Understand and characterize mental effort in a programming-oriented task

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Abstract—**The human brain is a very complex physiological system, involving billions of interacting physiological and chemical processes giving rise to the experimentally observed neuroelectrical activity measured through electroencephalographic signals (EEG). An EEG can reflect the state of mind and the human brain activity. The aim of this research was to analyze several important cognitive parameters (Attention, Meditation) using the Neurosky Mindwave Mobile Headset and EEG analyzer application, while students performed a programming problem-solving oriented task. The variability of Theta and Beta bands energy during the tasks was studied to understand its relation to the cognitive parameters. Our results suggest that beta frequency energy increased when the tasks demanded a higher level of reasoning, when a change in the task paradigm happened, when participants showed more difficulties or when they needed more time to complete tasks (Attention). On the other hand, a high level of energy in theta band was found in states of drowsiness and deep relaxation (Meditation).**

I. Introduction

Brain Computer Interfaces (BCI) are direct functional interactions between a human brain and an external device. BCI have recently gained a new interest in several areas such as Human Machine Interface or educational contexts. BCI measure the brain activity of a user and then identifies his/her thought pattern or desired action. Brain activity is measured by detecting minute voltage changes in specific areas of the brain. A new and emergent field in an educational context is the use of technology to better understand and promote learning processes. While traditional BCI devices allow a user to communicate or control a computer using only brain activity [1], [2], more recently these devices have also been used to extract information about the user and to infer his/her mental states (e.g. workload, attention) [3]. BCI devices and software collect and analyze user's electroencephalogram signals (EEG). These may be used in various fields of research, such as assistive technologies[4], video games [5], neurofeedback [6] and cognitive processes [7].

Increasingly, there is an interest in understanding the performance of users in tasks involving high cognitive processes. The goal is to find metrics and strategies that are adaptable to each user, looking to increase success in learning. For successful learning it is crucial to keep the participant's cognitive workload in his/her optimal range [2]. This can be achieved by adapting the difficulty of the learning activities to the individual competencies. Nowadays, it is known in more detail which brain areas are active when an individual recognizes stimuli, prepares and executes movements of the body or learns and memorizes things. As BCIs can be used to measure cognitive processes, a more direct and implicit monitoring of the learner's state is possible and should thereby allow a better adaptation of the training content to improve the user learning success. This work provides an overview of how brain computer interaction can intersect with issues in the field of education, namely in design and cognitive attention processes. It explores how the process of designing, which is a fundamental component of Human Computer Interaction (HCI), is important to maintain high levels of focused attention. Studies about the understanding of features that optimize the attention and the workload of the user in learning tasks can potentiate educational applications. Some studies describe the sensitivity of EEG changes with respect to mental effort. In the literature there is a strong evidence of evoked theta activity (4-8 Hz) during paradigms that involve focused attention [8]. EEG activity in theta band and low-beta (13-15 Hz) over the frontal midline regions of the scalp have been observed when there is demand of executive control [9]. Otherwise in [10] the authors concluded that theta value decreases with increase mental arithmetic load namely in frontal and prefrontal channels. However the results could be different according to the used device [11]. Next sections describing and discussing the experiments done following this researching line.

II. The Study

The main goal of the study was to analyze important cognitive parameters (Attention and Meditation), while students were engaged in a programming problem-solving oriented task activity. Additionally, three EEG features were extracted namely the powers of Theta, Alpha and Beta bands and the variability of these bands' energy was analyzed and compared with the parameters obtained by the device. The time spending during the experiments and its correlation with the frequency bands were also studied.

A. Device and software application

In this sudy it was used Mindwave device [14]. Some studies, such as [12], [13] use this device to study the attention parameter and its influence during the learning process. The easy access to Mindwave devices can open new research lines in different areas, like game design, but also in the understanding of the cognitive behavior of human beings during learning. This simple and affordable device, consists of two electrodes, one for EEG dataset records (Fp1 channel), another for reference signals (the ear clip) [14], Figure 1. Sample rates as high as 512 Hz deliver raw signals in the Alpha, Beta, Delta, Gamma, and Theta bands. The Mindwave EEG sensor processes the brainwave into digital signals and uses the eSense algorithm to compute user's engaging attention and meditation. The eegID application was used [15] connecting to the Mindwave device via Bluetooth allowing the visualization and recording of specific data, namely PoorSignal, EEG raw data, Attention level, Meditation level, Blinking, Delta (1-3 Hz), Theta (4-7 Hz), Alpha Low (8-9 Hz), Alpha High (10-12 Hz), Beta Low (13-17 Hz), Beta High (18-30 Hz), Gamma Low (31-40 Hz) and Gamma Mid (41-50 Hz), Figure 2. Based on the literature framework, in this study only Theta and Beta_Low were used.

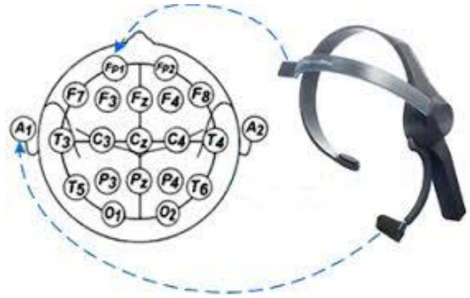

Figure 1 Mindwave and EEG acquisition

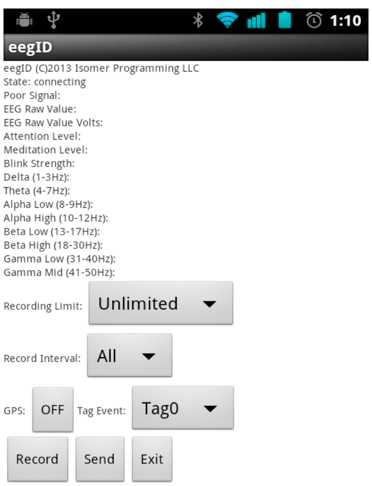

Figure 2 eegID application, [15]

B. Dataset

The study group included 30 students enrolled in the 2nd year of the Informatics Engineering Degree, aged between 18 and 50 years, with an average of 22.3 +/- 5.7 years, mostly male (98%). They participated in this study voluntarily. These students had already some programming bases developed during the previous year. The students were asked to play a classic Labyrinth - Angry Birds (Code) game - consisting of 20 levels whose difficulty gradually increases [16].

C. The Game

The goal of the Angy Birds game is to join 2 objects, using blocks of available code. Throughout the game different blocks are made available, as shown in Figure 3. At certain levels the paradigm shifts with the introduction of new elements.

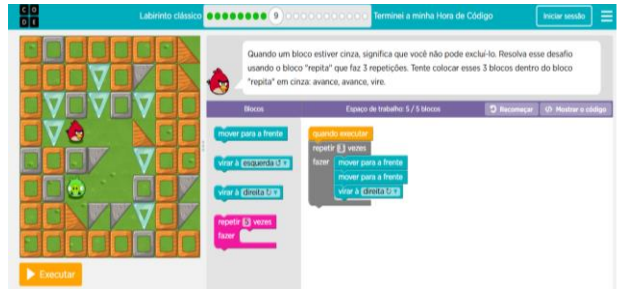

Figure 3 Angry Birds Game, [16]

To better understand the dataset, a summary description of the levels was made:

- Levels 1 through 5 are all of low difficulty consisting of sequential instructions. The 1st and 2nd levels only require "move forward" instructions. However, from level 3 to 5, moving instructions are required to the left or right, with a slight increase in difficulty as the level rises.
- At level 9 the degree of difficulty increases with the introduction of a loop that cannot be removed from the code, that is, it must be used and it is not possible to change the number of repetitions.
- At level 10, although the degree of difficulty is not considered greater, compared to the previous one, there is the introduction of a new type of loop (do ... while). Level 12, despite a slight increase in difficulty compared to levels 10 and 11, includes a "sudden" change of scenery and structuring elements, and the board divisions are not immediately perceptible, causing confusion in the number of times the element has to move. Level 13 is similar to the previous one.

D. Protocol Acquisition

The dataset acquisition is divided into three steps, as shown in Figure 4. First (1^{st}) and Last (3^{rd}) Step - To have an evaluation of the mental workload before and after playing the game (3 minutes + 3 minutes). Game (2^{nd}) Step- To have an evaluation of the mental workload during the game. (maximum 10 minutes).

Figure 4 Protocol acquisition: 1^{st}, 2^{nd} and 3^{rd} step description.

For control of the dataset, we collected each student EEG signal for 3 minutes in his/her normal or relaxation state, before starting to play the game. After 3 minutes, the participants started to play the game during a maximum of 10 minutes, trying to pass as many levels as possible. The time spent in each level was saved as well as the EEG signal and the energies of the signal in several frequency bands. Note that the frequency energy is computed as an average considering a window of 10 msec of the signal. After the game was over, the EEG signal was collected again for 3 minutes, in order to characterize the state of the participants after playing the game.

III. Results and Discussion

A. *Time and Participants Score*

In this study the performance evaluation of participants reflects the level reached during the game phase truncated temporarily by 10 minutes.
Table 1 shows the number of participants that reached each of the levels considered in the game (20 levels). Note that all participants reached level 9.

Table 1 Number of participants who achieved each level

Level	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
# Ind	27	25	18	15	9	5	3	1	0	0	0

The mean time that each participant spent at each level, as well as the average energy of the bands at each level differs per participant, figure 5. The highest values, levels 9 and 12, are related to the levels where there is the introduction of a new block or paradigm.

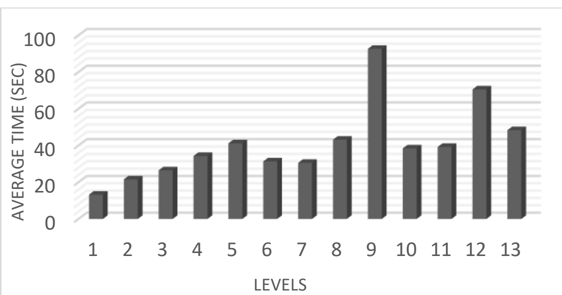

Figure 5 Average Time in each level of the game (level 1 to level 13).

B. *Attention and Meditation Values*

Meditation and Attention were two parameters measured by the device in this work, during the three phases of the EEG acquisition.
The Meditation meter indicates the level of a user's mental “calmness” or “relaxation” and the Attention meter indicates the intensity of a user's level of mental “focus” or “attention”, such as what occurs during intense meditation and directed (but stable) mental activity.
Figure 6 shows the average of Attention and Meditation values of all participants during the three steps of this experimental procedure: first step, game step (1-9 level) and last step.

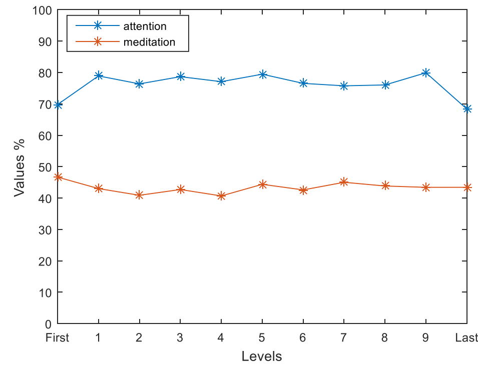

Figure 6 Average of Attention and Meditation values considering the three steps of the EEG acquisition protocol: First Step; Game (1-9 level) and Last Step.

The level of Attention is always higher than 70%, reaching higher values during the game. Here we highlight the level 9 with the highest value of Attention. In regards to Meditation, the values are all less than 50% revealing that the participants in all phases of the experimental process were not relaxed. Note that the attention level decreases in first and last step, when the participants are not play the game. The deviation of attention and meditation values for each level are in the next table. By the Table 2 we can see that the values variability of the meditation (Med.) levels is higher than the attention (Att.) values.

Table 2 Standard deviation of the meditation and attention values for all participants considering the dataset represented in Figure 6.

Steps		**1st**	**1**	**2**	**3 4**	**5**	**6**	**7**	**8**	**9**	**3rd**
Att.	2,4	2,3	2	1,5	2	0,6	0,9	0,6	1,2	0,6	1,8
Med.	8,7	9,5	8,7	6,7	6,6	7,1	7,3	6	5,9	4,5	4,7

C. *Frequency analysis: Theta and Beta Bands*

For a better interpretation of the values of Attention and Meditation measured by the device, Theta and Beta frequency energy were also analyzed, Figure 7.

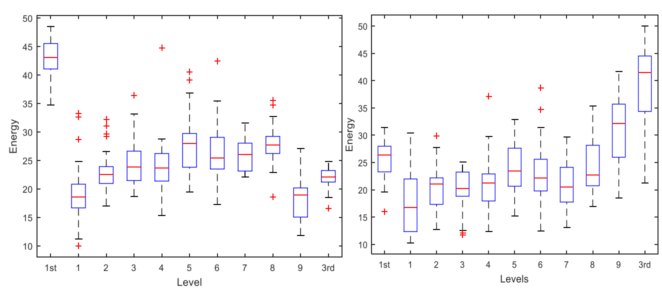

Figure 7 Average of Theta (left) and Beta (right) Energy (psd)

Being Theta waves are directly related to the state of drowsiness and deep relaxation, it is possible to verify a high energy of these waves in the initial moment, Figure 7 (left graphic), concluding that the participants were calm before the task. In contrast, the levels of this band decreased abruptly during the game and after the game, suggesting that they undergo an activity in which their ability to solve problems is tested causing a state of tension.

Concerning Beta waves, the values of this band were consistent throughout the game, however the levels 5 and 9 stood out with higher values. As described in the literature the beta waves are associated with states of tension and anxiety intensification and the increase of these waves promotes creativity and problem solving.

To note that in initial step (1st), theta waves have a high energy and beta waves presents a low energy. The opposite happens in the last step (3rd). These means that the participants were relaxed in the beginning of the activity and more tense (due to the workload) in the last.

D. Correlations

Considering the 30 participants, the correlation of each energy band with the time spent per level was calculated. From Figure 8 we can see that there is a significant variation of the values in the high energy bands, with a slight variation for the Delta, Theta and Alpha low bands.

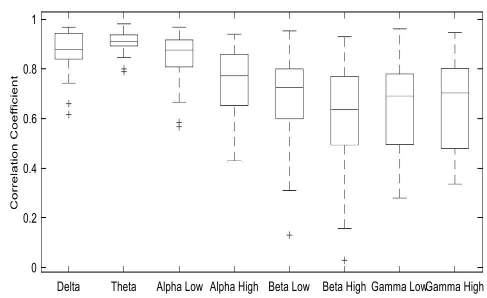

Figure 8 Correlation Coefficient values between all frequency bands and the time spent in each level, considering the 30 participants.

In the analysis of the correlation values with time, the Theta and Alpha Low waves stand out with values above 0.8. In this way, it was observed that the longer the time spent in solving a given level, the higher the energy load of these two bands, meaning a higher cognitive load.

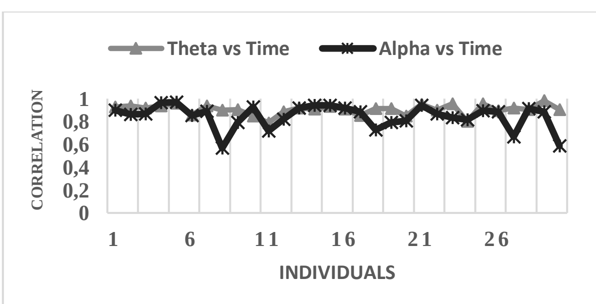

Figure 9 Correlation coefficient between the average of bands energy (theta and alpha low) and the time dispended in each level

In order to understand the dynamics among the 30 participants, the correlations between Theta and Alpha bands and the time spent at each level was calculated for each participant, Figure 9. The values are close to 1, with a higher correlation for the Theta and Alpha bands.

IV. Conclusions

From the results analysis it was possible to conclude that there was an increase in frequency Beta energy when the tasks demanded a higher level of reasoning and recourse to previous knowledge, but also when a change in the game paradigm happened. We also verified that the values were closer in the levels where the participants showed more difficulties and needed more time to complete the activity. We could also conclude that when the time required to solve a task was high, there was also a high energy load of the Beta bands, which means, a higher cognitive load. Although much work still needs to be done, there is evidence of a relation between the attention and the meditation levels and the energy of several bands in cognitive demanding tasks.

References

[1] L. F. Nicolas-Alonso and J. Gomez-Gil, "Brain computer interfaces, a review.," *Sensors (Basel).*, vol. 12, no. 2, pp. 1211–79, 2012.

[2] P. Gerjets, K. Scheiter, and G. Cierniak, "The Scientific Value of Cognitive Load Theory: A Research Agenda Based on the Structuralist View of Theories," *Educ. Psychol. Rev.*, vol. 21, no. 1, pp. 43–54, Mar. 2009.

[3] M. Spüler, T. Krumpe, C. Walter, C. Scharinger, W. Rosenstiel, and P. Gerjets, "Brain-Computer Interfaces for Educational Applications," in *Informational Environments*, Cham: Springer International Publishing, 2017, pp. 177–201.

[4] J. D. R. Millán *et al.*, "Combining Brain-Computer Interfaces and Assistive Technologies: State-of-the-Art and Challenges.," *Front. Neurosci.*, vol. 4, 2010.

[5] M. Ahn, M. Lee, J. Choi, and S. C. Jun, "A review of brain-computer interface games and an opinion survey from researchers, developers and users.," *Sensors (Basel).*, vol. 14, no. 8, pp. 14601–33, Aug. 2014.

[6] D. C. Hammond, "What Is Neurofeedback?," *J. Neurother.*, vol. 10, no. 4, pp. 25–36, 2007.

[7] L. Carelli *et al.*, "Brain-Computer Interface for Clinical Purposes: Cognitive Assessment and Rehabilitation," *Biomed Res. Int.*, vol. 2017, pp. 1–11, Aug. 2017.

[8] P. Luu, D. M. Tucker, and S. Makeig, "Frontal midline theta and the error-related negativity: neurophysiological mechanisms of action regulation," *Clin. Neurophysiol.*, vol. 115, no. 8, pp. 1821–1835, 2004.

[9] J. Onton, A. Delorme, and S. Makeig, "Frontal midline EEG dynamics during working memory," *Neuroimage*, vol. 27, no. 2, pp. 341–356, Aug. 2005.

[10] Li Huo, Zhihua Chen, and Wei Zheng, "Relationship research between mental workload and theta wave based on approximate entropy analysis," in *2012 IEEE International Conference on Oxide Materials for Electronic Engineering (OMEE)*, 2012, pp. 799–801.

[11] W. K. Y. So, S. W. H. Wong, J. N. Mak, and R. H. M. Chan, "An evaluation of mental workload with frontal EEG.," *PLoS One*, vol. 12, no. 4, p. e0174949, 2017.

[12] R. L. Vast, R. L. Young, and P. R. Thomas, "Emotions in sport: Perceived effects on attention, concentration, and performance," *Aust. Psychol.*, vol. 45, no. 2, pp. 132–140, Jun. 2010.

[13] G. U. Navalyal and R. D. Gavas, "A dynamic attention assessment and enhancement tool using computer graphics," *Human-centric Comput. Inf. Sci.*, vol. 4, no. 1, p. 11, Dec. 2014.

[14] Neurosky Mindwave User Guide, "Neurosky Mindwave User Guide," 2018.

[15] "eegID." [Online]. Available: https://store.neurosky.com/products/eegid. [Accessed: 30-Jan-2019].

[16] "Code.org - Labirinto clássico." [Online]. Available: https://studio.code.org/hoc/1. [Accessed: 30-Jan-2019].