An Online Single Trial Analysis of the P300 Event Related Potential for the Disabled

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***Abstract* – Brain computer interface (BCI) enables nonmuscular interaction with the environment. This interaction is particularly beneficial for those with impaired voluntary muscular activity. In this study, an online single trial analysis of a P300 dataset acquired using the six choice paradigm from four disabled subjects was conducted using a methodology involving the fuzzy k nearest neighbors classifier since an offline analysis and averaging many repeated trials in P300 based BCI are not always practical in real applications. The results showed that this methodology is favorable for the single trial analysis of the P300 event related potential for the disabled. Further research is warranted to achieve additional improvements in the single trial classification accuracies to the levels adequate for use in real applications.**

Keywords – Brain computer interface (BCI), disabled, fuzzy k nearest neighbors (FKNN), online analysis, P300 event related potential (P300 ERP), single trial analysis

I. INTRODUCTION

People interact with the environment through verbal and nonverbal means. However, neurological disorders like motor neuron diseases may impair this interaction as they prevent voluntary muscular activities [1]. Provided that the cognitive ability is not affected by these disorders, a direct communication channel between a brain and an external device enables nonmuscular interaction with the environment using only cognitive functions. Brain computer interface (BCI), which involves the acquisition of the brain activity using a neuroimaging technology followed by its analysis using preprocessing, feature extraction and classification operations, provides such a channel. Electroencephalogram (EEG) is a neuroimaging technology commonly used to acquire brain activity for BCI [2, 3] due to its noninvasive nature, low cost and ease of use [4]. One of the most popular features of EEG utilized in BCI is the P300 event related potential (P300 ERP) [5, 6]. An advantage of the utilization of the P300 ERP over other EEG features in BCI is that the P300 ERP does not require any training since it is an automated response [7].

The P300 ERP is a brain wave elicited over the parietal lobe in response to an auditory or a visual stimulus. It is observed as a positive deflection in an EEG recording approximately 300 ms after such a stimulus however this latency can be greater for those with neurological disorders (Fig. 1). It is best elicited using the oddball paradigm which involves the presentation of an infrequent target stimulus among frequent nontarget stimuli [8]. One of the many implementations of the oddball paradigm is the six choice paradigm which involves the presentation of a matrix of six elements (Fig. 2) and a random intensification of these elements [9]. In order to select a target, attention is focused on the element containing the target by counting the number of times it is intensified. The P300 ERP is elicited after the intensification of the element containing the target. The target is then identified as the element after which the P300 ERP is elicited.

An offline analysis is usually preferred for the investigation of the P300 ERP [10, 11]. Although this approach is suitable for research purposes, it does not always reflect the real performance of a BCI system. Also, in many studies the classification is done by averaging many repeated trials due to the low signal to noise ratio of the P300 ERP [12, 13]. While this approach can provide higher classification accuracies than the single trial analysis, it is not always practical in real applications since repeating trials decreases the speed of the BCI system and would be tiresome for the user.

In this study, an online single trial analysis of a P300 dataset acquired using the six choice paradigm from four disabled subjects was conducted using a methodology involving the fuzzy k nearest neighbors (FKNN) classifier in order to overcome the shortcomings of the offline analysis and averaging many repeated trials in P300 based BCI.

The organization of this paper is as follows: In the next section, the dataset used in this study as well as the preprocessing, feature extraction and classification operations are explained. In the third section, the results are discussed and compared to those of another study using the same dataset [9]. In the last section, the conclusions are presented.

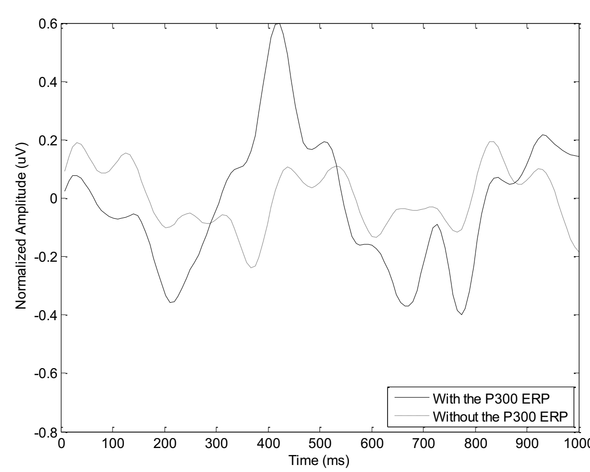

Fig. 1 Average signals with and without the P300 ERP (straight and dashed, respectively) acquired using the Cz electrode from four disabled subjects from [9]

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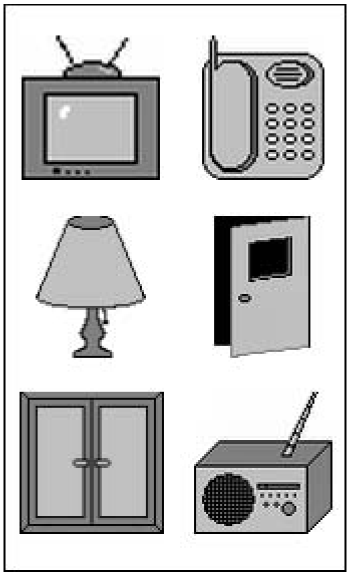

Fig. 2 A matrix that can be presented in the six choice paradigm, similar to the one presented in the acquisition of the dataset from [9]

II. Materials and Methods

The experiments were conducted using MATLAB on a P300 dataset acquired using a six choice paradigm from four disabled subjects [9]. First, the training data were constructed including all the samples with the P300 ERP and randomly selecting only one sample without the P300 ERP from each trial in order to keep the number of samples with and without the P300 ERP equal. Then, the preprocessing operations including electrode selection, referencing, filtering, winsorization and normalization were applied on the training and testing data. The preprocessing of the testing data was carried out casually i.e. without using any future data. Fisher's linear discriminant analysis (FLDA) was then performed for feature extraction. Finally, the testing data were classified using the FKNN classifier. After the classification of each testing trial, the testing sample with the P300 ERP and a random testing sample without one were added to the training data in order to achieve a continuous learning process. The experiment was repeated using the same methodology with offline analysis as well as using the k nearest neighbors (KNN) classifier to compare the results.

A. Dataset

The dataset from [9] was used. The dataset consisted of signals acquired using 32 electrodes placed at the standard positions of the 10-20 international system (Fig. 3) and with a sampling rate of 2048 Hz from four healthy and four disabled subjects. The six choice paradigm, which involved the presentation and random intensification of a 3 by 2 matrix of images (Fig. 2), was used to collect the data. In this study, the experiments were conducted on the data of only the disabled subjects. For each subject, there were four sessions, each consisting of six runs. In each run there was a different target image for which an average of 22.5 trials were made. At the beginning of each trial, all the images had the same intensity. Each image was then intensified for 100 ms and after each intensification, all the images had the same intensity for another 300 ms. This resulted in an interstimulus interval of 400 ms. Each of the four sessions was used once as a testing set while using the remaining three as a training set.

B. Preprocessing

The following preprocessing operations similar to those in [9] were performed:

1) Electrode Selection

Eight electrodes were selected for processing (Fig. 3).

2) Referencing

The average data from the T7 and T8 electrodes were subtracted from the data from the selected electrodes.

3) Filtering

The data from the selected electrodes were zero phase filtered using a 6th order bandpass digital Butterworth filter [14] with cutoff frequencies of 1 and 12 Hz in both the forward and reverse directions.

4) Downsampling

The data from the selected electrodes were downsampled to 32 Hz.

5) Sample Extraction

Samples were extracted from each trial for a period of 1 s starting at stimulus onset.

6) Winsorization

The amplitude values of the samples from the selected electrodes that were below the 10th and above the 90th percentile were set to those of the 10th and 90th percentile, respectively.

7) Normalization

The samples from the selected electrodes were normalized to the closed interval of -1 and 1.

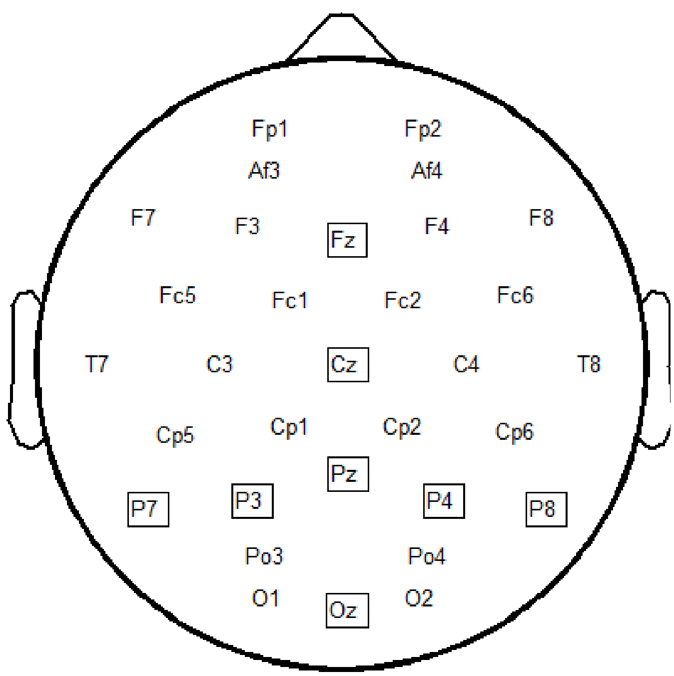

Fig. 3 The electrodes used to acquire and analyze the data (all and in a square, respectively), plotted using [15]

C. Feature Extraction

The features of the samples were extracted using FLDA [16]. FLDA finds a linear combination of features that best separates data in a least square sense by projecting its features on a line maximizing the between class scatter and minimizing the within class scatter. All the samples from the selected electrodes were concatenated, and the projection matrix was constructed from the training data. The concatenated samples were then projected onto the line defined by the projection matrix. This projection resulted in one dimensional feature vectors.

D. Classification

The classification was carried out using the FKNN classifier [17] which is a variation of the KNN classifier. The KNN classifier assigns a class label to a testing sample however it does not specify the degree of membership to that class. In certain cases, this approach might not be suitable. For example, in the six choice paradigm, instead of labeling all six testing samples from a trial as with or without the P300 ERP independently, the testing sample with the highest degree of membership to the “with the P300 ERP” class needs to be identified. The FKNN classifier overcomes this problem by assigning a membership value to a testing sample indicating how much it belongs to a particular class. The membership value for a class is calculated by first finding the distance between the testing sample and each training sample and then dividing the number of training samples from that class within the nearest neighbors by the number of nearest neighbors.

The number of nearest neighbors has a substantial effect on the performance of the classifier. On that account, different numbers of nearest neighbors were tested. In all cases, the maximum number of nearest neighbors was limited to the square root of the total number of the training samples [18]. In a two class problem, normally an odd number of nearest neighbors is selected in order to avoid any ties that may occur. However, since the classification is carried out as mentioned above, the possible ties on the membership values did not pose a problem thus no such restrictions applied. The performance is also affected by the dimensionality of the data. While being inefficient with a high dimensional data [19], the KNN (and FKNN) classifier is efficient on a low dimensional data [20]. Thus, FLDA was employed as the feature extraction method since it produces one dimensional feature vectors which in turn makes the FKNN classifier efficient.

III. Results and Discussion

In this study, single trial classification accuracies of all the sessions were calculated (as the percentage of the correctly classified trials) for each subject (Table I) and were averaged to find the overall performance of the subject (Table II).

The highest and lowest average online classification accuracies were 64% (subject 3) and 39% (subject 1), respectively (Table II). The differences in the online classification accuracies of the sessions ranged from 1% (subject 2) to 19% (subject 3) (Table I).

TABLE I Classification Accuracies (in Percentage) Achieved With the Online Analysis (Using the FKNN Classifier) for All the Subjects and Sessions

Session	**Subject**			
	1	**2**	**3**	**4**
1	45	46	63	51
2	49	45	58	56
3	32	42	68	53
4	36	51	77	55

TABLE II Average Classification Accuracies (in Percentage) Achieved With both the Online (Using the FKNN and KNN Classifiers) and Offline (Using the FKNN Classifier) Analyses for All the Subjects

Methodology	**Subject**			
	1	**2**	**3**	**4**
Online FKNN	39	44	64	52
Offline FKNN	42	47	67	55
Online KNN	25	30	41	34

The average classification accuracies obtained with the offline analysis were only 3% higher than those obtained with the online analysis for all the subjects (Table II). The results of the online FKNN classifier were higher than those of the online KNN classifier by 14% to 23%. Compared to the single trial results of [9] (which used only offline analysis), the results of this study were higher for the subjects 1, 2 and 3 (by 6% to 14% in online analysis and 9% to 17% in offline analysis) however, they were lower for subject 4 (by 6% in online analysis and 3% in offline analysis).

A relation between the average amplitude of the P300 ERP elicited by a subject (Fig. 4) and the overall performance of the subject (Table II) was observed such that the subject with the highest average P300 ERP amplitude had the best overall performance (subject 3) whereas the subject with the lowest had the worst (subject 1). The number of nearest neighbors was also an important factor on the overall performance such that for all subjects, there was a rapid increase in the average classification accuracies until 10 nearest neighbors however after this point, the average classification accuracies were almost constant with only small fluctuations (Fig. 5). The

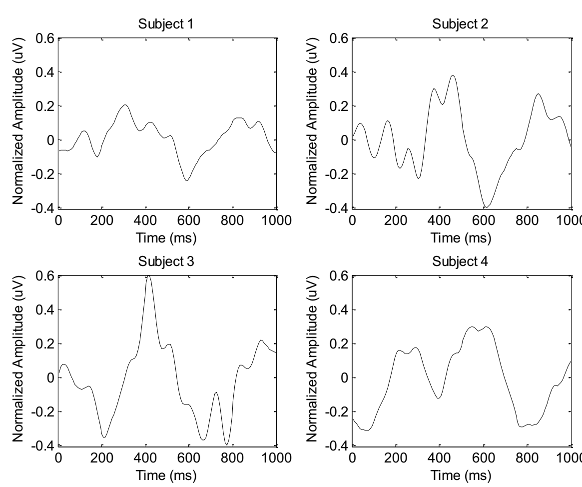

Fig. 4 Average signals with the P300 ERP from the Cz electrode for each subject

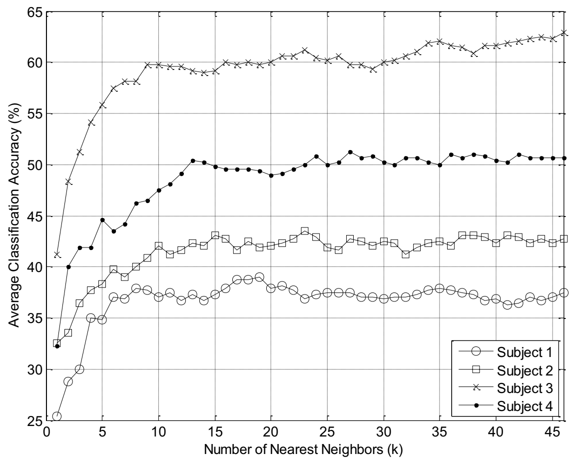

Fig. 5 Average classification accuracies obtained using number of nearest neighbors ranging from one to 46 for all the subjects

numbers of nearest neighbors that provided the best results were 19, 23, 46 and 27 for the subjects 1, 2, 3 and 4, respectively.

Decreasing the size of the training data by randomly selecting only one training sample without the P300 ERP out of the possible five from each trial increased the speed of the system due to an increase in the performance of the FKNN classifier. This improvement was achieved without decreasing the classification accuracies. Continuously expanding the training data also improved the performance of the system, but it can result in a decrease in the speed of the system in the long run due to a decrease in the performance of the FKNN classifier. Limiting the expansion of the training data can be considered to mitigate this effect.

IV. Conclusion

Offline analysis and averaging many repeated trials in P300 based BCI is not always practical in real applications. In this study, a methodology involving the FKNN classifier was presented in order to overcome this shortcoming. The results showed that this methodology is favorable for the online single trial analysis of the P300 ERP for the disabled. Further research is warranted to achieve additional improvements in the single trial classification accuracies to the levels adequate for use in real applications.

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References

[1] N. Birbaumer, “Breaking the silence: Brain-computer interfaces (BCI) for communication and motor control,” *Psychophysiology*, vol. 43, 2006, pp. 517-532.

[2] G.E. Fabiani, D.J. McFarland, J.R. Wolpaw, and G. Pfurtscheller, “Conversion of EEG activity into cursor movement by a brain-computer interface (BCI),” *IEEE Transactions on Neural Systems and Rehabilitation Engineering: A Publication of the IEEE Engineering in Medicine and Biology Society*, vol. 12, 2004, pp. 331-338.

[3] B. Blankertz, K. Müller, G. Curio, T.M. Vaughan, G. Schalk, J.R. Wolpaw, J. R, A. Schlögl, C. Neuper, G. Pfurtscheller, T. Hinterberger, M. Schrder, and N. Birbaumer, “The BCI Competition 2003: Progress and Perspectives in Detection and Discrimination of EEG Single Trials,” *IEEE Transactions on Bio-Medical Engineering*, vol. 51, 2004, pp. 1044-1051.

[4] A. Kübler, and K. R. Müller, “An introduction to brain-computer interfacing,” in *Toward Brain-Computer Interfacing*, G. Dornhege, J. D. R. Millan, T. Hinterberger, D. J. McFarland, K. R. Müller, Eds. Cambridge, MA: The MIT Press, 2007, pp. 1-25.

[5] E. Donchin, K.M. Spencer, and R. Wijesinghe, “The mental prosthesis: Assessing the speed of a P300-based brain-computer interface,” *IEEE Transactions on Rehabilitation Engineering*, vol. 8, 2000, pp. 174-179.

[6] S. Andrews, R. Palaniappan, A. Teoh and L. C. Kiong, “Enhancing P300 component by spectral power ratio principal components for a single trial brain-computer interface,” *American Journal of Applied Sciences*, vol. 5, 2008, pp. 639-644.

[7] F. Beverina, G. Palmas, S. Silvoni, F. Piccione, S. Giove, “User adaptive BCIs: SSVEP and P300 based interfaces,” *PsychNology Journal*, vol. 1, 2003, pp. 331-354.

[8] M. Fabiani, G. Gratton, D. Karis, E. Donchin, “The definition, identification, and reliability of measurement of the P300 component of the event-related brain potential,” in *Advances in Psychophysiology*, vol. 2, P. K. Ackles, J. R. Jennings, M. G. H. Coles, Eds. Greenwich, CT: JAI Press Inc, 1987, pp. 1-78.

[9] U. Hoffmann, J. Vesin, T. Ebrahimi, and K. Diserens, “An efficient P300-based brain-computer interface for disabled subjects,” *Journal of Neuroscience Methods*, vol. 167, 2008, pp. 115-125.

[10] L. Farwell and E. Donchin, “Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials,” *Electroencephalography and Clinical Neurophysiology*, vol. 70, 1988, pp. 510-523.

[11] A. Rakotomamonjy, V. Guigue, G. Mallet and V. Alvarado, "Ensemble of SVMs for improving brain computer interface P300 speller performances," *Artificial Neural Networks: Biological Inspirations – ICANN 2005 Lecture Notes in Computer Science*, vol. 3696/2005, 2005, pp. 45-50.

[12] H. Serby, E. Yom-Tov, and G.F. Inbar, “An improved P300-based brain-computer interface,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering: A Publication of the IEEE Engineering in Medicine and Biology Society*, vol. 13, 2005, pp. 89-98.

[13] E. W. Sellers, D. J. Krusienski, D. J. McFarland, T. M. Vaughan, and J.R. Wolpaw, “A P300 event-related potential brain-computer interface (BCI): the effects of matrix size and inter stimulus interval on performance,” *Biological Psychology*, vol. 73, 2006, pp. 242-252.

[14] S. Butterworth, “On the theory of filter amplifiers,” *Wireless Engineer*, vol. 7, 1930, pp. 536–541.

[15] A. Delorme and S. Makeig, “EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis,” *Journal of Neuroscience Methods*, vol. 134, 2004, pp. 9-21.

[16] R. Fisher, “The use of multiple measurements in taxonomic problems,” *Annals of Eugenics*, vol. 7, 1936, pp. 179-188.

[17] J. M. Keller, M. R. Gray, and J. A. Givens, Jr., "A Fuzzy K-Nearest Neighbor Algorithm", *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 15, 1985, pp. 580-585.

[18] J. L. A. Rosa and N. F. F. Ebecken, “Data mining for data classification based on the KNN-fuzzy method supported by genetic algorithm,” *Proceedings of the 5th international conference on High performance computing for computational science*, Porto, Portugal: 2003, pp. 126-133.

[19] K. Müller, M. Krauledat, G. Dornhege, G. Curio, and B. Blankertz, “Machine Learning Techniques for Brain-Computer Interfaces,” *Biomedizinische Technik*, vol. 49, 2004, pp. 11-22.

[20] F. Lotte, M. Congedo, A. Lécuyer, F. Lamarche, and B. Arnaldi, “A review of classification algorithms for EEG-based brain–computer interfaces,” *Journal of Neural Engineering*, vol. 4, 2007, pp. R1-R13.