decision makers in an experimental setting, and investigate what the EEG signals can tell us about those decision-makers' behaviors.

The human brain releases EEG signals in various frequency bands, usually categorized into five bands: Alpha (8–13 Hz), Beta (14–31 Hz), Delta (4 Hz or less), Gamma (greater than 32 Hz) and Theta (4–7.5 Hz). Among them, Alpha, Beta, Delta and Theta are most widely used for EEG signal analysis, especially for various cognitive functions. These will also be the EEG signals we focus on in this paper.

Neuroscience literature has established the various and distinct roles for each of these EEG signal bands in human cognitive functions [7]. It has been shown in studies that in subjects who are awake, Delta waves can relate to cognitive concentration. Several experiments have demonstrated that there is a clear relation between cognitive concentration and increased activity in the Delta frequency band [8]. Theta is an indicator of stress. The study presented in [9] shows that EEG Theta/Beta ratio as a potential biomarker for effects of stress on attention. The study confirmed a negative relation between Theta/Beta ratio and stress-induced attentional control [9]. Statistical analyses in literature have also shown a positive relationship between stress and theta power spectrum density value [10]. Beta waves are associated with cognitive processing. Activity in this frequency band will increase when there is cognitive challenge and increased demand for a cognitive task [11]. According to [12], increasing Beta activity has been identified with high concentration and attention. Alpha waves are well known for their correlation with a relaxed state. During a resting period, the Alpha frequency band is seen to have maximum magnitude. The magnitude of Alpha waves is higher when eyes are closed compared to when eyes are open [11]. According to [13] decreasing Alpha activity is consistent with higher cognitive demand in decision making. In addition, cognitive activity typically suppresses alpha and elevates beta activity [14], and frontal theta signal may serve as an index for mental effort [14, 15].

We conduct an experiment in which participants are asked to perform tasks of various levels of cognitive processing (data entry vs. application programming) under various levels of stress (no time limit for the task vs. with time limit). Through the analysis of the processed EEG signals from the participants, we replicate the results that Alpha band signal power is higher when the task requires lower cognitive demands, and Theta band signal power is higher when the task involves higher stress. Surprisingly, our data also indicate that when performing a high-cognitive-demand task, the participants' Alpha signal power is higher when the stress level is higher. We look into the experiment design and propose some possible explanations for this surprising observation.

The rest of the paper is organized as follows: in Sect. 2, we discuss the experiment design and signal processing techniques, followed by data analyses and discussion in Sect. 3. We conclude in Sect. 4.

2 Experiment

2.1 Method

We recruited 25 participants to participate in our experiments; 15 were male and the other 10 were female. All participants were between the ages of 18 and 34 years old and were graduate or undergraduate students in the Department of Computer Science and Engineering in University of North Texas. The EEG recordings of 5 of the participants are incomplete and for this research we used the EEG signals from the other 20 participants. Participants were asked to perform 6 tasks in total. EEG signals generated from four of the tasks are used in this study (the other two tasks are not relevant to our research questions). For Task 1 participants were asked to perform data entry (login to a database system and update the student records using the information provided). Task 2 was a similar data entry task (update the same student information but with twice the number of student records) but with a time limit. Task 3 was to perform a computer programming exercise (complete a coding project for designing a calculator, using a language they felt most comfortable with) and Task 4 was a similar programming exercise (complete the same calculator application but using a different language) with a time limit. All four tasks are typical representatives for IS activities that require rational cognitive decision making in completing those tasks. The experiments were conducted in a dedicated EEG laboratory, and the room was set up to keep the same environmental conditions for all tasks and all participants. The experiments were conducted for each participant separately and at different times during the day. The participants were seated in a comfortable chair. After the relevant areas on the face and mastoids were cleaned, the Geodesic Sensor Net (GSN) was positioned on the participant's head. The examiner checked for signal impedances, applying additional saline solution and readjusting sensors as needed to ensure minimal impedance and optimal signal quality between each electrode and the participant's scalp. The examiner then explains the task and what the participant had to do step-by-step using a predefined script located on the computer desktop. The participants were given five minutes to read the script before each task and to feel comfortable with the test environment.

The second and fourth tasks were conducted at the end of the work day, so that the participants would have attended classes, exams or labs during the day prior to coming to participate in the experiment. And the experiment was time constrained to induce further stress among the participants.

To measure the participants' brain activities, we used EGI's Geodesic EEG System 400 [16], with a 256-channel HydroCel GSN. We used a sampling rate of 1000 Hz. The device has been widely adopted by the clinical and research community because of its ease of use, comfort, and ability to produce high-quality and high-resolution data.

2.2 EEG Recording

EEG recordings from all sensors were used for analysis. Signal analysis was performed in LabVIEW. Recordings were analyzed in 100 s segments. Recordings were processed to remove artifacts from muscle movements such as eye blinks. A fast Fourier transform using hamming window with 50% overlap was used. A digitized version of an analog signal is an approximation of the analog signal. This signal analysis platform designed in LabVIEW decomposes the signal into the approximated frequency component of the original signal. However, EEG is not a stationary signal. During analysis the components change in frequency and amplitude at every window as transient waveforms appear intermittently. Choosing short window duration minimizes the effect of being non-stationary and generates a smoother PSD plot [16]. In this case a window length of 1024 was used. The overlap in this design is set to 50% which is half the window length. This means each sample will make equal impact on the spectrum. The design was verified with simulated EEG to confirm that design input meets design output. For verification testing, 100 s of simulated EEG recording was used at 1000 Hz sampling rate. For experimental recordings, signal power in frequency band activity of Delta (0.5–4 Hz), Theta (4–7.5 Hz), Alpha (8–13 Hz) and Beta (14–26 Hz) were calculated. Mean signal power of each frequency band for each recording (for each task, for each participant) was computed. Ratios of these mean signal power values across tasks were used for data analysis to draw conclusions.

2.3 Workflow of the Design

Each EEG recording is uploaded into Read Biosignal VI in LabVIEW. The entire design is placed inside a single while loop. This tool reads bio-signals block by block. The block sizes are in seconds and they can vary depending on the length of the EEG recording. In this case, the block size is set to 100 s. The loop stop condition is wired with the End of File (EOF) terminal of the block. The loop stops when it reaches the end of the uploaded EEG recording. The signal powers and percentages are calculated for each loop and saved in the respective arrays for Alpha, Beta, Theta and Delta. Each additional loop adds a new calculated value to the array for the subsequent 100 s of recording until the end of the recording. The mean values are calculated as the loops are iterated and the final mean values reflect results for the entire recording. EEG FFT Spectrum VI is used to separate the frequency bands (Alpha, Beta, Delta and Theta) from the raw signal. This VI computes the single-sided power spectral density (PSD). The time series is then divided into overlapping subcategories of signal elements. Periodograms of these subcategories are then averaged to plot the PSD. For this design the VI returns the PSD values in linear scale. Frequency bands for EEG are defined in the VI to be extracted accordingly. An unbundling function is used to extract the elements. It obtains the FFT spectrum as a cluster and creates terminals for respective frequency bands for the measured value to be used independently. The signal power value returned is the absolute value of power in each frequency band. The percentage of each frequency band shows the distribution of power in respective frequency bands. Signal power and percentage values for each iteration are saved in an *n*-dimensional array. Each time the while loop runs and a new value results from EEG FFT Spectrum VI, this function enters the value into its respective array. The feedback node attached to its output to input stores data from one iteration to another. Therefore, at the end of the final loop the array contains values from all iterations. This array is an input to the Mean VI which then takes the values from all iterations in consideration in order to compute the final mean value. The signal power mean values and power distribution percentages are then recorded in a data sheet for all the frequency bands for further analysis.

3 Results and Analyses

3.1 The Impact of Cognitive Demand and Stress Level

To investigate the impact of the tasks' cognitive demand on brain signal power, we calculate the Alpha/Beta ratio generated from the four tasks. We then perform a paired *t*-test comparing the ratio for the data entry task vis-à-vis the ratio for the application programming task. When the tasks are performed without a time limit, the Alpha/Beta ratio is shown to be significantly higher for the data entry task than

Table 1 The paired *t*-test result for Alpha/Beta ratio between data entry and programming tasks without time constraints and with time constraint

Pair 1a	Mean	Std. Dev.	*t*	df	Sig.
A/B: data entry—programming (without time limit)	0.24520	0.41985	2.612	19	0.017
Pair 1b	**Mean**	**Std. Dev.**	***t***	**df**	**Sig.**
A/B: data entry—programming (with time limit)	−0.15576	0.63030	−1.119	19	0.277

for the application programming task (see Pair 1a in Table 1). When the tasks are performed with time limit, the ratio difference is not significant between the two tasks (see Pair 1b in Table 1).

These results are aligned with the literature that Alpha signals are positively related to relaxation. While engaging in a more cognitive demanding task, people tend to be less relaxed, thus generating lower levels of Alpha signals. The lack of statistical significance in the results from the time-constrained tasks seems to suggest that the relaxation state is quite vulnerable to stress level.

To investigate the impact of stress level on the brain signal power, we calculate the Theta/Beta ratio generated from the four tasks. We then perform a paired *t*-test between the ratio when performing low stress tasks (in this case, the tasks with no time constraint) vis-à-vis the ratio when performing high stress tasks (in this case, the tasks with time limit). When the participants perform the application programming task, their Theta/Beta ratio is shown to be significantly higher under time constraint compared to without time constraint (see Pair 2a in Table 2). When they perform the data entry task, the ratio difference is not significant (see Pair 2b in Table 2).

These results are aligned with the literature that Theta signals are positively related to stress level. While engaging in cognitive tasks with time constraints when the participants are mentally/physically tired, they tend to experience higher stress levels compared to engaging in tasks with no time constraints and when they are relatively fresh, thus the participants generate higher levels of Theta signals. The lack of statistical significance in the results from the data entry tasks seems to

Table 2 The paired *t*-test result for Theta/Beta ratio between tasks without time constraint versus with time constraint

Pair 2a	Mean	Std. Dev.	*t*	df	Sig.
T/B: no time limit—time limit (programming task)	−1.49532	2.63847	−2.535	19	0.020
Pair 2b	**Mean**	**Std. Dev.**	***t***	**df**	**Sig.**
T/B: no time limit—time limit (data entry task)	0.36237	1.98533	0.816	19	0.424

Table 3 The paired *t*-test result for Alpha/Beta ratio between programming tasks without time constraint versus with time constraint

Pair 3	Mean	Std. Dev.	*t*	df	Sig.
A/B: no time limit—time limit (programming task)	−0.33655	0.64671	−2.327	19	0.031

suggest that the low cognitive demand of the task may override the impacts from the stress level induced by the time constraints.

One surprising result we obtain while comparing the Alpha/Beta ratio is that when performing the programming task, the participants show significantly higher Alpha/Beta ratio when there is a time constraint versus when there is no time constraint (see Table 3).

This seems to suggest that for the programming task, the participants are more relaxed (higher Alpha/Beta ratio) when there is a time constraint than when there is no time constraint. One possible explanation to this counter-intuitive result is that in our experiment, all participants are computer science students, who may be well versed in creating applications in various programming languages. Thus the required task (creating a calculator application) is an easy task for the participants. Therefore, the time constraint did not impede their relaxation level. In addition, in our experiment design, their time-constrained task is after their no-time-constrained task, and they are the same task except that they need to use another programming language in the time-constrained task, thus they are already familiar with the task requirements, and as a result, they show a higher relaxation level for the second implementation (the time-constrained task), perhaps their familiarity with the task overrides the impact of their lower familiarity with the programming language.

4 Conclusion

In this paper, we demonstrate how EEG signals can be used to analyze people's mental states while engaging in cognitive processes during decision making. We design an experiment in which participants are required to complete several cognitive tasks with various cognitive demands and under various stress levels. We collect their EEG signals during their task performance and analyze the signal to infer their mental state such as relaxation level and stress level based on their EEG signal power. We find that when people engage in decision-making cognitive process, higher cognitive demand from the decision-making processes results in lower Alpha/Beta signal ratio, which indicates a lower level of relaxation; and higher stress level usually results in a higher Theta/Beta ratio. For future work, we plan to refine our experiment and conduct cross-factor analyses of the impacts of various factors that influence brain signals during decision-making cognitive processes.

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