P300 Speller System for Brain Computer Interface

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***Abstract*—The P300 Speller System for Brain Computer Interface has an objective of effectively communicating with patients having motor neuron diseases. The system makes use of the electroencephalogram (EEG) signals recorded from the scalp, as the patient responds to some visual stimuli. A rare visual event leads to an event-related potential (ERP), which is detected in the electroencephalogram after approximately 300 ms as per the oddball paradigm. The recorded data is then used to train a classifier for predicting the sequence of characters that the patient wants to convey. Such a system would act as a potent manner of expression for the suffering patients.**

***Index Terms*—Brain Computer Interface (BCI), electroencephalogram (EEG), SVM, event-related potentials (ERPs), oddball paradigm, P300.**

I. Introduction

People having neurological disabilities may face immense difficulties in communicating with others. Brain Computer Interface (BCI) proves to be an effective means of communication for them. Over the years, the BCI technology has had implementations from controlling wheelchairs to providing as an additional channel of control in computer games. An electroencephalograph placed on the scalp of the patient, can record their brain waves as a function of time. This electroencephalogram on analysis, shows elevated event related potentials as the patient's response to external stimuli.

The P300 Speller System involves working with the electroencephalogram recorded in response to visual stimuli. For this purpose, the electrodes of the electroencephalograph are placed on the scalp, directly above the two occipital lobes of the human brain. These lobes are located in the rearmost portion of the cerebrum and are responsible for generating waves in response to what the patient sees. This specific arrangement is derived from the international 10-20 system.

A machine learning model trained on this temporal data allows us to predict, based on current wave patterns, if the patient is being visually stimulated and how. The data recorded for this purpose is highly imbalanced and has to be appropriately processed and filtered before being acted upon. The model detects and labels anomalous wave patterns, identifying similar patterns while testing.

In this paper, a survey of the various researches done on this subject, talking about the methods adopted and the results obtained has been done. Further, the system flow has been discussed and the common naming conventions used throughout the research have been defined. Later, methods for data collection, its description, communication, pre-processing and analysis have been addressed. The classification technique, which employs the machine learning algorithm: support vector machines and neural networks, has also been discussed at the end.

The work done in this research deals with devising the data collection methods, handling network channels, pre-processing the data and training a classifier on it. The research has led to the fabrication of an end to end system for the purpose described above.

II. Literature Survey

A. Literature Survey Study

Although work in this domain has been majorly based on the freely available dataset by BCI, a few researchers have collected their own datasets by designing separate systems for this purpose. Multiple researches have been done based on which certain conclusions have been derived.

In the paper by L.A. Farwell and E. Donchin [1], where a system for communication through a computer was developed and tested, a study of 5 healthy volunteers was done. The system was used to communicate a 5 letter word to a computer and the primary purpose was to determine the number of trials and the rate of event presentation that are required to achieve a specific level of accuracy in communication. Four different algorithms were used to compute the scores: Stepwise linear discriminant analysis (SWDA), Peak Picking, Area and Covariance. A low rate of communication was achieved at 1 character every 26 seconds or 2.3 chars per minute. Also, data from only 5 subjects was used, so it did not perform well across subjects and across sessions.

Alain Rakotomamonjy and Vincent Guigue [2] used methods like SVM and LDA on the data made available by BCI. They presented an algorithm that had the best classification performance on the dataset, produced with the help of a P300 speller matrix, of the BCI III competition. An ensemble of classifiers was trained for each subject, where each of the single classifier was a linear support vector machine. They achieved a correct classifier performance of 73.5% and 96.5% for 5 and 15 character sequences respectively and this performance had been evaluated on a test set composed of 200 spelling characters. Drawback of this paper was that it provided only offline analysis of the classification algorithms and online capacity had to be verified. Although from different acquisition sessions, BCI competition III had only provided datasets from 2 different subjects. Hence, the algorithm used cannot handle inter-subject variability as signals from the same subject were used for both training as well testing. This issue of inter-subject variability made it difficult for the BCI based speller to work efficiently with a new subject, without the need of training a new session.

Matthias Kaper, Peter Meinicke and Thomas Lingner [3] developed a system which involved a subject being shown a 6x6 matrix, containing 36 characters. Every trial included a sequence of highlighting the rows and columns, where each row and column was highlighted once. Whenever the character on which the subject was concentrating was highlighted, a P300 component occurred in the EEG. An SVM classifier was trained for binary classification in a training set labeled with 1 and -1 for the presence/absence of P300 spike. This trained classifier then computed the value of its discriminant function within a test set, with a high score indicating presence of a P300 spike. By performing five-fold cross validation on the training set, they obtained optimal values for the parameters of SVM. This helped them in achieving an accuracy of 84.5% in distinguishing between the P300 and non-P300 signals.

Sourav Kundu and Samit Ari [4] used normalization methods like Z-Score Normalization, Min-Max Normalization and Median Absolute Deviation (MAD) with the same ensemble technique, to normalize the scores of each of classifiers for reducing classifier variability. The proposed Min-Max normalization achieved 76% on 5 epoch and 97% on 15 epoch compared to initial method of 73.5% and 96.5%. the accuracy for Z-score was 75.5% and 97.5% respectively and that for MAD was 76% and 98% respectively.

Benjamin Blankertz et al. [5] recorded the BCI Competition III Dataset II, which represented a record of P300 associated potentials. This recording comprised of data from three sessions per subject, using the paradigm described in and originally by Farwell and Donchin [**?**]. The objective of the competition was to train a classifier on the data from two sessions (a total of 42 characters), using which 31 characters in the one remaining session were predicted. The subject was presented with a 6 by 6 matrix of characters. His/Her job was to focus attention on the characters in a character sequence that was prescribed by the investigator (i.e., one character at a time). The rows and columns of this matrix were successively and randomly intensified at a rate of 5.7 Hz. The desired character was highlighted twice in an epoch as a result of two out of the 12 intensifications (one row and one column). Digitized at 240 Hz, the signals were collected from one subject in three sessions and each session consisted of a number of runs. In each run, data was collected for a particular character for a certain number of epochs. On further analysis, it was concluded that 5 epochs produced the same result as 15 epochs.

B. Literature Survey Conclusion

Since all these proposed system are based on the offline data that are provided by BCI there is little knowledge about the performance of these same algorithms on real-time EEG data. Also the dataset provided only consist of 2 or 5 subjects which leads to less accurate results for person not present in the training and testing phase.

III. Methods

In the P300 speller paradigm, we present a 6x6 matrix containing 36 characters. Each row and column of the matrix is highlighted in a single trial called epoch. Whenever the character that user focuses on is highlighted in a trial, a P300 spike is seen in the electroencephalogram signals. Out of the 12 intensifications in a single epoch, only two correspond to the row and column of the character that was focused by the subject.

After highlighting the rows and columns for a fixed number of epochs, all the epochs are averaged out and then a specific row and column from this set of rows and columns which is mostly likely to be associated with the P300 spike is determined.

A. Overall System Flow

EEG signal data from the User (Subject) is collected by the Enobio EEG machine module which then communicates the signal data to the NIC module which stores the data. The other modules involved are the Machine Learning (ML) module and P300 Graphical User Interface (GUI) module, which are submodules of the P300 module. The GUI module sends the markers to the NIC module during the stimulation of the rows and columns. The NIC sends the collected EEG signal data containing markers and timestamp to the ML module. ML module analyses the data and predicts the character which is then communicated to the GUI module, which highlights the respective character on the P300 speller grid. All the modules and the relationships among them are shown in the overall system diagram shown in Fig. 1.

B. Data Collection

The data has been collected using an Enobio-8 3G device. Enobio-8 3G is a wireless and portable electrophysiology sensor system for the recording of the electrical activity of the human brain having 8 channels. Refer Fig. 2a and Fig. 2b for snapshots of the Enobio device used for collection of EEG data. The device is connected to Neuroelectrics Instrument

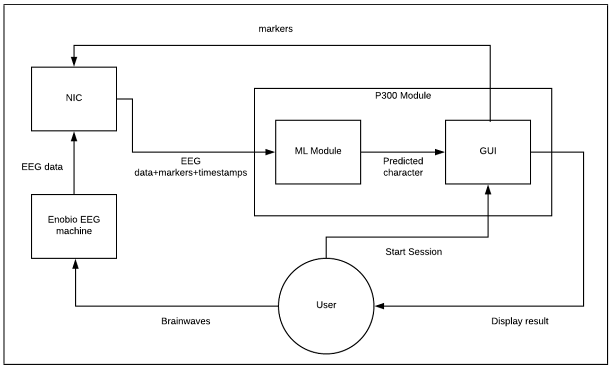
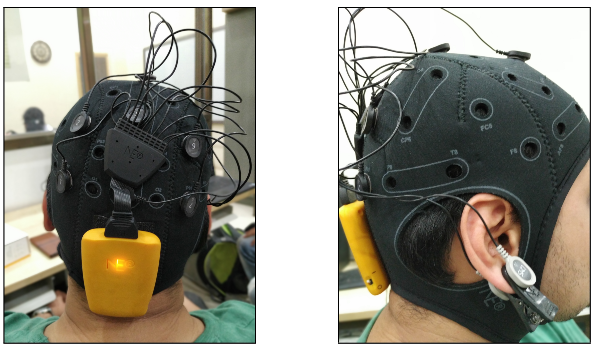


Fig. 1: System diagram for P300 Speller.



(a) Back-view. (b) Side-view.

Fig. 2: Enobio EEG device snapshots

Controller (NIC) software which collects the recordings from the device and stores them in different file formats namely ".edf" and ".easy". It also stores the configuration settings during the session in the ".info" file. The recorded file contains 8 fields containing EEG data values in nano-volts, a column for marker and timestamp column for additional information about that particular record. Sample of the raw EEG data collected using the device is shown in Fig. 3.

Channel#1	Channel#2	Channel#3	Channel#4	Channel#5	Channel#6	Channel#7	Channel#8	Markers	Timestamp
-109883525	-112856297	-74587216	-304887361	-110331011	-109582660	-125725803	-108782566	0	1.54401E+12
-109883968	-112859009	-74588472	-304892453	-110331363	-109584926	-125728502	-108782127	0	1.54401E+12
-109883227	-112858410	-74587781	-304893637	-110330114	-109582414	-125727448	-108779319	0	1.54401E+12
-109874103	-112850067	-74578653	-304885113	-110319239	-109572234	-125715594	-108770359	0	1.54401E+12
-109872648	-112851029	-74580232	-304889825	-110320801	-109571874	-125716854	-108771873	0	1.54401E+12

Fig. 3: Raw EEG Data file.

A P300 speller system has been implemented which generates visual stimulus and has characters organized in a 6x6 grid. A snapshot of the P300 Speller is shown in Fig. 4. The 6 rows and 6 columns are randomly intensified and de-intensified one by one for 150 ms and 100 ms respectively in a single epoch. An epoch is a sequence of intensification of the rows and columns of the P300 grid. During an epoch each row and column is intensified exactly once in random manner. For each row and column highlighted in a given epoch, we have taken the voltage or amplitude values for the 300 ms after the onset of the stimuli from the electrode positions PO7, P3, Fz, Cz, Pz, P4, PO8, and Oz. Placement of the electrodes has been done using the International 10-20 system. Selected electrode positions are shown in Fig. 5. After that, the collected data was band-pass filtered (5-30 Hz) and sent for preprocessing.

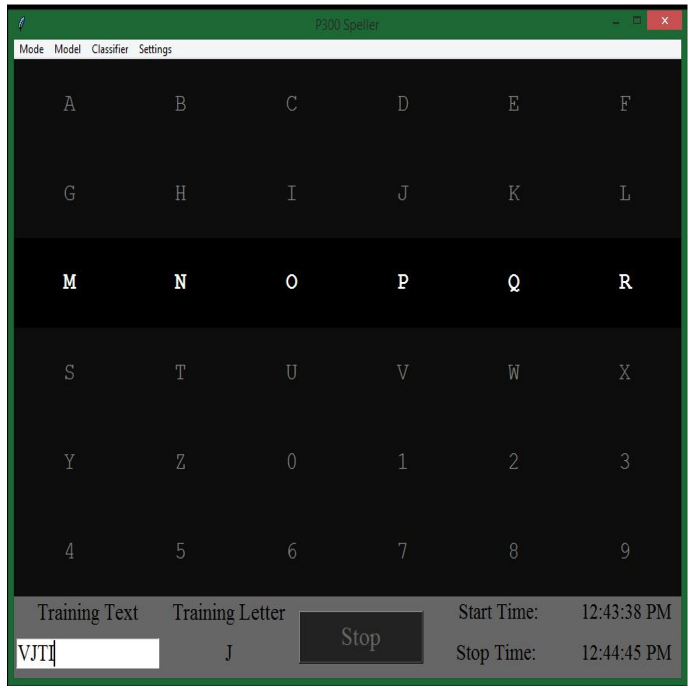


Fig. 4: P300 Speller.

C. Dataset Used

The data is collected in different sessions. Every session is made out of various runs and for every run a subject is asked to spell a character. As Discussed earlier the rows and columns of the character matrix are intensified for 150 ms followed by a de-intensification of 100 ms. This is repeated for a predefined number of epochs. For each epoch a total of 12 intensifications including each row and column are repeated for a single character. The EEG data is continuously collected from the 8-channel Enobio3G device. There is a word training mode in which the subject is trained on a user-defined set of characters and the collected data is used for training the classifier. Other data collection mode is the Subject mode in which the user is presented all the characters in a predefined order as stimulus and the data is recorded and used for training the classifier. After the classifier is trained on the data collected, it can be used in the testing mode where the subject is asked to concentrate on a character of their choice. The trained classifier makes predictions as to which row and column has a P300 wave associated with it, on the basis of the real-time data being fed from the device. Based on the row and column predicted

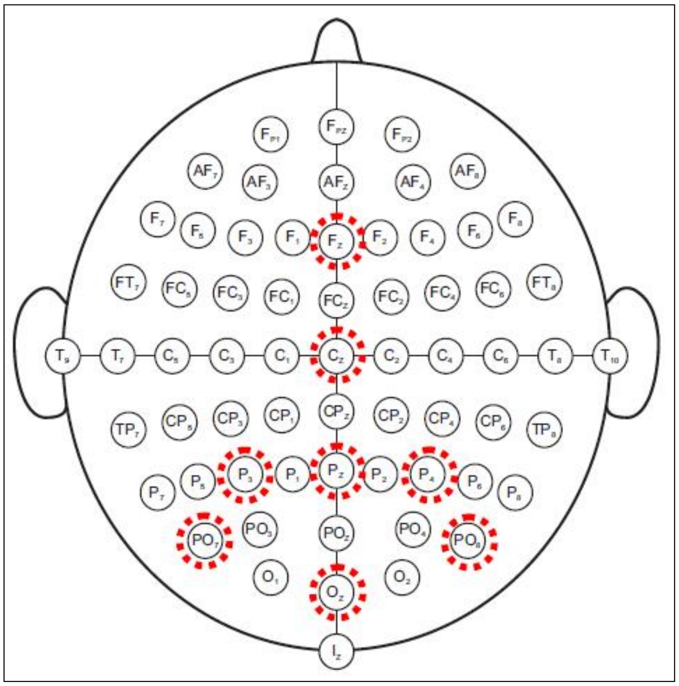


Fig. 5: International 10-20 System.

by the classifier, the corresponding character is highlighted as the output.

D. Data Communication

The real time data collected using the Enobio device through NIC software is communicated to the P300 speller system which does the data processing. For this communication *Lab Streaming Layer (LSL)* is used.

Lab streaming layer is a system for synchronizing streaming data for live analysis or recording. LSL is an convenient and reliable way to send EEG stream to applications that can record or manipulate the data, which in our case is the P300 speller system. Marker's are sent to the NIC software using LSL, to mark the EEG recording at the start of an stimulus. Markers are the index of the row or column that was intensified at the corresponding timestamp in the P300 speller system. The rows are indexed from 1 to 6 and the columns are indexed from 7 to 12.

E. Data Preprocessing

Initially, the raw file which is in the ".easy" file format is read and data is labelled as positive and negative according to the markers present in the marker field. Data obtained in the range of 250-500ms after the presentation of the stimulus is marked with the marker of row or column that was intensified and presented as stimulus. Unnecessary data which does not pertain to the task is trimmed off. Then ICA is applied to remove irrelevant signal components present in the EEG signals. The EEG signal data is then re-referenced and also baseline correction is applied to the data. Baseline corrected signal data is then bandpass filtered (5-30Hz). Averaging of EEG signal data across epochs is done. An average of all the epochs for a particular character is taken where each epoch consists of 125 * 12 = 1500 records. This is done to remove noise which might be present in a specific epoch and to increase the signal-to-noise ratio, as well as to reduce the size of the data for each character. These preprocessing steps are shown in Fig. 6.

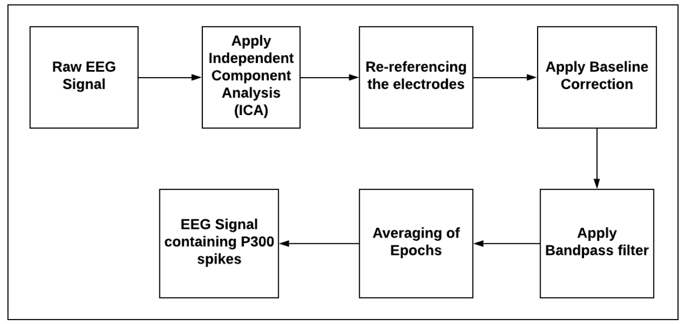


Fig. 6: EEG data preprocessing steps

Channel#1	Channel#2	Channel#3	Channel#4	Channel#5	Channel#6	Channel#7	Channel#8	Marker	Timestamp
-12926.94833	-28548.30537	-1059.092065	10165.04295	138.5802581	2014.485767	-14070.73706	-5637.579067	12	1.55143807e+...
-12211.7047	-29449.72411	-81.03598624	10424.94753	49.06419868	1692.981698	-12861.74747	-5327.772533	12	1.55143807e+...
-11383.89737	-30533.25793	532.0560326	10363.7761	-77.60087574	1196.105117	-11572.3105	-4937.967002	12	1.55143807e+...
-10537.89207	-31595.5115	688.3818084	10020.32596	-94.73179826	583.5451095	-10288.78866	-4554.094444	12	1.55143807e+...
-9767.558537	-32399.34722	465.2040253	9553.625297	115.9785937	-7.086033817	-9162.993677	-4283.215752	12	1.55143807e+...
-9131.446005	-32764.01811	81.50342971	9191.756848	603.1190304	-398.1591795	-8367.410115	-4207.447327	12	1.55143807e+...
-8636.252518	-32653.20248	-192.7257026	9137.584097	1326.165504	-437.5069621	-8033.774042	-4347.004683	12	1.55143807e+...
-8220.194101	-32209.23036	-137.2782927	9496.472673	2171.705729	-52.09296464	-8181.637137	-4631.032051	12	1.55143807e+...
-7784.29107	-31733.13402	327.2619719	10221.05285	2987.802801	710.6749025	-8693.356415	-4919.926567	12	1.55143807e+...
-7222.169524	-31592.64739	1115.7446	11132.86943	3632.865334	1691.759162	-9337.427497	-5050.012961	12	1.55143807e+...
-6484.138761	-32113.77218	2000.738377	11970.48504	4006.399873	2650.94976	-9850.261488	-4914.890431	12	1.55143807e+...

Fig. 7: EEG Data after Data Preprocessing.

F. Data Analysis

After preprocessing, data is analyzed to detect the presence of the P300 waves. A P300 wave is an Event Related Potential (ERP), i.e., a positive deflection in the electroencephalogram (EEG) signal that occurs between 250 ms to 500 ms after stimulus onset. P300 is based on the oddball paradigm, which presents the participant with a sequence of repetitive audio or visual stimuli, infrequently interrupted by an unexpected stimulus.

IV. Support Vector Machines

A Support Vector Machine (SVM) is a discriminative classifier and an excellent tool for classification problems which generalizes well to unseen data. The SVM classifier was designed by Vapnik for the binary classification problem. An optimal hyperplane (a 2-D curve in this case) can be constructed to perform binary classification, which maximizes the separation margin between the two classes of the data. Considering a training data of M points:

$$(x_i, y_i)_{i=1}^{M}$$

where $x_i \in \mathbb{R}^M$ is input and $y_i \in \{-1, 1\}$ is output. We find an optimal hyper-plane which maximizes the margin boundary and minimizes the error (ξ). We use quadratic programming to solve this optimization problem.

$$\min_{w,\xi} \left[\frac{1}{2} \left\| w^2 \right\| + C \sum_{i=1}^{M} \xi_i \right] \tag{1}$$

where w is the weight vector and C is the regularization parameter.The regularization parameter affects the prediction of the classifier. When we use small values for C the classifier ignores points near the margin and increases the margin boundary, whereas when C takes larger values classifier considers all the points and to do so it reduces the margin boundary.

Using the Lagrangian representation of above equation results in the nonlinear discriminant function

$$S(x) = \sum_{i=1}^{M} y_i \alpha_i k(x_i, x_j) + b \tag{2}$$

where b is bias and a real constant

V. Artificial Neural Networks

An artificial neural network is a mathematical model that tries to simulate the structure and functionalities of biological neural networks. A neuron is the basic building block of every artificial neural network. Artificial Neural Networks are used to develop nonlinear classification boundaries. While there are many variations and flavors of neural network(NN) like Recurrent NN, multilayer perceptron, etc., we use a single hidden layer NN for this work. This basic neural net, sometimes called the single hidden layer back-propagation network, or two layer perceptron is a two-stage regression or classification model. It consists of an input layer, a hidden layer and an output layer. In the case of K-class classification, there are K output units, and each of the K output units models the probability of class k so that

$$Y_k = [0, 1] \quad \forall Y_k, k = 1, ..., K \tag{3}$$

Derived features Z_n are created from linear combinations of the inputs, followed by a nonlinear activation function. The output Y_k is modeled as a function of linear combinations of the Z_n,

$$Z_n = \sigma(W_m^T X + b_m), \quad n = 1, ..., N, \tag{4}$$

$$Y_k = W_k^T X + b_k, \quad k = 1, ..., K, \tag{5}$$

$$f_k(X) = g_k(Y). \quad k = 1, ..., K \tag{6}$$

where Z = (Z_1, Z_2, ..., Z_M), and Y = (Y_1, Y_2, ..., Y_K).$\sigma(v)$ is the activation function and is chosen to be a sigmoid defined as

$$\sigma(v) = \frac{1}{1 + e^{-v}} \tag{7}$$

and for output function $g_k(Y)$, which does the final transformation of the vector of outputs Y, is chosen to be the softmax function

$$g_k(Y) = \frac{e^{Y_k}}{\sum_{i=1}^{K} e^{Y_i}} \tag{8}$$

Using artificial neural network, an accuracy of 85.14% was achieved.

VI. Discussions

In this research project, the attempt is to implement an efficient P300 speller system. Data has been collected from a wide range of subjects. The motive is to achieve an end to end system which can work on real-time data and can also be personalized for each individual subject. The approach is to use SVM and Artificial Neural Network(ANN) for classifying the real-time EEG signals in order to predict the sequence of characters that the subject has in their mind. For ANN different hyperparmeters like epochs, batch size and type of optimizer are tuned to detect the P300 signal in the captured EEG data.

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