An Exploratory Study of Brain Computer Interfaces in Computer Science Education

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*Abstract***— This work offers an outline of how brain computer interactions can interconnect with education, specifically with regard to the cognitive and emotional processes occurring during difficult learning. We believe that understanding how to optimize the learner's attention and workload in learning tasks can improve the efficacy of educational processes, especially in tasks involving highly cognitive activities, such as programming problem solving. The main objective of this study was to examine several brain parameters (attention, concentration and the energy of several brain waves) in a programming orientated task, as well as their variability during tasks of varying complexity. We consider that this work presents very promising future developments, including the possibility of incorporating this technology into a customised automatic system adapted to the student's cognitive and emotional state.**

*Index Terms***— Attention, brain computer interaction, computer science education, concentration, programming problem solving.**

I. Introduction

THIS article is an extension of the paper published inside the EDUCON 2019 conference [1]. In this extension we included a better definition and contextualization of Brain Computer Interactions (BCIs) in their various application areas, with an emphasis on Education and in particular in Programming Education. The study objectives were clarified, and a new section included to characterize the various EEG waves, in terms of frequency and meaning. New data was also introduced, namely the Attention and Meditation values and Frequency analysis for the Theta and Beta band levels. The interpretation of the results was enhanced, especially in its relation with useful educational aspects.

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A new and emergent field in the educational context is the use of Brain Computer Interaction (BCI) technology to better understand and promote learning processes. BCI allow direct functional interactions between a human brain and an external device [2]. BCIs enable the measure of a user brain activity (detecting voltage changes in specific areas of the brain) and the corresponding identification of the thought pattern or desired action of the user. This can be done in different ways: in an invasive way (putting electrodes on the brain itself), in a partially-invasive way (putting electrodes in the skull), and in a non-invasive way (putting electrodes on the scalp) [3]. Electroencephalography (EEG) is, presently, the unique available non-invasive method to measure the brain activity and as such it is the most extensively used.

While traditional BCI devices allow a user to communicate or control a computer using only brain activity [4], [5], more recently these devices have also been used to obtain information about the user and presume his/her mental states (e.g. attention, concentration) [6]. BCI devices collect and analyse user's electroencephalogram signals (EEG). They may be used in various fields of research, such as assistive technologies [7], video games [8], neurofeedback [9] and cognitive processes [10].

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. An effective learning implies the preservation of the individual's cognitive workload in his/her optimal range [5]. This can be accomplished by adapting the difficulty of the learning activities according to the individual capabilities. 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. BCIs can be used to gauge cognitive processes. Therefore, 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 increase the user learning success.

The measure of Attention and Concentration capacities are fundamental aspects that can contribute to a more adjusted learning specially in activities demanding high mental effort. They are, in fact, parameters considered as the basic cognitive capacities of humans in order to perform any task or to develop a certain capacity. Usually learning is more effective when attention and concentration are high.

Some studies describe features of EEG changes related to mental effort. In the literature there is strong evidence of evoked Theta activity (4-8 Hz) during activities that involve focused attention [11]. Increase of EEG activity in Theta band and Beta Low (13-15 Hz) over the frontal midline regions of the scalp have been observed when there is demand of executive control (attention and working memory) [11].

This paper presents one of the introductory works we have been undertaking in order to study several parameters of interest such as attention, concentration and energy of several brain waves of individuals while perform tasks oriented to solve programming problems. As we also believe that student's motivation, the self-perception of competence and the type of feelings they have while doing a task are key factors in learning, in our experiment we were also interested to know the type of feelings students had during the activities. For that, we used the Geneva Emotion Wheel2 (GEW) [12], [13].

II. Programming Education

The high dropout and failure rate in introductory programming courses is a common problem in higher education institutions worldwide [14], [15]. Numerous reasons have been identified and several proposals have been put forward and presented in the literature to help reducing student's difficulties [16], [17]. Although there are studies that show some improvements [18], this problem continues to be registered in many institutions.

Several authors pointed out some reasons for students' difficulties, such as the abstract nature of programming, having no correspondence with the development of the students' abstraction abilities and problem solving skills, the lack of a solid problem solving and mathematical background, the use of studying approaches not suitable for programming and also the teaching approaches and conditions present in many institutions [19]–[21].

One less mentioned aspect is the heterogeneous nature of most classes. It is usual to have students with very different levels of knowledge, interests, commitment and learning paces. Consequently, it is very hard for the teacher to use an appropriate and interesting pedagogical approach for each student. Frequently, teachers try to reach all students, designing activities to the "average student". However, in programming classes it is common to find mostly good students and weak students. The "average student" is often less common. Only with a personalized supervision and support the difficulties of weaker students can be reduced. In this sense, we see BCIs as a tool that may create conditions to foster knowledge about the processes involved in learning in general (and how to improve them), but also about individual students, namely how to improve crucial aspects like attention and concentration in each of them.

For us, the major cause of the students' difficulties is their deficient problem-solving ability. Several authors frequently viewed this skill as the most important cognitive activity in everyday, professional and educational contexts. Therefore, in this study, we are interested in measure the cognitive load associated with the difficulty of each task, measuring several energy bands that can assess this aspect.

III. EEG and Programming Education

There is a growing interest to use BCI and EEG in several areas, including educational contexts [22], [23]. For example, [24] presents a compilation of the use of BCIs in several areas, such as medical applications (prevention of diseases, detection and diagnosis, rehabilitation or restoration), neuroergonomics, smart environments, neuromarketing and advertisement, security and authentication fields, games and entertainment. It also refers BCIs application in educational systems, namely, to give personalized feedback to each learner [25] and to promote self-regulation and skill learning [26].

However, the application of EEG based systems in learning contexts is still not common, and the number of studies on this topic is relatively small [27]. The main focus of the available studies is on attention and motivation aspects, seeking to measure students' attention levels while performing mental tasks (such as reading, or viewing didactic content). A recent survey [27] found only 22 papers on this issue to include in its analysis. They concluded that the EEG was mainly used in online learning environments and not in offline traditional contexts. They have been used mostly in connection with motor skills and less with intellectual skills. The authors also pointed out that this technology is not frequently used to support courses in specific topics, such as mathematics or programming. They refer the use of BCIs to assess the learners' reading performance in several contexts [22], [28]–[30], to study the best characteristics of learning materials [26], [31]–[33], to get information on the interactive behaviour and feedback given by students to teachers questions [23], [28], [34]–[36], and in general research on e-learning [28], [33], [37].

IV. The Study

A. Objectives

The main purpose of this study is to analyse how the levels of attention and concentration, and the energy of the main EEG signal bands vary as a function of complexity in programming problem solving tasks. Additionally, another objective is to improve the understanding of the phenomena associated with the synchronization and desynchronization of the brain processes inherent to the various difficulty levels of the task in question.

B. Participants

The study group included 30 students enrolled in the 2nd year of the Informatics Engineering Degree of the Informatics and Systems Department (DEIS) from the Engineering Institute of Coimbra (ISEC) of the Polytechnic Institute of Coimbra (IPC), aged between 18 and 50, with an average of 22.3, mostly male (98%). These students had already had some programming bases developed during the previous year. The students were asked to play a classic Labyrinth - Angry Birds (Code) game consisting of 20 increasingly difficult levels. The goal of the game is to join 2 objects, using blocks of available code. Throughout the game different blocks are made available. At certain levels the coding paradigm shifts.

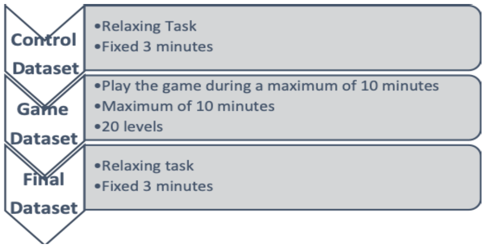


Fig. 1. The flow chart of the activity phases.

C. The Task Procedure and Design

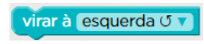
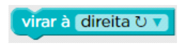
Participants played the game in a quiet location with no external interference. As a first step, they were asked to answer a survey to allow the group characterization. Subsequently, a brief explanation of the procedure to be followed was made, following immediately to the implementation stage of the activity (playing the game). During the activity there was no communication between the participant and the researcher. Each participant had a limit of 10 minutes to complete the game. The experimental EEG protocol collection was designed considering three important steps (“Fig. 1”). For the control of the dataset, we collected each student EEG signal for 3 minutes in his/her normal or relaxed 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. During this period, a sample frequency of 1 second was used, making a total of 600 samples per participant. 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.

1) The Game: The game used was a version of the classic Angry Birds (Code) [38] game, illustrated in “Fig. 2”. It consists of 20 levels with an increasing difficulty. The objective of the game is to get the main character to reach the target object, using blocks of available code, as shown in “Table I”. Throughout the game different blocks and scenarios are made available.

Levels 1 to 5 have low difficulty using only sequential instructions. The 1st and 2nd levels only require “move forward” instructions. However, from level 3 to 5, turning instructions are required to the left or right, with a slight increase in difficulty from level to level. In level 6 the difficulty increases with the introduction of simple loops. Levels 7 and 8 also require the use of a single loop, but small differences, such as a turn instruction or more than one loop are introduced. In 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. Level 10 has a similar difficulty, but a new type of loop (do…while) is used. In level 11 the degree of difficulty slightly changes from the previous level, requiring only the extra use of a “turn” instruction. 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 main character has to move. Level 13 is similar to the previous one. Level

TABLE I

BLOCKS DESCRIPTION

Blocks	JavaScript	Function
	moveForward();	Move character forward.
	turnLeft();	Rotate the character 90º to the left, from where it is.
	turnRight();	Rotate the character 90º to the right, from where it is.
	for (var count=0; count<5; count++) { }	Have the character repeating instructions a certain number of times.
	while (notFinished()) { }	Have the character repeating instructions until it reaches their goal.
	if (isPathRight()) { }	If there is a path in a certain direction, execute instructions.
	if (isPathForward()) { } else { }	If there is a path in a certain direction, execute instructions. If not, execute other instructions.

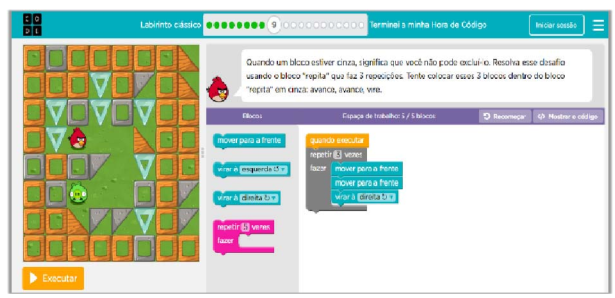


Fig. 2. Angry birds game.

14 also includes unmovable blocks, but additionally includes a selection within the “do…while” repetition. Levels 15 to 19 have a similar degree of difficulty and resolution paradigm. The last level of this game is also the most difficult, presenting 3 mandatory blocks consisting of a loop (do...while) containing chained selections.

2) Emotions Interpretation: After the participant finished the activity, an emotion-based questionnaire was used to figure out the emotions triggered by the game playing and their relationship with the electrophysiological data found. For that, we used the Geneva Emotion Wheel2 (GEW) [12], [13]. It is an empirical self-reported instrument based on the theoretical placement of several labels corresponding to emotions in order to measure emotional reactions to things, actions and circumstances. It consists in 20 emotional conditions combining both the dimensional and discrete emotions approaches. The GEW combines the two approaches through the placement of the reported emotions on a certain position of a circumference according to the intensity of the expressed emotion. In addition, there are two dimensions/approaches to consider, the Valence and the Control/Power. Valence is used to verify if the experience was

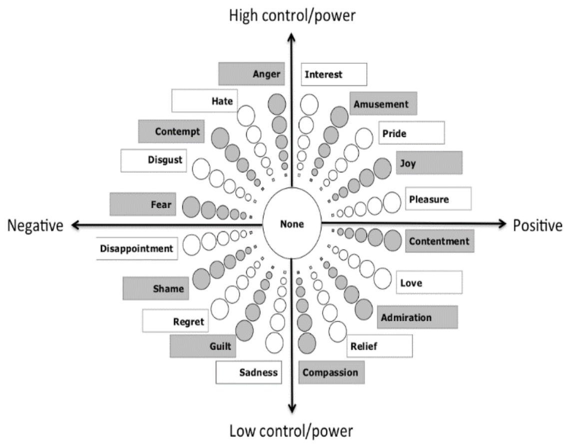


Fig. 3. Geneva Emotion Wheel2 for emotions quantification.

seen by the person as positive/agreeable/enjoyable or if it was negative/unpleasant/undesired. Control/Power indicates if the person believes and has confidence in influencing the situation to control, maintain or improve it [12].

In our experiment, after the students played the game, they were asked to select the emotions that they considered to best correspond to the feelings they experienced while playing the game. They were also asked to define the intensity level with which they experienced those emotions. At the end they marked one of the circles corresponding to this emotion group ("Fig. 3"). Less intense emotions correspond to smaller circles and more intense emotions correspond to larger circles. There are five degrees of intensity, represented by circles of different sizes. The students could choose several emotions. They were told to check the lower half circle (labelled "Other"), if they experienced an emotion that was very different from any of the emotions in the wheel.

3) EEG Recording and Preprocessing: We used the Mindwave device in our study. This simple and affordable device includes two electrodes, one for EEG dataset records (Fp1 channel), another for reference signals (the ear clip) and a power switch [39]. The sample frequency is 512 Hz. The Mindwave EEG sensor processes the brainwave into digital signals and uses the eSense algorithm to compute user's engaging attention and concentration.

The eeg_ID software was used. It allows the connection to Mindwave through Bluetooth. In addition to allowing the visualization of EEG data, such as Attention levels, Meditation levels, Blinking levels, the EEG Raw Data also provides information about the types of brainwaves: Delta, Theta, Alpha Low, Alpha High, Gamma Low, Gamma High, Beta Low and Beta High. Another advantage of this application is that it has the possibility to record the data easily (in a.csv file), including the date and time at which the data was obtained.

D. Behaviour Data

At the different stages of signal acquisition (Initial Moment, Game and Final Moment), the energy in the Delta, Theta, Alpha Low, Alpha High, Beta Low, Beta High, Gamma Low and Gamma High bands were calculated.

The time spent at each level, as well as the energy of the bands, was considered and related in this study.

In general, the different bands can be characterized as follows [40]. The Delta band (0.1Hz to 4Hz) occurs frequently in adults during sleep but is quite common in children throughout the day. The Theta band (4 Hz to 8 Hz) occurs when the individual is in a state of deep relaxation. The Alpha band (8 Hz to 13 Hz) is the most common wave in adults in a common state of relaxation, such as with their eyes closed, without any kind of thinking. Drowsiness or lethargy lowers the amplitude of these waves. The Beta wave (13 Hz to 30 Hz) is common in alert adults, concentrated in some kind of problem. There are studies that consider the division of this type of wave into Beta Low (13 Hz to 17 Hz) and Beta High (17 Hz to 30 Hz). Gamma waves (30 Hz to 100 Hz) are less studied, but some claim they are related to hyperalert states, visual perceptions of their surroundings [41] and memory related brain work. Knowing the waves and the ratio of their energies allows us to infer certain parameters related to certain mental states, which may be crucial for learning success.

E. Pearson Correlation and t-test

The Pearson correlation between the various brain waves and the time spent in each game level, per individual, was calculated. For each game level the average energy in each band was calculated, and the *t-test* was used with a confidence level of 95% between the levels. The underlying idea was to perceive the levels that produced significant changes considering all energy bands.

F. ERS/ ERD

For a better characterization of the data, an analysis of the Event-Related Desynchronization (ERD)/Event-Related Synchronization (ERS) complex was made in order to reflect the activation or inhibition of brain activity during the game. ERD usually reflects activation or excitation of cortical areas, contrasting with the ERS that usually represents the inhibition of cortical areas. The ERD value can, therefore, be interpreted as a correlation of an activated cortical area with increased excitability or desynchronization. A desynchronized EEG means that in the neuronal circuit, a small number of neurons or neuronal cluster works in an independent or desynchronized manner, representing a state of maximum agility as well as a large capacity to store information. On the other hand, ERS is referred to as a deactivated state and decreased information processing, as well as decreased excitation of cortical neurons [20], [42]. Therefore, spatial mapping of ERD/ERS can be used to study the dynamics of cortical activation patterns [42]. Having a desynchronization state during a learning moment in the Theta or Beta bands means moments of great agility and mental focus, meaning that an individual will be in a state of full concentration reflecting high activation and excitation of cortical areas. For example, we are interested in knowing if a student at a particular point in time is more or less concentrated in order to understand the focus of the brain. For this, it is extremely important to analyse the frequency signal of certain

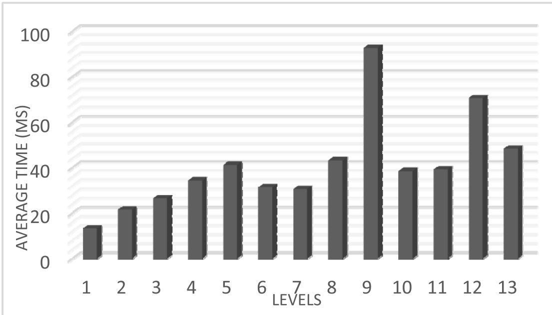


Fig. 4. Average time in each level of the game (level 1 to level 13).

TABLE II
NUMBER OF INDIVIDUALS 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

waves such as Theta or Beta as well as their synchronism ratios.

To obtain percent values of the ERD/ERS complex, the energy within the frequency band of interest in the interval of activity (given by A) regarding the initial reference interval (given by R) is calculated. ERD/ERS is a measure to quantify the percentage of energy defined as: (ERD/ERS) = (R-A)/R. Based on the equation it is possible to distinguish two conditions. If R>A the ERD/ERS complex has a positive value. This means that the test intervals band power is lower compared to the reference interval. This also indicates that the oscillations increase their synchrony, translating in a synchronization. If R<A the ERD/ERS complex has a negative value. This means that the test intervals band power is higher compared to the oscillations, indicating that the oscillations decrease their synchrony, translating in a desynchronization.

V. RESULTS AND DISCUSSION

In this section the results obtained in the study will be presented and discussed.

A. Performance Data

The game level reached ("Table II") and the time spent ("Fig. 4") by each participant in the allowed 10 minutes of play defines his/her performance. "Table II" shows the number of participants that reached each of the 20 game levels. Note that all individuals have reached at least level 9.

The average time that each individual spent at each level, as well as the average energy of the bands at each of them varies per individual. "Fig. 4" shows that more time was spent in levels 9 and 12. This was not surprising, as in those levels a new block or paradigm was introduced, increasing the mental effort.

1) Attention and Meditation Values: We measured the Meditation and Attention using the Mindwave device during the three stages of EEG acquisition. The Meditation parameter shows the level of a user's mental "calmness" or "relaxation". The Attention parameter shows the strength of a user's level of mental "focus" or "attention".

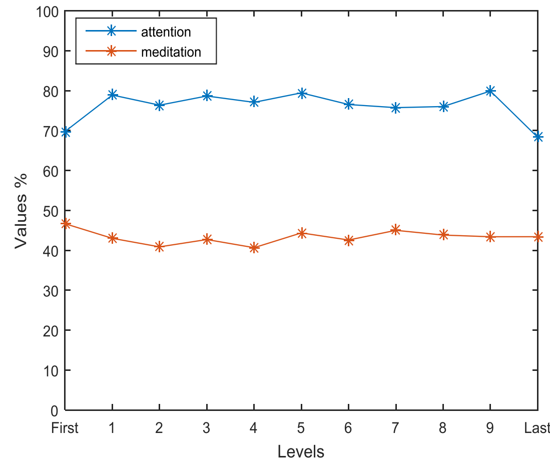


Fig. 5. Average of attention and meditation values considering the three steps of the EEG acquisition protocol: First Step; Game (1-9 level) and last step.

TABLE III
STANDARD DEVIATION OF THE MEDITATION AND ATTENTION VALUES FOR ALL PARTICIPANTS CONSIDERING THE DATASET REPRESENTED IN "FIG. 5"

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

"Fig. 5" represents the average values of Attention and Meditation for all the participants during the three phases of this research process: first stage, game steps (1-9 level) and last stage.

It was observed that the average Attention of all students level was always higher than 70%, reaching about 80% in some levels of the game. The peak average Attention level was reached in level 9. As the average time spent in level 9 was also the maximum, we considered that attention was stimulated by challenges and new elements introduced in the sequence, triggering higher brain activity.

The values of Meditation were always lower than 50% showing that the participants were not relaxed, through all the stages of the experimental activity. It should be noted that the Attention level was reduced in the first and last steps, corresponding to the moments where the participants were not playing the game.

"Table III" shows the attention and meditation standard deviation values in each level of the activity game. It can be seen that there was a higher variability in the meditation (Med.) values than in the attention (Att.) values.

2) Frequency Analysis: Theta and Beta Bands: In order to better understand the values of Attention and Meditation, the frequency energy of Theta and Beta waves were also analysed, considering the boxplots as shown in "Fig. 6" and "Fig. 7", respectively.

"Fig. 6" shows a high energy of Theta waves in the initial stage. As these waves are typically associated with the state of sleepiness and profound relaxation, we can conclude that the participants were in a calm state before the game activity.

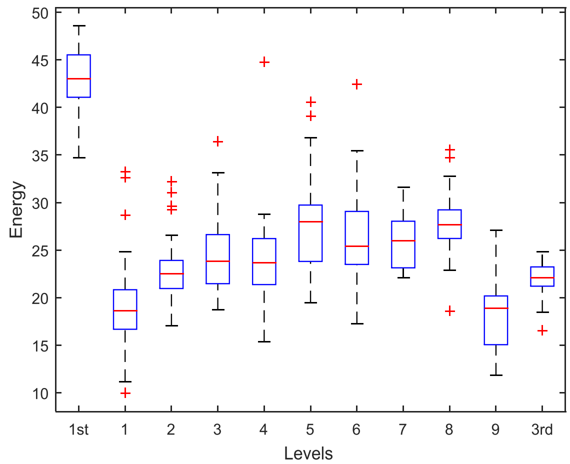


Fig. 6. Average of theta energy.

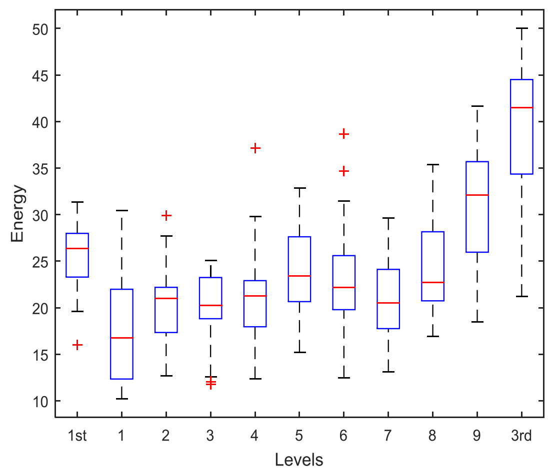


Fig. 7. Average of beta energy.

This wave energy had an abrupt reduction at the beginning of the game activity. This suggests that the beginning of the task produced some tension, perhaps due to its problem-solving nature. During the game there was a small variability of the average of the Theta energy related with a small oscillation of the game difficulty. Note that, a high deflection is presented in level 9 motivated by the difficulty of this level.

"Fig. 7" shows that the average values of the Beta waves were steady during the game activity, with the exception of levels 5 and 9 that produced higher values. These waves are usually associated with the intensification of states of tension and anxiety. The literature also associates the increase of these waves with creativity, heightened state of alertness, logical thinking, problem-solving ability, concentration, when the mind is actively engaged in mental activities [44].

We can observe that in the initial stage (1^{st}), Theta waves presented high energy and Beta waves showed low energy. The contrary happened in the last stage, after game playing, (3^{rd}). This can be interpreted as a more relaxed state of the participants at the beginning of the activity and a more tense state (perhaps due to the workload) immediately after the game play.

We calculated the correlation of each energy band with the time spent in each level by the 30 participants ("Fig. 8").

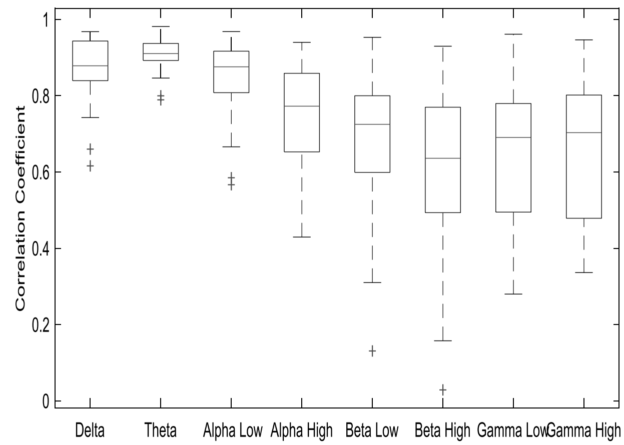


Fig. 8. Correlation coefficient values between all frequency bands and the time in each level, considering the 30 individuals.

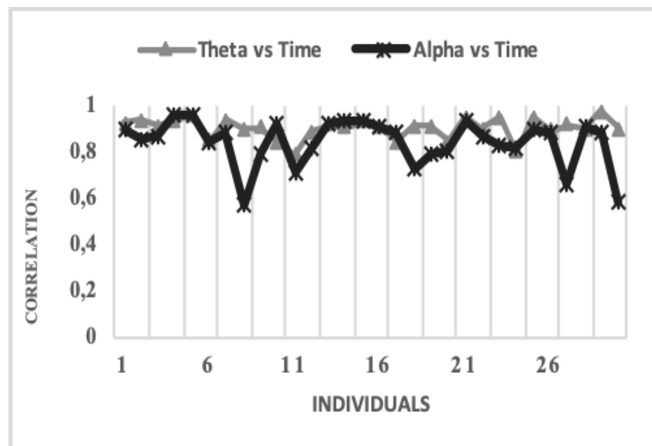


Fig. 9. Correlation coefficient between the average of frequency energy (theta and alpha low band) and the time used in each level.

We can verify that there was a small variation for the Delta, Theta and Alpha Low bands and larger variations in the remaining bands. In that cases the correlation values stood out over time, with values above 0.8. This means that the longer the time spent to solve a given level, the higher the energy load of these two bands, showing a higher cognitive load.

In order to understand the dynamics among the 30 individuals, the average of the correlations between Theta and Alpha bands and the time spent at each level was calculated for each individual ("Fig. 8"). The values are close to 1 for most students, showing a very high correlation between the two values.

Based on the data in "Table II" and "Fig. 9" two different case studies were considered:

1. Case 1: analysis of the total group, 30 individuals, up to level 9.

2. Case 2: analysis of the 15 participants who exceeded level 9 and reached level 13.

B. Frequency Analysis

We used the *t-test* to look for statistically significant differences between the averages of the different waves in

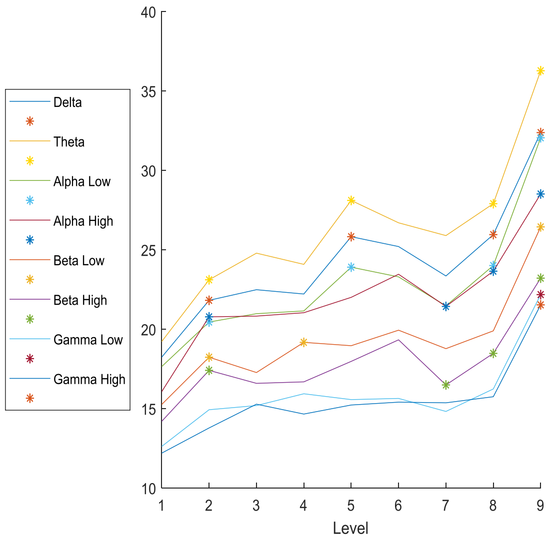


Fig. 10. Graphical representation of the average energy levels of Theta, Delta, Alpha Low / High, Beta Low / High and Gamma Low / High waves in the 9 levels. The asterisks represent the levels at which the bands energy was statistically different.

TABLE IV

STUDY CASE 1:STATISTICALY SIGNIFICANT DIFFERENCES OF EACH BAND IN EACH TRANSITION LEVELS FROM 1 TO 9

	D	T	AL	AH	BL	BH	GL	GH
L1-L2	8.82e-21	0.002	0.045	0.002	0.013	0.025		
L2-L3	8.01e-04							
L3-L4					0.037			
L4-L5		5.80e-04	0.010					
L5-L6	0.002					0.003		
L6-L7				0.033				
L7-L8		0.006	0.008	0.010		0.016		
L8-L9	5.61e-04	1.78e-07	1.82e-08	1.02e-04	1.98e-07	2.60e-05	3.21e-06	

consecutive levels of the activities. A 0.05 significance level was used (a confidence level of 95%).

1) Study Case 1: 9 Levels: “Fig. 10” shows the mean energy variations of each band during the ativity levels. The p values are indicated for those that presented statistically significant differences. “Table IV” shows that those differences were found in all waves (Delta-D, Theta-T, Alpha Low-AL, Alpha High-AH, Beta Low-BL, Beta High-BH, Gama Low-GL, Gama High-GH) whenever participants changed levels where the difficulty increase in the game activity. To note the difference in energy in all waves specially when changing from level 1 to level 2 (L1-L2) except in the Gamma band and when changing from level 8 to level 9 (L8-L9) except in the Gamma High band. The passage from level 7 to level 8 (L7-L8) also presents some energy differences specially in Theta, Alpha High, Alpha Low and Beta High.

2) Study Case 2: 13 Levels: In order to better understand the behaviour after level 9, we selected the 15 participants that reached level 13 (out of 20 possible). The result is graphically represented in “Fig. 11” and shown in “Table V”. Note the difference in energy in all waves except in the Gamma band, especially when changing from level 8 to level 9 (L8-L9) and

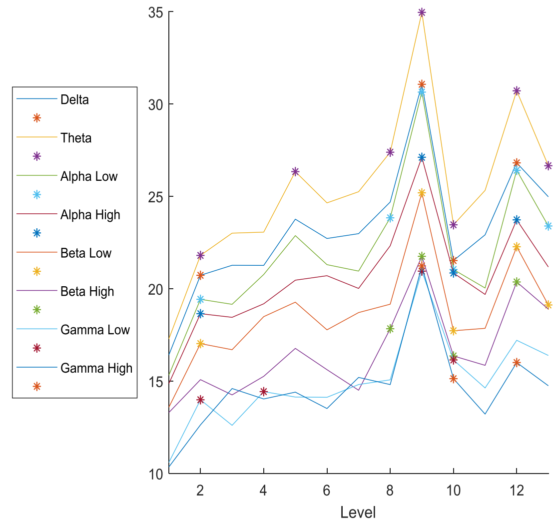


Fig. 11. Graphical representation of the average energy levels of Theta, Delta, Alpha Low / High, Beta Low / High and Gamma Low / High waves in the 13 levels. The asterisks represent the levels at which the bands energy was statistically different.

TABLE V

STUDY CASE 2:STATISTICALY SIGNIFICANT DIFFERENCES OF EACH BAND IN EACH TRANSITION LEVELS FROM 1 TO 13

	D	T	AL	AH	BL	BH	GL	GH
L1-L2	3.040e-04	8.760e-04	0.0265	0.0249	0.0207		0.0094	
L2-L3								
L3-L4							0.0348	
L4-L5		0.0218						
L5-L6								
L6-L7								
L7-L8		0.0131	0.0424			0.0033		
L8-L9	5.972e-04	4.395e-04	4.543e-05	0.0038	2.017e-05	0.0091	3.093e-04	3.523e-04
L9-L10	0.0036	0.0029	0.0078	0.0348	0.0051	0.0340	0.0188	0.0247
L10-L11								
L11-L12	0.0350	0.0166	6.897e-04	0.0130		8.481e-05		0.0303
L12-L13		0.0204	0.0415		0.0336			

when changing from level 9 to level 10 (L9-L10). The passage from level 1 to level 2 (L1-L2) and from level 11 to level 12 (L11-L12) also presented some energy differences specially in Delta, Theta, Alpha High and Alpha Low. These level changes also show differences in the remaining waves but in different bands for each level change. Although the bands at level 10 and level 13 presented statistical differences from the previous level, the average time spent by participants in these levels was lower. The graph of “Fig. 11” shows that there was a decrease in the energy of the brain waves. This event was not expected but can be justified by the slight decrease in difficulty after a complicated level.

The previous tables concerning the two Study Cases show some statistically significant differences in the energy of each band when changing levels, especially when that transition involves a clear difference in task difficulty. This aspect is evident in “Table IV” in the transition L8-L9 that corresponds to a clear increase in the difficulty level. In “Table V” the

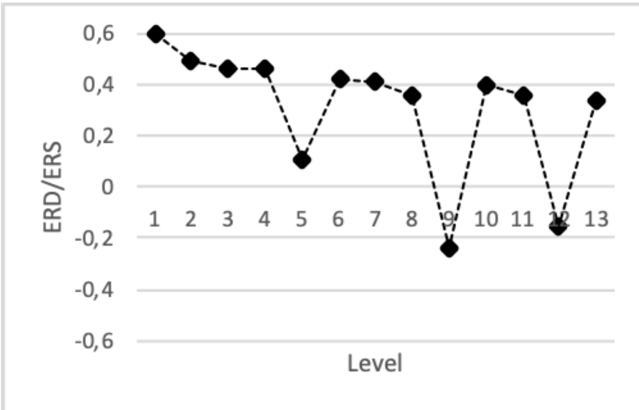


Fig. 12. ERD/ERS values considering Theta band.

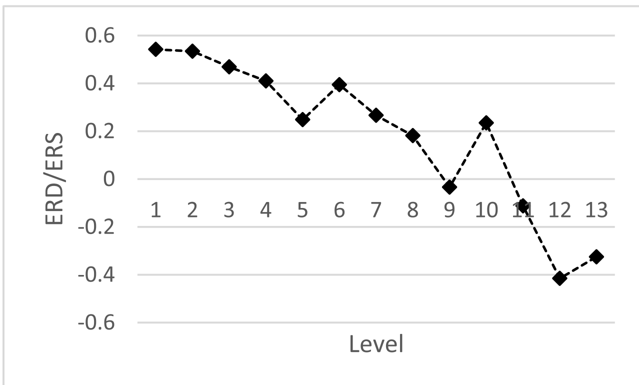


Fig. 13. ERD/ERS values considering Alpha low band.

same situation can be observed in L9-L10, corresponding to a decrease in difficulty. The same is true in L11-L12 and the L12-L13.

C. ERD/ERS Analysis

"Fig. 12" and "Fig. 13" represent the ERD/ERS values considering Theta and Alpha Low bands, respectively. It is possible to see that there is a decrease of the ERD/ERS complex at levels 5, 9 and 12 signalling a desynchronization.

There is an analogous situation in the Alpha band, with a desynchronization at levels 11, 12 and 13. We can conclude from these results that there is a desynchronization with respect to the initial state. It happens when the difficulty increases or the paradigm changes meaning higher difficulty. Also the literature refers to ERD as a localized and short-lived amplitude attenuation of rhythms within the Alpha band [42], meaning a decrease in relaxation state and an increase in anxiety.

D. Emotions Analysis

"Table VI" summarises the mean ($\boldsymbol{\mu}$) and standard deviation ($\boldsymbol{\sigma}$) of each classified emotion (#). The values range between 1 and 5 and it is possible to see a high variability in negative emotions when compared with positive values.

Besides that, the number of individuals that express positive emotions is high (for example: 29 individuals expressed interest).

TABLE VI

EMOTIONS RESULTS: # - NUMBER OF INDIVIDUALS; μ - AVERAGE VALUES; Σ - STANDARD DEVIATION

Emotions	**#**	$\boldsymbol{\mu}$	$\boldsymbol{\sigma}$
Anger	16	1,88	0,98
Contempt	10	1,10	0,18
Disgust	10	1,10	0,18
Hate	10	1,00	0,00
Regret	15	2,00	0,40
Disappointment	17	2,00	0,82
Guilt	10	1,00	0,00
Shame	15	1,80	0,75
Fear	13	1,69	0,75
Sadness	10	1,40	0,48
Compassion	10	1,10	0,18
Admiration	20	2,40	0,84
Relief	16	2,25	0,78
Contentment	12	2,08	0,63
Love	10	1,40	0,56
Pleasure	24	2,96	0,97
Joy	19	2,68	0,68
Pride	19	2,84	0,57
Amusement	27	3,19	0,77
Interest	29	3,72	0,57

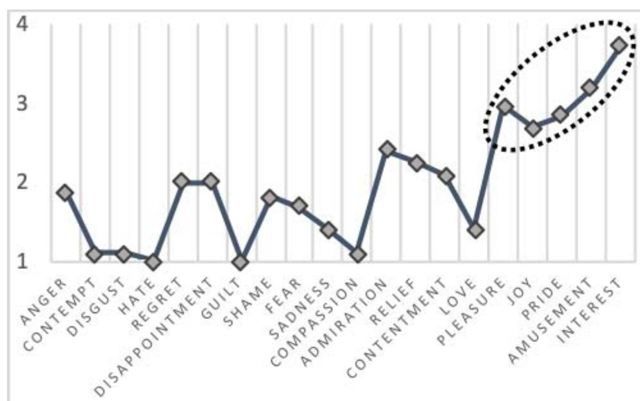


Fig. 14. Average of emotions classification.

"Fig. 14" illustrates the emotions referenced by the students regarding the performed task. Although there was some oscillation in relation to the most negative emotions, it was evident the satisfaction manifested by the positive emotions (Pleasure, Joy, Pride, Amusement and Interest) that obtained the highest averages.

VI. LIMITATIONS OF THE STUDY

Our study has some limitations caused by the type of device used and the number of students involved.

Although Mindwave has high portability and easy and reliable signal acquisition, the existence of a single channel means that the results are not comprehensive in terms of brain analysis. Using a device with a larger number of channels might allow the study of other brain zones, as well as other parameters leading to broader findings and conclusions.

The number of students involved limits the possibility to generalize results. Anyway, that was not our main objective, as the idea was to collect indicators that may be explored in future research.

VII. Conclusions

The Neuropsychological Assessment plays an important role in the diagnosis of development and learning problems. One of its important research topics is the study of executive functions. The problem being investigated is the study of brain waves that can provide us useful indicators of an individual's cognitive, mental, emotional and other states while doing a challenging cognitive task. In our case, the main objective is to measure what is really happening with the user when doing a programming orientated task.

The results of our study showed that in tasks where the level of difficulty increased in some way or a new element or paradigm was introduced, the attention levels were higher and the meditation levels were reduced. Regarding the energies of the bands, with special interest in Theta and Beta, it was noted that the values of Theta decreased, meaning a decrease in relaxation. This also happened at the last level and at the end (Last step), meaning that the individuals were less relaxed or more exhausted. In situations where the difficulty of the task increased the values of the Beta decreased, meaning an increase in cognitive load (note that in the initial stage it was almost zero). The opposite is true for the levels of attention, meditation and energy of the Theta and Beta bands in tasks where the difficulty is lower.

Regarding the ERD/ERS complex, it was found that in tasks where the complexity is higher there is Theta and Beta band desynchronization. This didn't happen in easier tasks or where the difficulty was not increased. The correlation between the energy of the bands (Theta and Beta) and the time at each level is also high, which also happens in the other bands but less abruptly.

After these preliminary results, we believe that the use of BCIs to understand and support learning of complex issues, like programming, should be further explored, eventually using systems that may analyse in real time the information produced, and react accordingly, for example in the definition of the level of support given to a particular student.

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