AN EFFICIENT ASYNCHRONOUS BRAIN-COMPUTER INTERFACE FOR ASSISTIVE TECHNOLOGY: A NOVEL APPROACH

NEBIA BENTABET[1], NASREDDINE BERRACHED[2]

Key words: Brain computer interface, Synchronous systems, Asynchronous systems, Electroencephalography (EEG), Smart home, Assistive technology.

Constructing a general and a daily used controller remains the main concern for brain-computer interfaces (BCIs) systems. The most characterized problems in synchronous based BCI systems are the dependence on the stimulation and the number of stimulation sequences set in advance, the ignorance of the current user's state, and the requirement of operator intervention since the user can neither start nor stop the BCI system. Thus, to solve these issues, it is important to know at any given time if the user is paying attention to the system. To this end, an asynchronous P300 based BCI approach is introduced in this paper, where a subject can control home appliances by switching ON or OFF a device to attain a self-paced control. We introduce a new classification approach which uses separate rows and columns classifiers in BCI2000 framework. Each dataset is analyzed separately in order to find differences in their characteristics and utilize these differences in improving the performance of the P300Speller paradigm. Then we combined the output of each classifier to recognize the desired action. A threshold-based approach was applied to help our system to take a decision or to abstain from doing so. The asynchronous classifier reached promising results. This approach would enhance the system performance by increasing the selection speed and the number of sequences needed to take a decision. It produced remarkably better results than classifying row and column together.

1. INTRODUCTION

The assistive technology is one of the most important areas on which brain computer interface researcher groups focus. It has known a growing interest, giving paralyzed people an autonomous system to control their environment. brain computer interfaces (BCI) use electroencephalogram (EEG) signals as a communication channel between human brain and computers [1, 2]. These signals are acquired using either planted electrodes on the brain using neurosurgery (invasive methods), or electrodes placed on the scalp (non-invasive methods). BCI applications are meant to drive the technology in the area where cerebral activities are utilized to prop users in their daily life. Many groups worldwide invest more money and time in this new field, predicting that it will be the language of the future.

Event related potential (ERP) [3–6] is one of the EEG control patterns used in the EEG-based BCIs. This pattern does not need training but necessitates external stimuli. P300 paradigm is used by this pattern to guaranty a very effective synchronous mode. The participant focuses his attention on a matrix containing the desired command. This triggers a P300 response which is a positive wave appearing 300 ms after the onset of the desired row or column holding that action. while the rows and columns of this matrix illuminate continuously and arbitrarily in front of the user, the later is counting how many times the desired command gleams [7]. An instantaneous interpretation is done by BCI, as soon as a stimulus response is detected. This response is then translated into commands that match the user's desire, and a control can be sent at a particular time. The row/column (RC) paradigm is the most used in BCI field. In this paradigm, a P300 response necessitates two correct identifications: one for the corresponding column and another one for the corresponding row. As a result, the ERP segments related to the rows and the one related to the columns are classified together.

A wrong identification of a column or a row causes a misclassification, which decreases the system accuracy. According to [8] classifying column and row samples independently, then combining the output of the classification would enhance the system performance and increase the selection speed and number of sequence needed to take a decision. This approach presents better results than classifying row and column together. It reduces 44 % the number of stimulations needed to reach an accuracy of 100 %.

One of the drawbacks of the conventional P300 based BCI is that the synchronous system does not take in consideration the current user state. Moreover, it depends on the stimulation and the number of stimulation sequences set in advance by the user. If the user is involved with another task, the system will not wait for the user to intervene; it will make its own decision. As a result, the user has to monitor visually the interface continuously, since he can't neither start nor stop the BCI system. It would be helpful if the BCI system detects whether the user wants to send a control command or not. The solution is that the user interacts with the interface in an asynchronous way. To achieve this goal, it is important to know at any given time, if the user is paying attention to the system or not. This requires a real distinction between two user states: the control states where the subject is concentrating on target icon, and the non-control state where the user does not pay attention to any icon on the interface.

According to methods used to identify the control state, we can distinguish two types of asynchronous P300 based BCI: those based on hybridization of EEG signal patterns [9–11], and those based on statistical P300 amplitude patterns. Zhang et al [12] proposed a first computational methodology to create an asynchronous P300 based BCI using a statistical and probabilistic model. They developed an algorithm which, at first, identifies the control state, then looks for the target, providing a classification result after 3 rounds at least. Another work from F. Aloise *et al.* [13] presented a dissimilar approach helping to control real demotic appliances, and it was demonstrated to be

[1,2] Université des Sciences et de la Technologie d'Oran, Laboratoire de Recherche En Systèmes Intelligents (LARESI), P.O. Box 1505, El Mnaouar, Oran, Algerie; E-mails:nebia.bentabet @univ-usto.dz, laresi.usto.2015@gmail.com

trustworthy in avoiding false positives when the users were not focusing on the stimulation interface. Nevertheless, they didn't provide any enhancement in speed selection in respect of a synchronous system. They validated their work with participants of potential end users [14].

In this paper, we were inspired by the works released in [8] and [13] to demonstrate a new asynchronous classification approach, that uses a separate row and column classifier. Our method will allow to build an asynchronous P300 based BCI to control home appliances, where a subject can switch a device ON/OFF for attaining a self-paced control. The reminder of this paper is organized as follow: Section 2 describes our motivation and the proposed approach. Section 3 describes technical details and system paradigm. Experiment results and discussion are presented in Section 4, and finally, Section 5 will summarize our study.

2. THE PROPOSED APPROACH

The P300 wave is well known by its amplitude and latency. they are considered as the most characterized features of P300 wave [15–17]. The variation of those characteristics depends on different conditions such as age, gender , physical conditions, and user's state [18, 19], in addition to the size of the matrix displayed to the subject [20, 21]. To identify the P300 response, we studied the row samples and column samples separately. Firstly, we divided dataset to two subsets corresponding to the rows and columns. Secondly, we calculated the score values related to each subset individually. Therefore, the score values of each new sequence are accumulated to the previous sequences within the same trial. Threshold values are linked to the number of added sequences in the trial. At the end of each sequence, the maximum rows and columns values are matched to the specific threshold. If thresholds exceeded simultaneously because of the maximum row and column values, the system would classify the icon at their intersection. Inversely, if the threshold values did not exceed throughout the maximum number of stimulation sequence fixed *a priori* (10), the system would abstain from taking a decision. Figure 1 illustrates the flowchart of the proposed method.

2.1. MATERIALS AND METHODS

To develop an environmental control based BCI, a dataset representing a full record of "P300 evoked potentials" was recorded with an asynchronous approach, which is implemented within BCI2000 framework. As it is showed in Fig. 2, a non-blinking cross symbol was fixed, located in the interface center, and used in some no-control trials [13]. In these experiments, 16 icons were introduced as a target with the same frequency for the synchronous and the asynchronous mode in order to have the same icons probability appearance for further analysis. A user focused his attention on one of these icons at the time. In the synchronous approach, the goal is to predict the desired icon. While in the asynchronous mode, 15 icons were used for control trials, and the last icon (a smiley face) was never used as target in the alternate runs for the reason that it indicated the no-control trials to the subjects.
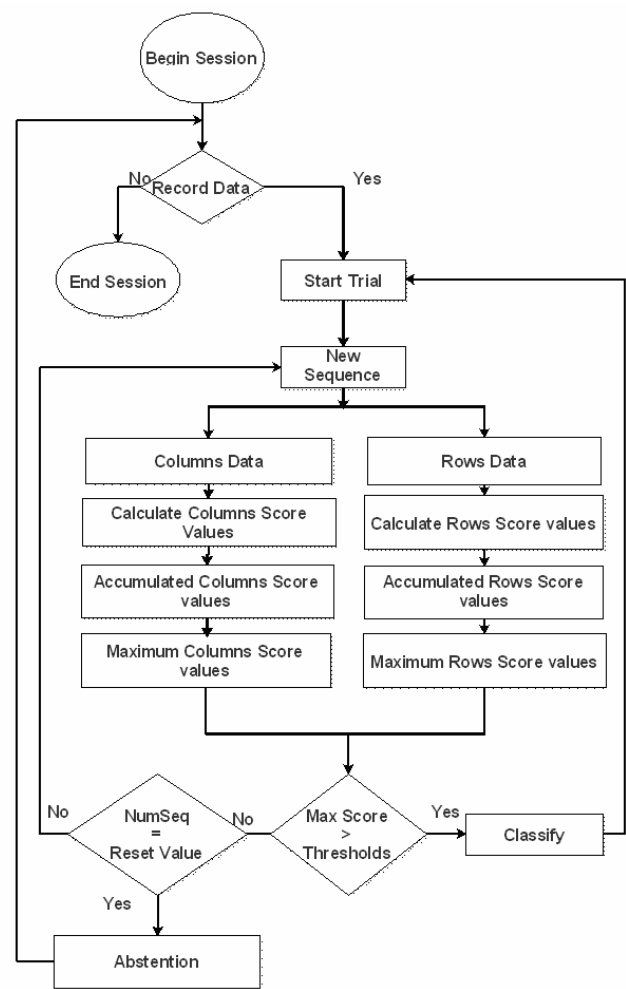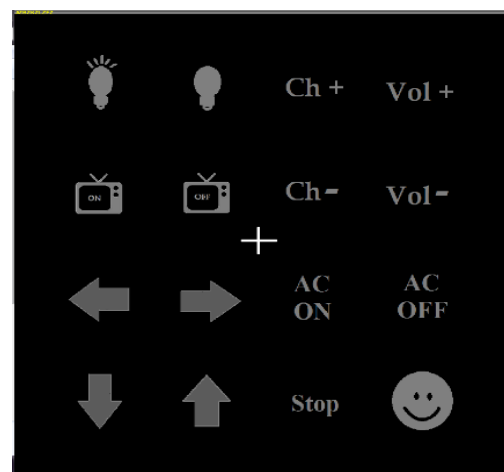

Fig. 1 – Flowchart of proposed method.

Fig 2 – 4x4 matrix used in the study.

Six healthy subjects participated in the study. All the subjects took two acquisition sessions over two weeks. Each session contains five runs as presented in Fig. 3. Two of them define the control trials. The other 3 runs represent the alternate runs. Scalp EEG potentials were recorded (g.USBamp, gtec, Austria, sampling rate 256 Hz) from nine positions according to 10–20 standard: Fpz, Fz, Cz, Pz, Oz, P3, P4, PO7, and PO8. Each channel was referenced behind the ears and grounded at AFz position.

Fig 3 – Organization of each session.

As indicated previously, asynchronous P300 based BCI requires real distinction between two user states: the control state where the subject is concentrated on a specific item on the screen for a number of stimulation sequences fixed a priori. Moreover, the no-control states where the subject is involved in other things. To this end, we have proposed the following protocol:

Figure 4 represents the organization of asynchronous mode. Each run consists of 10 trials that interchange between control and no-control trials. In the no-control trials, and during the matrix illumination, the subjects are asked to perform three dissimilar scenarios in order to guarantee that the dataset would include trials representing a daily life conditions in which the participant could turn his attention from the stimulation interface.

- In the first scenario, the participants were directed to pay their attention on the fixed cross symbol placed in the middle of the monitor and ignore the flashing;
- In the second scenario, the operator asked computational questions to the participant who must answer them while focusing on the fixed cross symbol; and
- The third scenario, the participants were directed to look to the second half of the monitor where a movie was played.
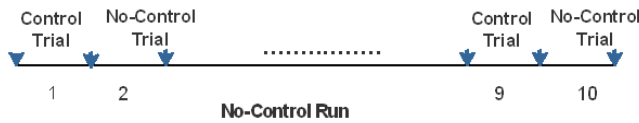

Fig 4 – Organization of asynchronous mode: non control runs.

Whereas, the parameters of the control trials were set based on the synchronous mode as it is described in Fig. 5 which it represents the organization of the control runs. Each run in Control mode consists of 8 trials showing the moment when the user is engaged with the interface. The rows and the columns of the matrix flash continuously and arbitrarily in front of the subject while he focuses his attention on the desired icon by counting how many times it gleams.
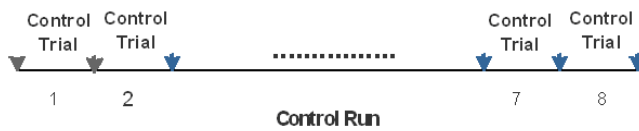

Fig 5 – Organization of synchronous mode control runs.

3. EEG DATA ANALYSIS

We used offline data to assess the system performance and select the best features for the online session. In a synchronous P300Speller, the primary objective is to determine the P300 waves in the EEG instantly and correctly. Thus, the high information transfer rate will be guaranteed by the accuracy of this detection. To prepare the data for further processing as presented in Fig. 6 it shows different stage of P300 classifier within BCI2000. Red boxes represent in which level our contribution was.

3.1. PRE-PROCESSING AND FEATURES EXTRACTION

The EEG signal was split into 800 ms epochs, starting from the onset of each stimulus. Moreover, to remove the signal's high frequency, a moving average (MA) filter was used as a low-pass filter [18, 22].

Depending on the low frequency response of the P300 and the sampling rate of the EEG signals the application of a down-sampling of 20 Hz on each epoch of 800 ms [21–23] will decrease the computational complexity. Thus, each segment was represented as a vector 144 samples (16 samples x 9 channel). Each action is modeled as characteristics matrix (see eq. (1)):

$$X = \left[C_1, C_2, \text{K} \; C_m\right]^T, \tag{1}$$

where m = (number of rows + number of columns) x number of sequences.

Afterwards, we set all the outliers to a given percentile in order to reduce their effect (subject movement, eye blinks and movement, muscle activity) on our data. A Winsorization of 80 % was applied: data under the 10th percentile were set to the 10th percentile and data greater than the 90th percentile were set to the 90th percentile [8, 15].

3.2. ERP CLASSIFICATION USING SWLDA

The main classification problems in the P300Speller paradigm are detecting the P300 wave's presence in the EEG signal and selecting the desire action. Differentiating between the presence and absence of the P300 wave is equivalent to a binary classification problem. As a matter of fact, the expectation of the P300 response is related to the experiment, and the user. Usually, the subject does not generate a P300 wave at a specific time due to various artifacts. Indeed, the P300 wave's generation is not happening by awareness, but is generated through the matrix's illuminations at a specific moment [18].

It is known that the P300's amplitude differs instantly with the relevance of the evoking events and inversely with the appearance target's probability [1, 2, 10]. Usually, a target's misclassification produced an incorrect identification of a row (or column) when the resultant column (or row) was properly recognized, which decreases the classification accuracy [8].

As it is figured out in Fig. 6, there is a difference between target epochs of columns and targets epoch of the rows, while there is no dissimilarity in non-target epochs of both column and rows. Furthermore, the R-squared value is used to show the feature difference between target and non-target epochs within rows dataset and columns dataset (Fig. 7). It shows that the epochs of columns and rows demonstrated marked dissimilarities in their characteristics. This variation might carry out a misclassification if we did not take in consideration that difference cause the epochs of the columns; it is not same as the epochs of the rows. Thus, studying the change in those features might discriminate better the target column and the target row individually. Hence, we divided the data into two sub-datasets: columns dataset and rows dataset, which we studied separately. For the result, we incorporated each classifier's output to determine the desired command [8].
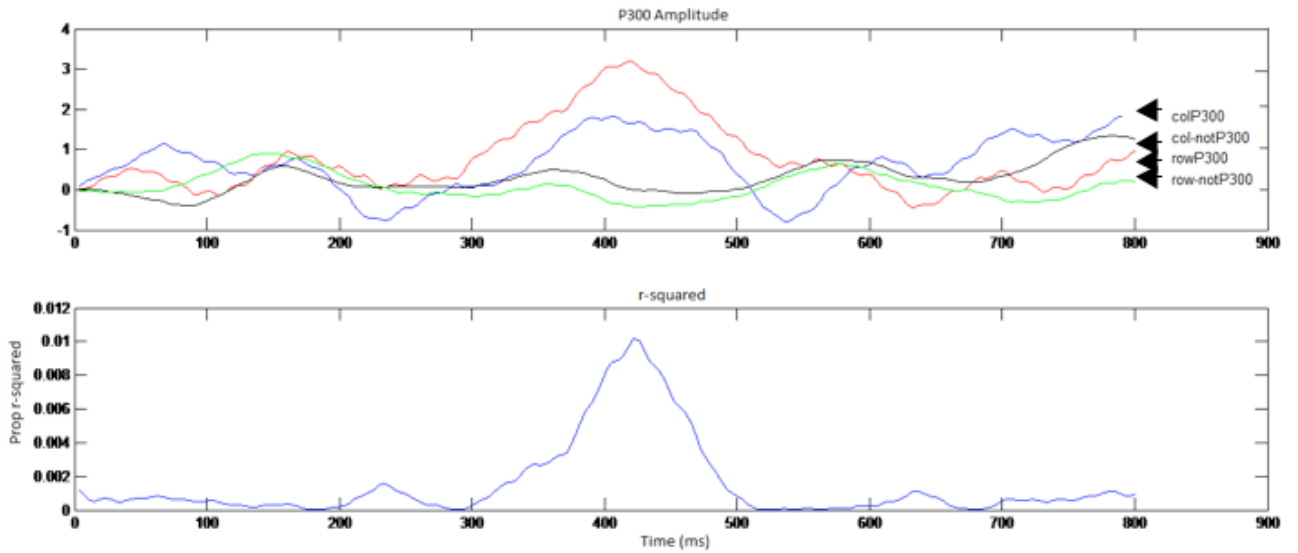
Fig. 6 –Target not target for each sub-dataset (columns and rows separately) with R-squared.
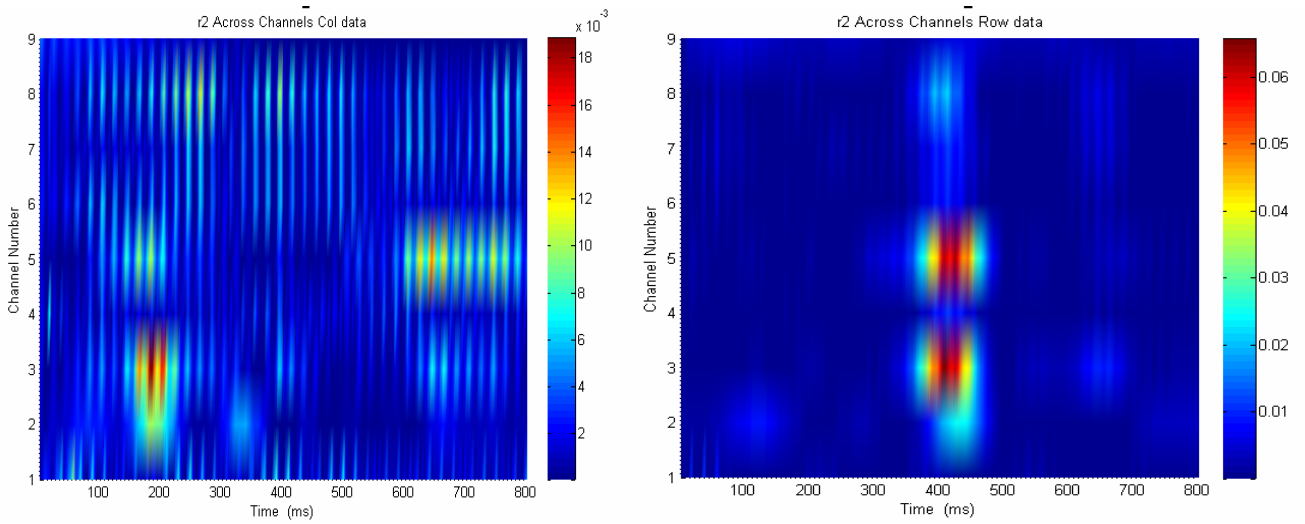

Fig. 7 – R-squared for each sub-dataset (columns and rows separately).

By using stepwise linear discriminate analysis (SWLDA) on training sets including no-control trials as classification method, we can separate between target, non-target and no-control. Usually, decreasing dimensionality and conserving the most essential feature in the model are the linear discriminate analysis's objective that can distinguish between the groups, (*i.e.* reducing the distance between the features in the same group, and maximizing the distance between the groups). By beginning with no initial model, add or remove a characteristic from the model by a mixture of forward selection (add the most statistically significant element with *p* value < 0.10) and backward elimination (remove the least statistically significant element with *p* value > 0.15) steps, are decided by the stepwise approach [11]. Thus, to ensure providing discriminative information to the model, significant differences (*p* value < 0.05) between models with and without the current assessed characteristic are evaluated [10, 24]. In this case, The discriminate function restricted to include up to 60 spatio-temporal features to a linear equation that show the highest unique variance (*i.e.* the amplitude value at a specific channel location and time sample) [10, 21, 22, 24]. Therefore, signal amplitudes at specific times and locations were considered for analysis without explicit consideration of spatial location. In order to determine the target, the columns and rows classification samples were yielded separately. We used a training set containing only row samples or columns samples for their classification.

The proposed approach (see Fig. 8) is as follows: Primarily, the training set is constructed of two learning subsets corresponding only to column and row samples respectively. Then, the test sets are constructed of two new subsets of tests as the training data. Furthermore, the samples posterior probabilities in row (column) training set are estimated using row (column) testing set. The samples that match to the same row or column flashing were gathered [8]. Thus the vector weight is calculated under the hypothesis of equal covariance for both classes where noise is distributed normally. Discriminant score values are calculated as:

$$\begin{cases} score_{i_{col}}^{seq} = w_{col}^{T} * x_{i_{col}}^{\sec} \\ score_{i_{row}}^{seq} = w_{row}^{T} * x_{i_{row}}^{\sec} \end{cases}, \qquad (2)$$

where *w* is the weight assigned based on the training data and x_i^{seq} represents the EEG data on i^{th} candidate in seq^{th} sequence. Each training data is labeled as P300 epoch or

non-P300 epoch. The score distribution is assumed as normal distribution. The log-likelihood ratio of SWLDA's output belongs to the wanted class (presence of P300) [10, 25]. The output is presented as the Euclidean distance, which (it) is calculated between the projected data and the projected mean of the wanted class [10], as follows:

$$I = \left\| (w, x) - (w, \mu_{P300}) \right\|, \qquad (3)$$

where w denotes the weight vector, x the feature matrix and μ_{P300} the mean of the positive class.

Finally, the results of the preceding classification are grouped to classify the main actions of the matrix. In the P300Speller paradigm, a couple (x, y) determines an action because the intensifications are on each column and row. The desired action can be generated by the column and row intersection in the matrix with the highest score value from each class. Furthermore, the discriminants score values on the target row / column represented by:

$$\begin{cases} score_{t\arg et_{col}}^{seq} = score_{i_{col}}^{seq}, i = c\hat{o}l \\ score_{t\arg et_{row}}^{seq} = score_{i_{row}}^{seq}, i = r\hat{o}w \end{cases}, \qquad (4)$$

where $c\hat{o}l$ and $r\hat{o}w$ represent the estimated target column and row based on EEG data.

Thus, the ensemble of target score values denote as:

$$score_{t\arg et}^{seq} = \begin{cases} score_{t\arg et_{col}}^{seq} \\ score_{t\arg et_{row}}^{seq} \end{cases}, seq = SEQ_S, SEQ_{S+1}, ..., SEQ \quad (5)$$

As mentioned before, P300Speller is a synchronous paradigm. This indicates that a decision will be made by the system whether the subject is focusing on the stimulation (the interface was continuously controlled by the subject) or not (the subject is in no-control state). Thus, an operability mode is necessary to overcome the above states and to refrain from a bad decision. In this study, we employed a threshold-based approach designed to differentiate between control and no-control states.

4. RECEIVER OPERATING CHARACTERISTIC ANALYSIS AND THE THRESHOLD VALUES EXTRACTION

In the beginning, the score values were calculated and summed up across the trial, then used to obtain the maximum values for each stimulation sequence. The control scores are estimated to be greater than no-control scores because of the presence of attention in control state comparing to the no-control state [26]. Accordingly, the distinction between control state and no-control state might be happen by using a constant threshold [26]. Furthermore, the receiver operating characteristic (ROC) curve plotted using the score values for both control and no-control state as two dissimilar groups. Thereafter, we grouped the maximum scores into two groups. We set the target scores to the positive class (label = 1), while the non-target and no-control scores to the opposite (label = 0). In this way, extracting the threshold by including the maximum score values associated to no-control segments in ROC curves insure that the occurring artifacts were taken into consideration when the participant was in no-control state.

The labeled scores were used to plot the ROC curve in order to extract the threshold values. As presented in Fig. 8, the ROC curve describes the relation between the true positive rate (TPR) and false positive rate (FPR), which they represent an important performance keys in the threshold detection. An efficient asynchronous based BCI might find a threshold that appropriates for the desired task. For example, a high bit rate is suitable for writing tasks. A speller task requires a lower threshold value when demands a higher TPR favoring speed over accuracy. Whereas a sensitive task like controlling home appliances as it is the aim of this study, requires augmentation in threshold value when demands a lower FPR preferring the safety concerns over the speed. To choose an adequate TPR while conserving FPR lower than a given limit, testing each threshold and checking the resultant TPR and FPR is needed throughout an offline analysis of the EEG data. Choosing the threshold value has a relation with finding the trade-off among the TPR and FPR. These values were chosen based on work released in [13], choosing the specificity (low FPR) regarding the sensitivity as the objective of this study is controlling home appliances. Therefore, the trade-off between the true positive rate (TPR > 0.5) and false positive rate (FPR < 0.05) determines the threshold values. If the true positive rate was superior to 0.5 then the intersection of the line through points (0.05, 0.5) and (0, 1) with the ROC curve represents the threshold value.
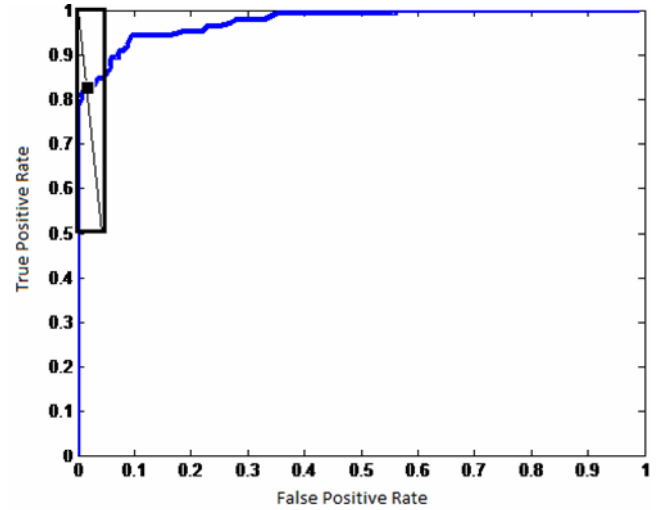

Fig 8 – Threshold value extraction using ROC curve.

A comparison between the threshold values and the row's maximum score and column's maximum score was made to take a decision. The classification is made at the intersection of the maximum score of both column and row only if the threshold values are exceeded; otherwise, if the number of stimulation sequences reached the reset value without overriding the assigned threshold, the system will refrain from making a decision, and a new trial will begin by assigning the accumulated score values to zero.

The green point on the curve (Fig. 8) represents the trade-off ($S_{threshold}$) between the values of true positive rate (TPR) and false positive rate (FPR). Thus, the classification of the desired action is made at the intersection of the maximum score of both column and row only if the threshold values are exceeded. Otherwise, if the number of stimulation sequences reached the maximum number of stimulation sequences fixed a priori without overriding the assigned threshold, the system will refrain from making a decision, and a new trial will begin by assigning the number of stimulation sequences to zero.

$$S^{SEQ} = \begin{cases} Control\_stat\_if\_Score^{SEQ}_{target} \geq S_{threshold} \\ Non - control\_state\_if\_score^{SEQ}_{target} < S_{threshold} \end{cases} . (6)$$

5. RESULTS AND DISCUSSION

In this study, we presented an asynchronous P300 based threshold mechanism to control household appliances. Figure 9 reflects the experiment carried out with each participant in synchronous mode. The number of stimulation sequences was averaged based on the percentages of correct classification. We offer proof that the P300 classification could be improved through treating and processing data rows and columns separately. The results showed that the proposed algorithm can increase the P300Speller paradigm's performance by decreasing the number of stimulation sequences needed to reach an accuracy of 100 %. The achieved accuracy values and the number of stimulation sequences were used to evaluate the performance of the system for both synchronous and asynchronous system. For asynchronous mode, only the control trials were taking in consideration.
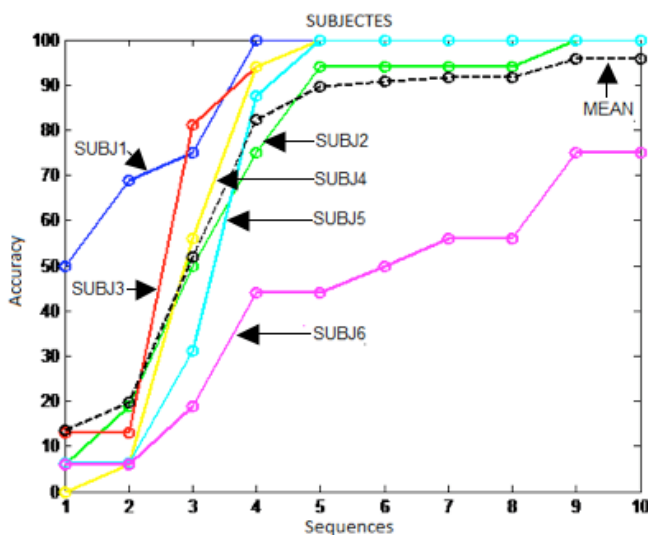

Fig 9 – Accuracy for synchronous system.

The accuracy for asynchronous system divides on two, depending on control state and non-control state as it shown in Fig 10. The accuracy of control state is estimated as follow:

1. Correct classification: correctly determined the result.

2. Wrong classification: erroneous determined result.

The accuracy of non-control state is estimated as follow:

1. **Abstention:** BCI system does not generate result.

2. **Missed abstentions:** The subject does not focus n interface but the system generates unwanted random control selection.

Furthermore, the detection thresholds criterion determination is one of the essential concerns for the asynchronous P300 based BCI system; it has a strong relation with the desired application. The detection of the attended command based on the user's desire using the implemented threshold mechanism offers the user an easy experiment, by rejecting the unattended choices during the no-control state, and at the same time keeps the control state selections. Figure 10 shows the ability of our system to avoid misclassification to achieve an average of 90 % for correct classification and 10 % for misclassification. The robustness

of the system is shown through the classification's abstention (*i.e.* the system abstains from making a decision) results that yielded an average of 84.44 %.

A comparison between the present work and the different studies cited in section 1 is hard because the dissimilarity in the classification methods, the paradigms applied, the number of subjects used in experiments, and specifically in the evaluation of the system performance. F. Aloise [13] reported on average of 88.73 % of correct classification, and the system's ability to abstention reached on average of 98.91 %. Nevertheless no important enhancement in speed selection could be attained in respect of a synchronous system.
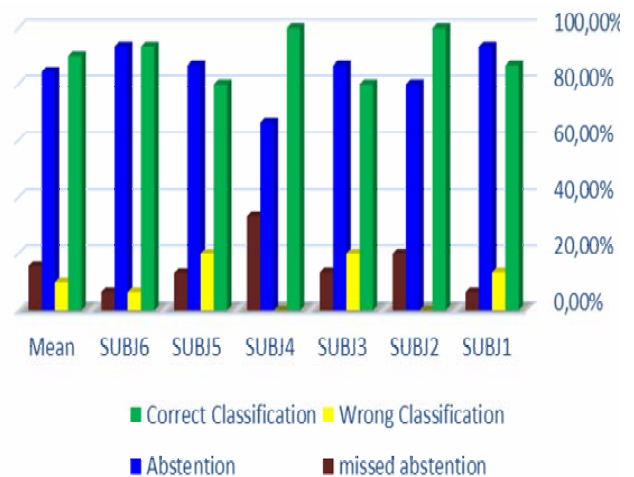

Fig. 10 – Asynchronous performance using alternate runs.

In addition, the classifier performance of each subject depends on the control state threshold, which is computed from the SWLDA scores. Hence, frequency characteristics, which are necessary for the detection of the correct state, could enhance the application performance by making the control state threshold independent of the scores' classifier. Nowadays, hybrid BCIs are promising, and there are many studies carried out on this field. It is a well-known fact that there is no easy way to modify the flashing of the P300Speller. In BCI2000 framework the use of different flashing frequencies forces many research groups to use different software. Thus, it is an interesting research idea using a mixture of Pinegger *et al.* proposal [27] and our approach by using the proposition that when a user is focusing at the illumination of the stimulation interface the frequency of illumination is indicated more or less marked in the signal from the occipital electrodes. The shape of this signal is similar to a steady state visually evoked potential (SSVEP) signal without concentrating on an attended command.

9. CONCLUSION

Transferring the BCI systems from a lab models to a real-world is a challenging task. Numerous technical enhancements are still required to use assistive technologies based BCI systems by paralyzed people in their own environmental control. One of the drawbacks of synchronous system is performing a selection in each N seconds which might increase the unattended choices and interaction difficulties.

This study offers some propositions to overcome the drawbacks of the traditional synchronous based BCI systems, by introducing an asynchronous mechanism which might suspend the control when the subject is not in the control mode and abstain from making a decision when there are not many features to decide. Therefore, the data

was divided into two datasets, rows dataset, and columns dataset. Each dataset was treated and processed separately. Then, combing the classifiers' outcomes to identify the wanted action. The threshold mechanism was based on the ROC curve. In each new sequence, we accumulated the score values to the previous ones, and we matched the maximum scores of the rows and the columns to the chosen threshold. If they passed at the same time a selection will be made. Otherwise, the system abstains from making a decision. The results were so promising with the proposed approach. It's carried out a correct identification of the target on average of 91.76 % with abstention of 81.66 %.

REFERENCES

1. J.R Wolpaw, N. Birbaumer, D.J. McFarland, G. Pfurtscheller, T.M. Vaughan, *Brain-computer interfaces for communication and control*, Clin. Neurophysiol., **113**, pp. 767–91 (2002).
2. G. Dornhege, J. del R. Millan, T. Hinterberger *et al.*, *Toward brain-computer interfacing*, MIT press, 2007.
3. E.W. Sellers, E. Donchin, *A P300-based brain-computer interface: Initial tests by ALS patients*, Clin. Neurophysiol., **117**, pp.538–548 (2006).
4. Y. Wang, R.Wang, X. Gao, B. Hong, S. Gao, *A practical VEP-based brain-computer interface*, IEEE Trans. Neural Syst. Rehabil. Eng., **14**, pp. 234–239 (2006).
5. H. Serby, E. Yom-tov, G.F. Inbar, *An Improved P300-Based Brain-Computer Interface*, **13**, pp. 89–98 (2005)
6. N. Xu, L. Gao, B.Hong, *et al.*, *BCI competition 2003-data set IIb: enhancing P300 wave detection using ICA-based subspace projections for BCI applications*, IEEE Transactions on Biomedical Engineering, **51**, *6*, pp. 1067-1072 (2004).
7. L.A. Farwell, E. Donchin, *Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials*, Electroencephalogr. Clin. Neurophysiol., **70**, pp. 510–523 (1988).
8. U. Güçlü, Y. Güçlütürk, A. Samraj, *A novel approach to improve the performance of the P300 speller paradigm*, Conf. Proc. - IEEE Int. Conf. Syst. Man Cybern., 2010, pp. 3786–3790.
9. R.C. Panicker, S. Puthusserypady, A.P. Pryana, Y. Sun, *Asynchronous P300 BCI: SSVEP-based control state detection*, Eur. Signal Process. Conf., **58**, pp. 934–938 (2010).
10. Y. Liu, H. Ayaz, A. Curtin, P.A. Shewokis, B. Onaral, *Detection of attention shift for asynchronous P300-based BCI*, Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. EMBS., 2012, pp. 3850–3853.
11. Y. Li, J. Long, T. Yu, Z. Yu, C. Wang, H. Zhang, C. Guan, *An EEG-based BCI system for 2-D cursor control by combining Mu/Beta rhythm and P300 potential*, IEEE Trans. Biomed. Eng., **57**, pp. 2495–2505 (2010).
12. H. Zhang, C. Guan, C. Wang, *Asynchronous P300-based brain-computer interfaces: a computational approach with statistical models*, IEEE Trans. Biomed. Eng., **55**, pp.1754–63 (2008).
13. F. Aloise, F. Schettini, P. Aricò, F. Leotta, S. Salinari, D. Mattia, F. Babiloni, F. Cincotti, *P300-based brain-computer interface for environmental control: an asynchronous approach*, J. Neural Eng., **8**, pp. 025-025 (2011).
14. F. Aloise, F.Schettini, P.Arico, S. Salinari, C. Guger, J. Rinsma, , M. Aiello, D. Mattia, F. Cincotti, *Asynchronous P300-Based Brain-Computer Interface to Control a Virtual Environment: Initial Tests on End Users*, Clin. EEG Neurosci., **42**, pp. 219–224 (2011).
15. N. Yu, Q, Ding, H. Lu, *Single-Trial Estimation of Evoked Potential Signals via ARX Model and Sparse Coding*, Journal of Medical and Biological Engineering, **37**, *2*, pp. 209–219 (2017).
16. J. Polich, *Updating P300: An integrative theory of P3a and P3b*, Clin. Neurophysiol., **118**, pp. 2128–2148 (2007).
17. L. Citi, R. Poli, C.Cinel, *Exploiting P300 amplitude variations can improve classification accuracy in Donchin's BCI speller*, 2009 4th Int. IEEE/EMBS Conf. Neural Eng. NER '09., 2009, pp. 478–481.
18. G. Li, B. Li, G. Wang *et al.* , *A new method for human mental fatigue detection with several EEG channels*, Journal of Medical and Biological Engineering, **37**, *2*, pp. 240-247 (2017).
19. Hoffmann, U., Vesin, J.M., Ebrahimi, T., Diserens, K. *An efficient {P300}-based brain-computerinterface for disabled subjects*, J. Neurosci. Methods., **167**, pp.115–125 (2008).
20. G. Dornhege, J. del R. Millan, T. Hinterberger, *et al.*, *Toward brain-computer interfacing*, MIT Press, 2007.
21. E.W. Sellers, D.J. Krusienski, D.J. McFarland, T.M.Vaughan, J.R.Wolpaw, *A P300 event-related potential brain-computer interface (BCI): The effects of matrix size and inter stimulus interval on performance*, Biol. Psychol., **73**, pp. 242–252 (2006).
22. D.J. Krusienski, E.W. Sellers, D.J. McFarland, T.M. Vaughan, J.R. Wolpaw, *Toward enhanced P300 speller performance*, J. Neurosci. Methods, **167**, pp. 15–21 (2008).
23. B.Z. Allison, J.A. Pineda, *ERPs evoked by different matrix sizes: Implications for a brain computer interface (BCI) system*, IEEE Trans. Neural Syst. Rehabil. Eng., **11**, pp. 110–113 (2003).
24. H. Cecotti, A. Graser, *Convolutional neural networks for P300 detection with application to brain-computer interfaces*, IEEE Transactions on pattern analysis and machine intelligence, **33**, *3*, pp. 433-445(2010).
25. D.J. Krusienski, E.W. Sellers, F. Cabestaing, S. Bayoudh, D.J. McFarland, T.M. Vaughan, J.R. Wolpaw, *A comparison of classification techniques for the P300 Speller*, J. Neural Eng., **3**, pp. 299–305 (2006).
26. V. Martínez-Cagigal, J. Gomez-Pilar, D. Álvarez, *et al.*, *An asynchronous P300-based brain-computer interface web browser for severely disabled people*, IEEE Transactions on Neural Systems and Rehabilitation Engineering, **25**, *8*, pp. 1332-1342 (2016).
27. A. Pinegger, J .Faller, S. Halder, S.C. Wriessnegger, G.R. Müller-Putz, *Control or non-control state: that is the question! An asynchronous visual P300-based BCI approach*, J. Neural Eng., **12**, p. 014001 (2015).