EEG and Eye Movement Maps of Chess Players

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Abstract: Due to a number of advantages to work in the chess environment and its cognitive complexity nature, this game has been used a lot in scientific experiments in order to study the human cognitive process. This article describes the steps to acquisition and processing of electroencephalography signals (EEG) and eye tracking of volunteers with different levels of proficiency in chess and, after the application of mathematical and statistical methods, maps are generated to discuss and verify patterns among the chess players. Results show neural activations in different brain areas as well as distinct eye movements for the investigated chess questions and volunteers who participated in this study.

1 INTRODUCTION

Among several games, chess is widely used for scientific experiments from the mid-twentieth century (Davis et al., 1973) and it has great importance in the values of a society (Kasparov, 2003). Working within the chess environment has advantages such as facility of transferring the information to the mathematical environment or computer languages, flexibility to experimental variations, the long history of matches that can be used for statistical analysis and allows working with players with different skill levels to analyze the cognitive process (Gobet, 1998). Because it is a platform that offers great complexity due to the amount of possibilities to be performed in the game, chess is used in experiments to cognitive brain mapping (Saariluoma, 1995).

Particularly in the chess game, the acquisition of knowledge becomes possible through a learning process and relevant information coding. Another characteristic is related to the professional chess players, for example, to become a grandmaster in chess a person must study and practice for at least ten years to learn and memorise a significant amount of gaming patterns and not only individual pieces movements (Hyötyniemi and Saariluoma, 1999; Amidzic et al., 2001; Ross, 2006; Calderwood et al., 1988).

Several experiments were performed in the chess environment using brain mapping techniques such as PET (Positron Emission Tomography), SPECT (Single Photon Emission Computed Tomography), magnetoencephalography and MRI (Magnetic Resonance Imaging) that brought a lot of information about human cognition regarding the practice of chess (Hänggi et al., 2014; Duan et al., 2014; Kazemi et al., 2012; Amidzic et al., 2001; Nichelli et al., 1994). However, few experiments were performed using electroencephalography as a resource to acquire the electrical variations of the brain (Rocha et al., 2016; Wright et al., 2013; Volke et al., 2002). Analogously, studies related to eye movements in chess games have been published showing differences in the behaviour between experts and non-experts, on which it was verified that chess players with greater proficiency fix their gazes on more important areas of the board and hence they have superior performance in this type of task (Sheridan and Reingold, 2015; Reingold and Sheridan, 2011; Blignaut et al., 2008; Reingold et al., 2001).

Despite several experiments in this area, there is no complete domain over the brain functioning and eye movements to solve problems in this field. One proposal is that chess can be used as an effective tool in the development of higher mental skills to improve the knowledge and educational learning(Rocha et al., 2016). As well as Bilalić (Bilalić et al., 2011a; Bilalić et al., 2011b), this article aims to acquire brain signals and eye movements of chess players, besides studying the relation between the implicit knowledge inherent in learning and codification of relevant information in chess. More specifically, we intend to acquire synchronously, and interpret the eye movements

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and electroencephalography signals of chess players with different levels of experience to recognize possible visual cognitive patterns and brain mapping for specific plays in a chess match.

This paper is organised as follows. Next, in section 2, we describe the equipment, method of data acquisition, proficiency calculation and signal processing techniques for electroencephalography and eye movement. Results have been explained in section 3. Then, in section 4 we discuss and compare the results in this work with previous studies. Finally, in section 5, we conclude the paper, discussing its main contribution.

2 METHODS AND MATERIALS

Brain electrical signals were obtained through electroencephalograph (EEG) device, OpenBCI. This equipment has sampling frequency of 250Hz, resolution of 32 bits per channel and it is an open-source tool. For this experiment, the electrical signals were acquired using eight channels: Fp1, Fp2, T3, T4, P3, P4 O1 and O2, these channels were chosen to embrace the most part of the brain as possible. Figure 1 shows the 10-20 conventional system which was used as reference for the positioning of the electrodes (Teplan, 2002; Jasper, 1958).

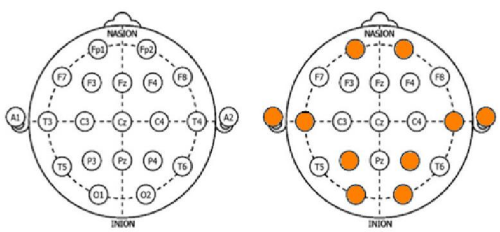

Figure 1: The left image shows the placement of electrodes in the 10-20 system and the right image shows the placement of the electrodes chosen for the experiment.

For eye-tracking, we used the equipment Tobii TX300, witch has sampling frequency of 300Hz, processing latency between 1ms and 3.3ms, and precision of 0.14°. Along with the eye-tracking, it was used a monitor 23” at a resolution of 1920 x 1080 pixels to display the questions and chess game situations at a resolution of 800 x 800 pixels, centralized on the monitor. Figure 2 shows the volunteer positioning for the eye movement data acquisition.

Figure 2: Volunteer positioning for the acquisition of eye movement signals.

2.1 Participants

Twenty volunteers participated in the experiment, consisting mostly of teenagers of school age (15.95 $\pm$ 3.93). In this group, none of the volunteers had ELO rating and, to separate them in groups according to their proficiency, we used an individual score calculation method proposed by Volke (Volke et al., 2002):

$$H_s = (N_{correct} - \frac{N}{2}) \cdot \frac{RT_m}{RT_s}, \tag{1}$$

where H_s = proficiency of each volunteer, $N_{correct}$ = total amount of correct answers, N = total amount of questions, RT_m = mean response time of all the volunteers in all questions and RT_s = mean response time of the volunteer.

This equation proves to be effective for this experiment because it takes into account not only the accuracy of the answer, but also the time spent in relation to provide that answer. Additionally, volunteers that answer all questions with the same alternative, trying to reach in the worst case 50 % of accuracy, but at a minimum possible time, end up with score equals to zero (Rocha et al., 2016).

2.2 Tasks and Stimuli

Each volunteer answered to thirteen different questions related to the chess game in CHESSLAB software proposed by Cesar et. al. (2015), adapted for the present work. Taking as basis the previous works presented by Cesar et al. (2015) and Rocha et al. (2016), the questions were elaborated to the present work. Precautions were taken in the test construction on the level of difficulty of the questions, number of questions elaborated for each category, balancing affirmative and negative responses and understanding of the questions proposed. Table 1 shows the categories

Table 1: Question categorization.

Category	*Description*
$C1$	Object recognition
$C2$	Checkmate in one move
$C3$	Checkmate
$C4$	Rule retrieval

that were used in this experiment, from which the categories 1, 2 e 3 were proposed by Volke et. al. (2002) and the category 4 was proposed by Nichelli et. al. (1994).

Regarding to the data acquisition system, it is established two distinct moments of interaction with the user. At first, the volunteers read a question presented in a written form on a monitor and must press the space key when they finish reading, understanding and memorising the presented question. In the second moment, the chessboard is displayed on a monitor with a coherent configuration expected in a chess game, the users must now press S to answer ”yes” to the question or the N key to answer ”no” (Cesar et al., 2015). Figure 3 shows an example of question and its respective chessboard presented to the users.

Before the beginning of the the test, the volunteer had register himself providing information on his level of education, age, area of study, gender, laterality and self-assessment of the level of proficiency in chess, besides to receive verbalized instructions that he had free time to read, understand and memorise the questions, being informed that after the chessboard was presented he could not read the question again, and the time elapsed in this stage was not counted.

Figure 3: Question example and its respective board.

2.3 Brain Signal Processing

The original data obtained by OpenBCI do not have any signal pre-processing. So, first it was implemented a high pass filter with cut-off frequency of 0.5Hz to remove the presented DC level of the electrical signal due to the electronic components. Thereafter, the signal passed through a low pass filter with cut-off frequency of 50Hz. This is usually the maximum frequency of operation of the brain (Gazzaniga et al., 2009). Finally, it was implemented a band-stop filter with cut-off frequency of 60Hz to remove possible noise regarding the frequency of the national grid. For all stages it were used Butterworth filters, changing only the settings and cut-off frequency for each case (Teplan, 2002).

After the electroencephalogram signals have been filtered, the processing of EEG signals was conducted by the method proposed by Rocha et al. (Rocha et al., 2005), which synthesizes, every 2 seconds prior to decision-making, the communication among the specialized neural agents in the solutions of the moves through the variation of the electrical activity recorded by each of the EEG electrodes. Figure 4 illustrates an example of an EEG summarisation of the previous 2 seconds immediately before the decision making.

After the steps of pre-processing were performed, we calculated the linear correlation coefficients of the electric amplitude of values recorded by each of the electrodes and all the other ones. To this end, it was adopted here the Pearson correlation for being a parametric test and using the absolute value of the results. After the correlation calculation, the results are used to perform entropy calculation among channels. Equation (2) shows how the calculation is done based

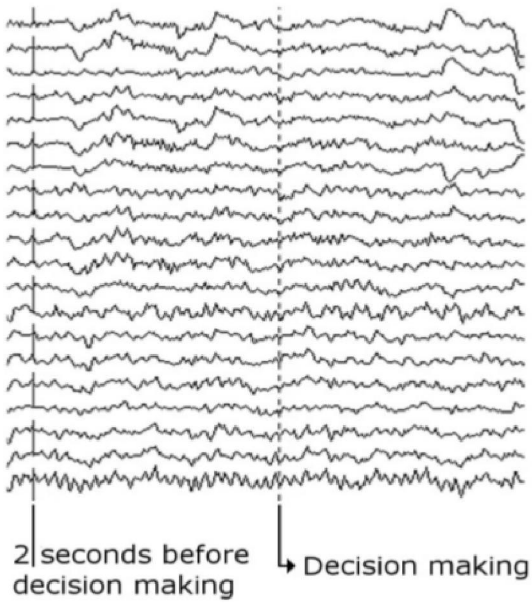

Figure 4: Example of an EEG summarisation channels.

on the Shannon entropy formula (Shannon, 1949):

$$h(c_{i,j}) = -c_{i,j}\log_2 c_{i,j} - (1-c_{i,j})\log_2(1-c_{i,j}), \quad (2)$$

where $c_{i,j}$ = correlation of two distinct channels. Equation (2) shows that, if the correlation between two channels is equal to 1 or equal to 0 the entropy will be 0. On the other hand, if the correlation is equal to 0.5 the entropy will be maximum, equals to 1, indicating the possibility of electrical activity of each electrode being associated with the electrical activity of each other.

$h(c_{i,j}) \to 1$, if $c_{i,j} \to 0.5$
$h(c_{i,j}) \to 0$, if $c_{i,j} \to 1$ or $c_{i,j} \to 0$

Analogously the entropy of the average correlation of each electrode can be calculated according to the equation (3),

$$h(\overline{c}_i) = -\overline{c}_i\log_2(\overline{c}_i) - (1-\overline{c}_i)\log_2(1-\overline{c}_i), \quad (3)$$

where,

$$\overline{c}_i = \frac{1}{(n-1)}\sum_{j=1}^{n-1} c_{i,j}, \quad (4)$$

and n is the number of electrodes. In this experiment $n = 8$.

The information provided by a single electrode is given by the sum of the differences between the average entropy correlation and the entropy of the electrode with the other channels, that is,

$$h(c_i) = \sum_{j=1}^{n}(h(\overline{c}_i) - h(c_{i,j})). \quad (5)$$

With the results obtained from the equation (5) and for the generation of brain maps, we applied the PCA (Principal Component Analysis) technique (Johnson and Wichern, 2007) to find a vector basis that represents the largest existing variance among the analyzed data. Then, we have used FA (Factor Analysis), to describe the association between the entropy values of the electrodes in a non-supervised way. The main idea behind FA is to disclose the correlation relationships among the original variables using a few unobservable random ones, called common factors, to adequately represent the data (Johnson and Wichern, 2007). After that, we applied the *varimax* rotation algorithm of the principal component calculated from the correlation matrix of the synthesized data to allow an interpretation of the EEG brain mappings with no overlapping. For the results shown in the following section it was considered only the first factor, the one with higher self-value of each group of volunteers.

2.4 Eye Movement Signal Processing

The first stage of pre-preprocessing of the acquired eye movements data is the interpolation of the incomplete informations, that is to interpolate the missing values to not affect the subsequent calculations, since considering the coordinate (0,0) as part of the eye movement could introduce errors in calculations to determine the fixations. Equation (6) describes the linear interpolation formula used for this purpose:

$$P_i = P_s + i \cdot \frac{(P_n - P_s)}{(n-s)}, \quad (6)$$

where P_i represents the missing values contiguous in vector, P_s is the value of the point immediately previous to the missing points, P_n is the value of the point immediately after to the missing points with $1 < i < n-s-1$.

This interpolation is only applied when the vector of missing dots is less than 60ms (about 20 samples in the eye-tracking device used). Interpolation in a very large array can generate non-existent fixations. The time of 60ms is very near to the time of a blink (50 milliseconds on average), thus conservatively, only minor flaws are corrected.

Then, the noises generated by the device itself as well as micro movements of the eyes or head are filtered. The existence of these noises can impair the detection of events such as the fixation of the look, because of this, it is necessary to detect the inertia in eye movements, and the noise can cause false movements. Equation (7) shows the filtering method, a weighted moving average.

$$P_i = \frac{1}{\sum_{n=0}^{k} W_n} \cdot \sum_{n=0}^{k} P_{i-n} \cdot W_n, \tag{7}$$

where P_i is a value in point vector, W is the weighted vector, k is the size of the window, P_{i-n} is the value of the umpteenth previous position in the vector (when $n = 0$, P_{i-n} will be equal to P_i). In this case $k = 20$ and W is linearly decreasing.

After the step of pre-processing of the data, it is used an algorithm that detects the fixations from the identification of the inertia of the eye movements in a particular location, called dispersion detection (Duchowski, 2002; Salvucci and Goldberg, 2000). This algorithm requires two parameters to define the fixations: the *space threshold* indicates the maximum acceptable dispersion to consider a point as belonging to a fixation; and *time threshold* that indicates the minimum time to consider a set of points as a fixation. These values were set equal to 120 pixels and 120ms, respectively.

For the generation of eye movement maps, a squared matrix is created (point matrix) with the same size of the original image, which receives the sum of exposure points from the fixations of a group of participants. Another matrix is generated, which values are filled by a Gaussian function. The filling of the point matrix is done by centralized overlay of the mask at the matrix point of each fixation. The original values of the mask points are added together by the values contained in the mask matrix weighted by the duration of fixation.

3 RESULTS

Figure 5 summarizes in histograms the test results in chess of volunteers with higher and lower proficiency, showing visually how they are distributed in relation to the number of correct answers, average response time for question and category regarding to the question.

According to the graphs in Figure 5, it is possible to verify that the answers of the volunteers had different percentages of accuracy by question and variation of the average response time. It is noted that the category 1 had a higher percentage of correct answers as well as the lowest average response time and the category 4 had low percentage of correct answers with high average response time.

Based on the proficiency results described and aiming to demonstrate the neural behaviour and discriminant eye movement among volunteers with

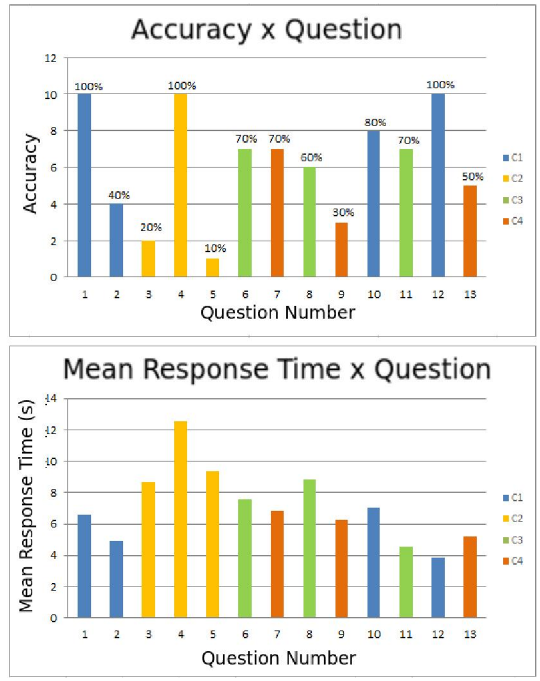

Figure 5: The top graph shows the amount and percentage of accuracy of each question. The bottom graph shows the average response time and category of each question. The categories are the same ones presented in Table 1.

higher and lower proficiency, cognitive maps and visual attention maps for the following two groups were generated: more proficient group that scored higher than 34 ($Hs > 34$); less proficient group that scored less than 11 ($Hs < 11$), through a division by quartiles (Bussab and Morettin, 2010).

Figure 6 shows the brain maps on a color scale that starts in the red color, indicating low influence of the brain area for the task solution, passing through orange, yellow, green, light blue and dark blue color that represents the factor loadings greater than 0.7 on a scale ranging from 0 to 1 (Rocha et al., 2016; Rocha et al., 2014). It is noted that the map of the category 1 for group of volunteers who had a performance higher than 34 points showed an association among connectivity measured from the electrodes O1, O2, P3, P4 and T4 while the group with the a performance lower than 11 points showed an association among connectivity measured from the electrodes O1, O2 and P4. For the category 4 the most proficient group presented a neural circuit among the electrodes O1, P3 and P4 and the least proficient group presented association among F1, F2 and P3.

Figure 7 shows two questions: question 12 of category 1 showing 100% accuracy of responses and the lowest average response time; question 13 of category

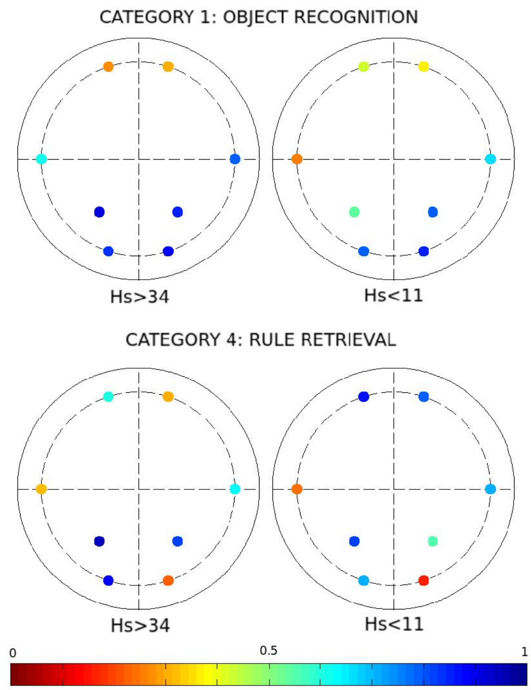

Figure 6: Brain maps.

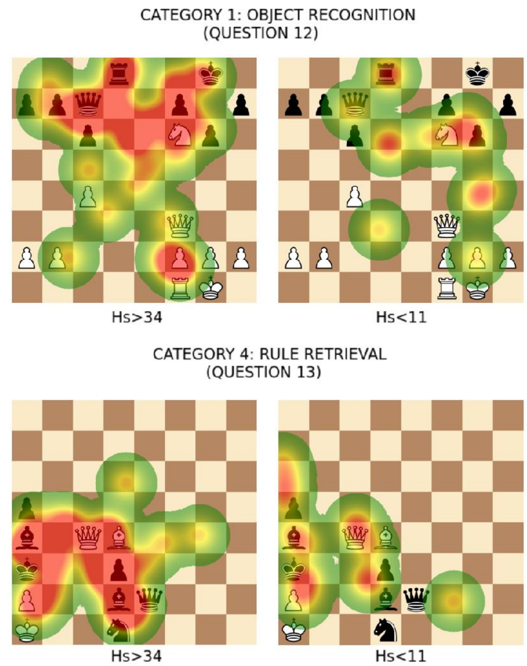

Figure 7: Visual attention maps.

4 for which there was 50% accuracy of responses and high average time response, as depicted in Figure 5. The visual attention maps show the areas of the board where each group of volunteers focused their gazes to solve the problems presented by a color scale that begins in green, indicating that there was little fixations in that spot, through the colors yellow, orange and red, color that indicates several recordings in that spot. Furthermore, the color scale is related to the intra-group information, that is, we considered only the data of the volunteers who were on the same proficiency group.

4 DISCUSSION

Through the methods described above we generated brain maps and visual attention maps shown in Figures 6 and 7 respectively, evidencing differences in neural activation patterns and eye movement between groups of volunteers with higher and lower proficiency in chess.

Observing the brain map in Figure 6 for the most proficient group, it is found that for category 1 there was a greater association in the occipital-parietal region and temporal region of the right hemisphere, these regions are related to visuospatial processing (Vanlierde et al., 2003), which shows consistency with the stimulus presented, as the category involves the recognition of parts on the board. The group with the lowest proficiency had a similar brain map in the occipital area which is the area related to primary vision processing (Martin, 2014).

For this same category, analyzing the visual attention maps of Figure 7, the highest proficiency group had a greater attention on positions of the board where there were no pieces, despite all the volunteers of this group answered correctly the questions. The main difference is found in the elapsed time for the solution of the questions, as the average response time for this one was 3.8s and 5.1s for groups of higher and lower proficiency respectively.

Analyzing the Figure 6 for category 4 it is noted that the group with the lowest proficiency had a stronger connection in the area of the frontal lobes, this area is related to the planning and memory (Martin, 2014; Gazzaniga et al., 2009), while the group with the highest proficiency had an association in the parietal region and occipital region in the left hemisphere, unlike what is found in the literature (Rocha et al., 2016; Hänggi et al., 2014). This difference found in relation to other studies may be attributed to the proficiency between groups of participants because spite of the differences, any of the groups is considered experienced in chess.

Regarding the map of eye movement for category 4 in Figure 7 it is verified that in both groups there is a greater focus on the localization of the pieces that are part of the solution for the question presented, and it is noted that the most proficient group fixed their gazes for a longer time in this region of interest, which can contribute to the best performance in this question, with four correct answers to the highest proficiency group and one corrected answer to the lowest proficiency group.

5 CONCLUSION

We have carried out a computational experiment that involves acquisition and processing of EEG signals and eye movements in chess, generating as final result cognitive maps that show the brain areas that were more activated for the solution of the presented stimuli and visual attention maps that highlight regions of preferred fixations of volunteers.

Our results have disclosed differences in the patterns of brain activation and eye movements among chess players with higher and lower proficiencies, analogously to other works in the literature (Rocha et al., 2016; Sheridan and Reingold, 2015; Wright et al., 2013; Reingold and Sheridan, 2011; Reingold et al., 2001). In short, chess players with lower proficiency presented higher dispersion of attention and visual fixations on non-relevant parts of the stimuli, demanding more time to analyze and answer the questions as well as major brain activations in the occipital areas rather than in the frontal ones.

As future work, we intend to extend the framework proposed increasing the number of volunteers, especially considering volunteers with ELO rating, the number of questions and categories to analyze other discriminant characteristics on chess, and the EEG spatial resolution.

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