Using Brain Computer Interaction in Programming Problem Solving

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***Abstract*—A new and emergent field in an educational context is the use of Brain-Computer Interaction (BCI) technology to better understand and promote learning processes. In this context, the idea is to obtain information about the user and deduce his/her mental states (e.g. workload, attention, concentration) through user's electroencephalogram signals (EEG). In future researches, we are interested in understanding the performance of users in tasks involving high cognitive processes such as programming problem solving. The goal would be to find metrics and strategies that are adaptable to each user, looking to increase the success in programming learning. However, this work represents a set of initial works that provides an overview of how brain computer interaction can intersect with issues in the field of education, namely in design and in cognitive attention and concentration processes. The main goal of this study is to analyse several cognitive parameters (Attention, Concentration) of crucial importance for learning, while students do a programming problem solving oriented task activity. For a better characterization of the data, an analysis of the ERD/ERS complex was performed, thus analysing the event synchronization or desynchronization, in order to reflect the activation or inhibition of the cerebral activity during the game and consequently the absorption of information and the capacity of learning. Additionally, five EEG features were extracted, namely the powers of Delta, Theta, Alpha, Beta and Gamma bands, as well as, the variability of these bands' energy.**

Keywords*—Brain Computer Interaction, Attention, Concentration, Programming problem solving

1. INTRODUCTION

A new and emergent field in an educational context is the use of Brain-Computer Interaction (BCI) 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 obtain information about the user and presume his/her mental states (e.g. attention, concentration) [3]. BCI devices and software collect and analyse 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. An efficacious learning implies the preservation of the individual's cognitive workload in his/her optimal range [2]. 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.

This work provides an overview of how brain computer interaction can intersect with issues in the field of education, namely in design and in cognitive attention processes. It explores how the process of design, 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.

There are several factors that can contribute to a successful learning. The elements of this team have been dedicated to the study of these factors in the teaching-learning of introductory programming [8], [9]. According to literature many students have a lot of difficulties in introductory programming courses [10], [11]. Several authors point out some reasons for these difficulties and also present varied proposals [12].

For us, the major cause of the students' failure in introductory programming courses is a deficient problem-solving ability. Several authors frequently viewed this skill as the most important cognitive activity in everyday, professional and educational contexts.

The Attention and Concentration capacity are also fundamental aspects that can contribute to an efficient resolution of a problem. 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, being acquired most effectively when attention/concentration is improved. This work represents one of the introductory works we have been undertaking in order to study the attention and concentration of individuals while perform tasks oriented to solve programming problems using EEG.

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 [13]. 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) [13].

Some studies, such as [14], [15], use the Mindwave device to study the attention parameter and its influence during the learning process. The easy access of Mindwave device can open new research lines in different areas, like game design, but also in the understanding of the cognitive behaviour of human beings during learning.

The main goal of the study is to analyse several important cognitive parameters (Attention, Concentration), while students were engaged in a problem-solving oriented task activity.

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. Consequently, we also believe that these factors must be considered in the design of any pedagogical strategy. Therefore, in our experiment we were also interested in knowing the type of feelings students had. For that, we used the Geneva Emotion Wheel2 (GEW) [16], [17]. 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 to selecting the emotions there are two dimensions/approaches to consider, the Valence and the Control/Power. Valence is used to determine if the experience was 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 [16].

In our experiment, after the task accomplishment, students were requested to select the emotions that they considered to best correspond to the type of feeling they experienced while doing the activities. They were also asked to define the intensity level with which they experienced the referred emotion. At the end they marked one of the circles corresponding to this emotion group, Figure 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 simultaneous emotions. The students were told, if they experienced an emotion that was very different from any of the emotions in the wheel, to check the lower half circle (labelled "Other").

2. METHODS

2.1 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 levels whose difficulty gradually increased. 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 paradigm shifts.

2.2 The Task Procedure and Design

Participants performed the test in a quiet location with no external distractions. This test was performed on a computer without any interference from another person. As a first step, the participants were asked to conduct a survey to allow the sample to be categorized and characterized. Subsequently, a brief explanation of the procedure to be performed was carried out, going to the implementation stage of the activity. 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 is done considering three important steps, as presented in Figure 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 1 second samples were taken making 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.

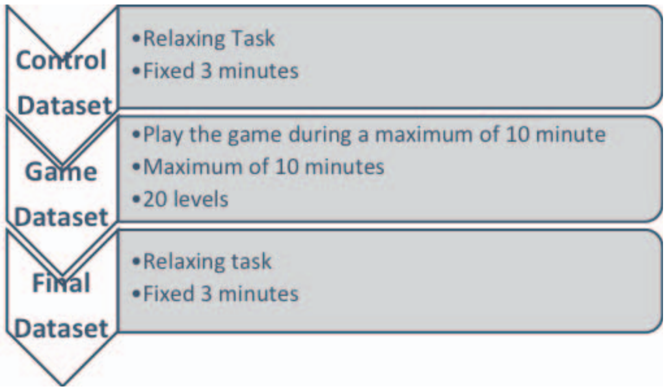

Fig. 1. The flow chart of methodology

2.2.1 The game

The test performed was based on playing a version of the classic Angry Birds (Code) [18] game illustrated in Figure 9, consisting of 20 levels whose difficulty gradually increased. The objective of the game is to get the main character to reach the target object, using blocks of available code shown in Table 1. Throughout the game different blocks are made available. At certain levels there is also the paradigm shift with the introduction of new elements.

Levels 1 through 5 are all 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 6 the difficulty increases with the introduction of simple loops. At levels 7 and 8 the required control structure is the same consisting in a single loop, but small differences such as a turn instruction or more than one loop are introduced.

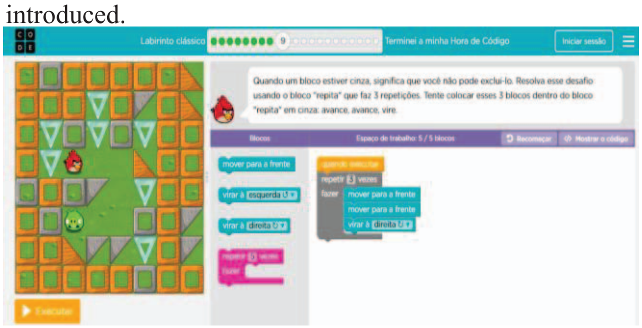

Fig. 2. Angry Birds Game

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.

Level 14, presents a paradigm equal to the previous one, presenting unmovable blocks, additionally it presents a selection within the "do…while" repetition. From levels 15 to 19 the degree of difficulty and resolution paradigm is similar to previous ones. The last level of this game is also the most difficult, presenting 3 mandatory blocks consisting of a loop (do...while) containing threaded selections.

2.2.2 Emotions Interpretation

After the test was performed, an emotion-based questionnaire was used to figure out the emotions triggered by the test and its relationship with the electrophysiological data found.

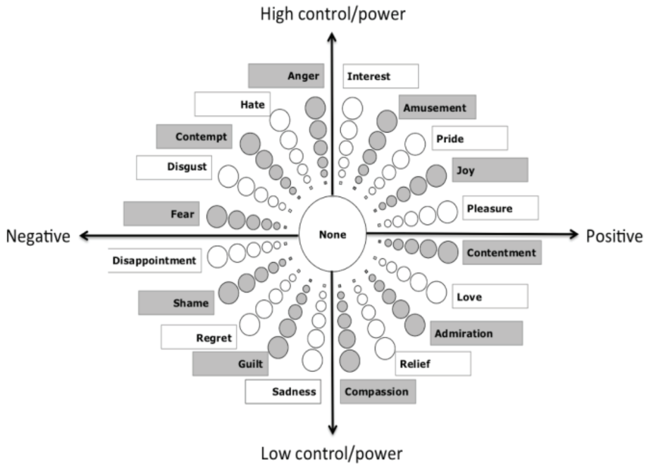

Fig. 3. Emotions Quantification

On a Likert scale of 1 to 5, where 1 represents the minimum value and 5 the maximum value, the participants ranked their emotions in the test run.

TABLE 1: BLOCKS DESCRIPTION

Blocks	JavaScript	Function
mover para a frente	moveForward();	Move character forward.
virar à esquerda ↺	turnLeft();	Rotate the character 90º to the left, from where it is.
virar à direita ↻	turnRight();	Rotate the character 90º to the right, from where it is.
repetir 5 vezes fazer	for (var count=0; count<5; count++) { }	Have the character repeating instructions a certain number of times.
repetir até fazer	while (notFinished()) { }	Have the character repeating instructions until it reaches their goal.
se há caminho para a direita ↻ fazer	if (isPathRight()) { }	If there is a path in a certain direction, execute instructions.
se há caminho em frente fazer se não	if (isPathForward()) { } else { }	If there is a path in a certain direction, execute instructions. If not, execute other instructions.

2.3 EEG recording and preprocessing

We used the Mindwave device in our study. This simple and affordable device, consists of two electrodes, one for EEG dataset records (Fp1 channel), another for reference signals (the ear clip) and a power switch [19]. 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, one of the applications available in the neuroscan that allows the connection of 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 record at which the data was obtained.

2.4 *Statististical Analysis*

2.4.1 Behaviour Data

For the different phases 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 Medium bands was calculated.
In the game phase several analyses were done, by level and considering all the individuals.
The time spent at each level, as well as the energy of the various bands, was considered and related in this study.

2.4.2 Pearson Correlation and ttest

The analysis of the correlation between the various brain waves and the time of execution at each level, per individual, was calculated in order to comprehend their correlation.
The correlation used was the Pearson correlation. For each level the average energy was calculated, and the t-test was used with a confidence level of 95% between the levels. The underlying idea is to perceive the levels with significant changes in means considering all energy bands.

2.4.3 ERS/ ERD

For a better characterization of the data, an analysis of the Event-Related Desynchronization (ERD)/Event-Related Synchronization (ERS) complex was performed in order to reflect the activation or inhibition of brain activity during the game.
To obtain percent values of the ERD/ERS complex, the energy within the frequency band of interest in the interval of activity is given by A, with the initial reference interval being given by R.
ERD/ERS is a measure to quantify the percentage of energy defined as:

$$\frac{ERD}{ERS}\% = \frac{R - A}{R} \qquad (1)$$

Based on the equation (1) it is possible to distinguish two conditions:

1. ERD: R>A (positive value) means that the test intervals band power is lower compared to the reference, indicating that the oscillations decrease their synchrony (desynchronize).
2. ERS: R<A (negative values) means that the test intervals band power is higher compared to the oscillations, indicating that the oscillations increase their synchrony (synchronize).

3. Results and Discussion

In this section the results will be presented considering several analyses in order to perceive the variability between the levels and the individuals.

3.1 *Performance Data*

In this study the performance evaluation of individuals reflects the level reached during the game phase temporarily truncated by 10 minutes.
In Table 2 the number of individuals that reached each of the levels considered in the game (20 levels) is represented. Note that all individuals have reached at least level 9.

TABLE 2: 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

The average time that each individual spent at each level, as well as the average energy of the bands at each level varies per individual. By Figure 4 it is possible to see that the highest values of spending time were in levels 9 and 12, related to those where there was the introduction of a new block or paradigm, increasing the mental effort.

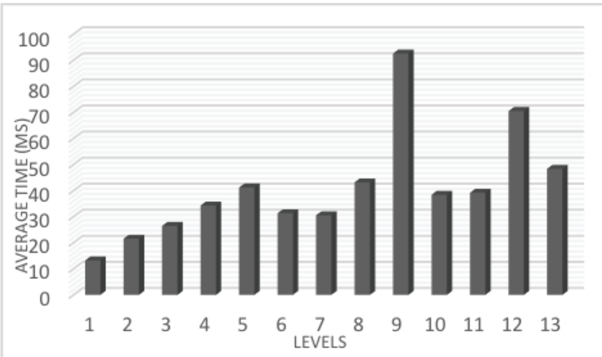

Fig. 4. Average Time in each level of the game (level 1 to level 13).

Regarding the 30 participants, the correlation of each energy band with the time spent by level was calculated. By Figure 5 we can verify 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.

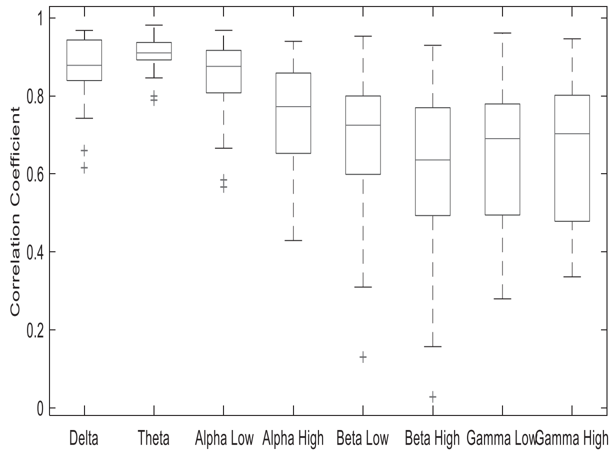

Fig. 5. Correlation Coefficient values between all frequency bands and the time in each level, considering the 30 individuals.

In the analysis of the correlation values, the Theta and Alpha Low bands stand out over time, 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, thus having 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, Figure 6. The values are close to 1, with a higher correlation for the Theta and Alpha bands.

Based on the data in Table 1 and Figure 4 two different case studies were considered:

1. Case 1: analysis of the total sample, 30 individuals, up to level 9.
2. Case 2: analysis of the 15 participants who exceeded level 9 and reached level 13.

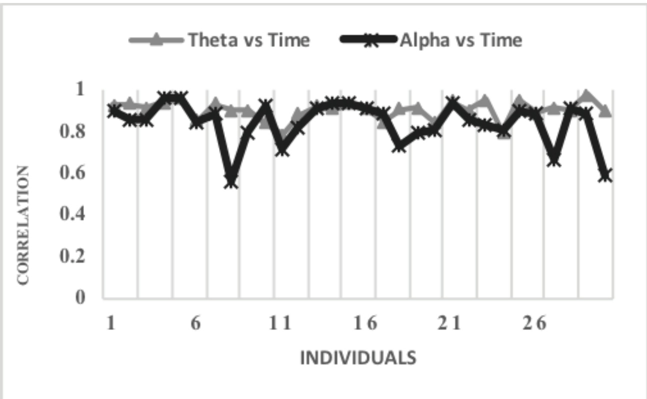

Fig. 6. Correlation coefficient between the average of bands energy (theta and alpha low) and the time dispended in each level

3.2 Frequency Analysis

The t-test was performed considering the statistical analysis between consecutive levels, the null hypothesis tested the mean value of the waves between levels. Considering the brain activity of a specific wave at a given level, and the brain activity of the same wave at the consecutive levels, it was verified if the means of each wave were equal at each level (H0) or if they present statistical differences. They were at a level of significance of 0.05 (a confidence level of 95%).

3.2.1 Study Case 1: 9 levels

Figure 7 shows the mean energy variations of each band along the levels, being indicated with a "*" those that presented statistical differences. It was observed that:

- When changing from level 1 to level 2, the bands Theta, Delta, Alpha and Beta were statistically different.
- When changing from level 3 to level 4, only the Beta Low band was statistically different.
- When changing from level 4 to level 5, the bands Theta, Delta and Alpha Low were statistically different.
- When changing from level 6 to level 7, the Alpha High and Beta High bands were statistically different.
- When changing from level 7 to level 8, the bands Theta, Delta, Alpha and Beta High were statistically different.
- When changing from level 8 to level 9, all bands were statistically different.

To better understand the statistical differences, we studied the mean time spent at each level (Figure 4), a strong relationship was verified. At the levels where the majority of the bands presented statistical differences, the time spent at the current level with respect to the previous one was also higher:

- When changing from level 1 to level 2 (Theta, Delta, Alpha and Beta);
- When changing from level 4 to 5 (Theta, Delta and Alpha Low);
- When changing from level 7 to level 8 (Theta, Delta, Alpha and Beta High);
- When changing from level 8 to 9 (all bands).

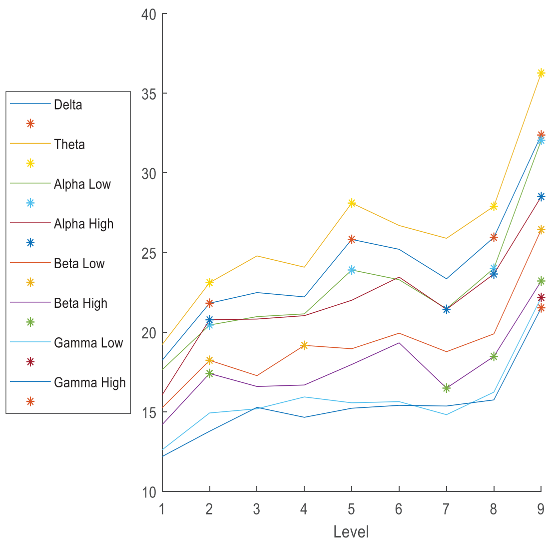

Fig. 7. Graphical representation of the energy levels of Theta, Delta, Alpha Low / High, Beta Low / High and Gamma Low / Medium waves in the 9 levels. The asterisks represent the levels at which the bands energy was statistically different.

3.2.2 Study Case 2: 13 levels

In order to better understand the behaviour after level 9, a selection of the 15 elements of the sample that surpassed this level reaching level 13 (out of 20 possible) was made. The result is graphically represented in Figure 8.

As can be seen, the statistical differences of the bands are as follows:

- When changing from level 1 to level 2, the bands Theta, Delta, Alpha and Beta were statistically different;
- When changing from level 3 to level 4, only the Gamma Low band was statistically different;
- When changing from level 4 to level 5, only the Theta band was statistically different;
- When changing from level 7 to level 8, the bands Delta, Alpha Low and Beta High were statistically different;
- When changing from level 8 to level 9, all bands were statistically different;
- When changing from level 9 to level 10, all bands were statistically different;
- When changing from level 11 to level 12, all bands, except Gamma Low, were statistically different;
- When changing from level 12 to level 13, all bands Delta, Alpha Low and Beta Low were statistically different.

To complement and understand the statistical differences, as was done in the case of the previous analysis, the average time in each level was analysed, Figure 4.

It was also found that, at almost all levels where the bands presented statistical differences, the time spent was higher. The most outstanding ones were:

- When changing from level 7 to 8 in which there were statistical differences in the Delta, Alpha Low and Beta High bands there was an increase of more than 10 seconds;
- When changing from level 8 to level 9, where all bands were statistically different, the time has risen to more than double, revealing the difficulty of level 9;
- When changing from level 9 to level 10, where all bands were statistically different, there was an awkward abrupt decrease of the time spent;
- When changing from level 11 to 12, where most bands were statistically different, there was an increase in time;
- When changing from level 12 to level 13, where the Delta, Alpha Low and Beta Low bands were statistically different, there was again a strange decrease of time.

Although the bands at level 10 and level 13 presented statistical differences from the previous level, the average time spent by participants was lower. However, through the graph of Figure 8 it is possible to verify that there was a decrease in the energy of the brain waves. This event, even if not expected, can be justified by the slight decrease in difficulty after a complicated level and with a different paradigm.

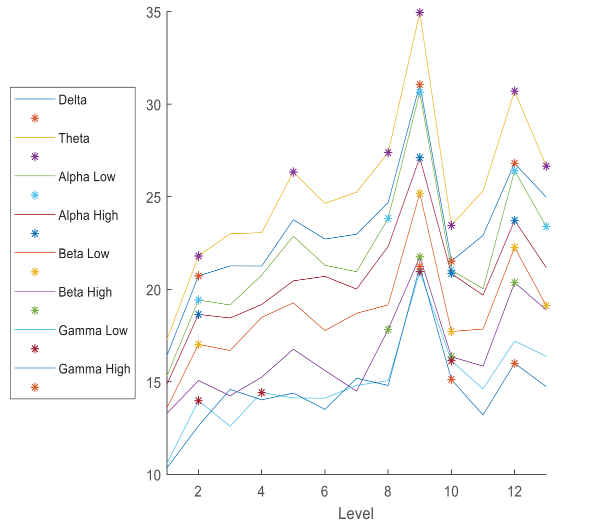

Fig. 8. Graphical representation of the energy levels of Theta, Delta, Alpha Low / High, Beta Low / High and Gamma Low / Medium waves in the 13 levels. The asterisks represent the levels at which the bands energy was statistically different.

3.3 ERD/ERS Analysis

Based on Figure 9 and Figure 10 we can see that there is a desynchronization in Theta band at levels 9 and 12, and there is a decrease of the ERD/ERS value in level 5. With respect to the Alpha band, there is an analogous situation, with a desynchronization at levels 11, 12 and 13. We can conclude from the results that there is a desynchronization with respect to the initial state, at the levels with a paradigm change. ERD represents a localized and short-lived amplitude attenuation of rhythms within the Alpha band [20], meaning a decrease in relaxation state and an increase in anxiety.

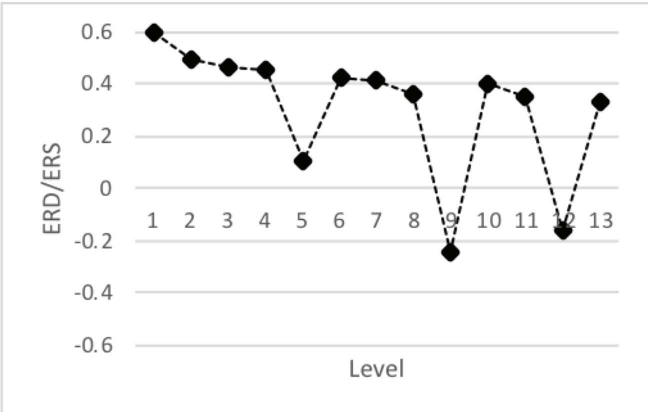

Fig. 9. ERD/ERS values considering Theta band

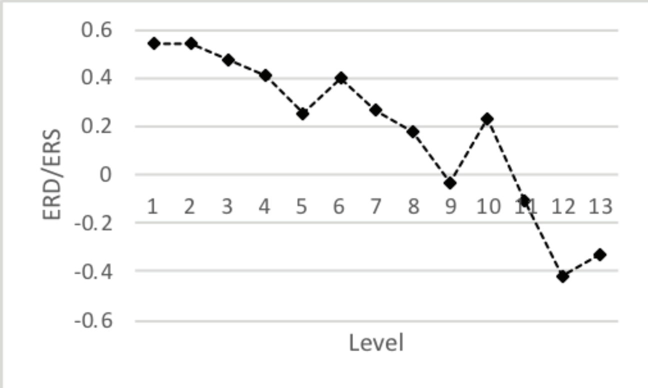

Fig. 10. ERD/ERS values considering Alpha low band

In contrast, ERS describes an improvement in amplitude, of short duration. In this way, the ERD pattern may reflect activation or excitation of cortical areas, contrasting with the ERS pattern that probably represents the inhibition of cortical areas [20]. The ERD value can, therefore, be interpreted as a correlation of an activated cortical area with increased excitability - 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. In the literature the ERD is described as being related to the capacity to store information and on the other hand the ERS is referred to as a deactivated state and decreased information processing, as well as decreased excitation of cortical neurons [20]. The spatial mapping of ERD/ERS can be used to study the dynamics of cortical activation patterns [20].

3.4 Emotions Analysis

Figure 11 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 expressed satisfaction manifested by the positive emotions (Pleasure, Joy, Pride, Amusement and interest) that obtained the highest ratings.

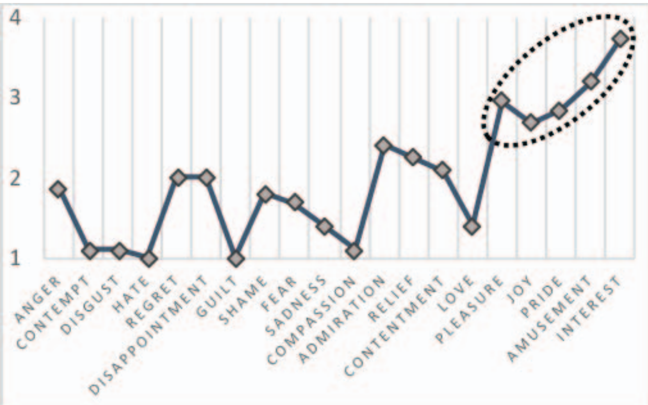

Fig. 11. Average of emotions classification.

Table 3 summarises the mean (**μ**) and standard deviation (*σ*) of each classified emotion by the individuals (#). The values range between 1 and 5 and it is possible to see a high variability in negative emotions in relation to positive values.

TABLE 2 EMOTIONS RESULTS: # - *NUMBER OF INDIVIDUALS*; **μ** - *AVERAGE VALUES*; Σ - *STANDARD DEVIATION*.

Emotions	#	*μ*	*σ*
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

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

4 CONCLUSIONS

The results obtained provide useful feedback about the attention and the levels that increased with the cognitive process, making evident which bands are related to it. The variability between participants is also reported. The complex ERS/ERD was computed and analysed to all bands. From the results analysis it was possible to conclude that there was an increase in brainwave 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 of attention and meditation were closer at the levels where the participants showed more difficulties and needed more time to complete them. We could also conclude that when the time required to solve a task was high, there was also a high energy load of the Theta and Alpha bands, that is, a higher cognitive load. A deeper analysis, using the t-test analysis was done. It was verified that in most levels where the bands presented statistically significant differences the time spent was higher, reinforcing the previously mentioned idea.

When comparing the best and the worst-ranked individuals, it was concluded that the worst-ranked participant showed a higher brain activity, probably caused by the difficulty that the tasks brought to this particular student. Finally, the study of the ERD/ERS complex showed positive results, with a wave desynchronization during the game play, in relation to the initial relaxation state, that is, a greater excitation of the neurons during the activity.

5 Future Work

We are interested in improving the teaching of programming learning. Some of the issues that we want to address are the following. What are the mistakes students make? Why do they commit them? Where do they block? What is the student's emotional state when they block? Which brain areas are overloaded when they block? What is the student's mental state at the start of a programming task? Why do they give up? What is the cognitive effort used in programming tasks?

The EEG data can effectively predict whether students are attentive or distracted inferring their cognitive states. These are important aspects to assess their learning efficacy. If instructors are aware of these cognitive states, they could lower the complexity of learning to program by designing alternative instructional materials. This could provide optimal conditions under which learning programming can be successful.

Cognitive load theory [21] and its associated effects describe the characteristic of the learner's memory during the learning process. By minimizing undesirable loads within the instructional materials, the learner's memory can hold more relevant information, thereby improving the effectiveness of the learning process.

Therefore, the main idea is to measure what is happening with the student while learning to program and determine how specific parts of the brain can measure different executive functions. This neuropsychological assessment enables us to have the EEG signal characterization of students programming learning.

We consider that the outcome of the present work is encouraging and has the potential for educational applications in several directions. For instance, after the features and patterns extraction and consequent classification we could have a BCI system that can provide proper decisions concerning the different programming learning abilities. We could, for instance develop an adaptive system based on this BCI, used to provide information on the learning capabilities of the user. With a BCI including a set of patterns on different programming learning performances it would be possible to build a learning system that will adapt to the abilities and interests of the user. For instance, if the user shows more difficulty in solving a specific problem the system will identify the patterns (for instance frustration levels) to provide clues or tips for the user in order to improve his/her learning abilities.

Another possibility is, to measure the subject's programming performance, enabling the identification of experts, experienced users or individuals who are a sign of future failure.

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