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Classification Performance of New Fusion Features of P300 in Visual Evoked Potentials from EEG to Distinguish Alcoholics and Controls

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ABSTRACT

Background: The health factor of alcoholics and controls can be measured significantly using Visually Evoked Potentials (VEP) based on their retort sharpness to visual stimuli. Alcoholism can affect the brain and human performance in assorted ways. People who have the habit of drinking have trouble with their balance, judgment and coordination due to the inflicted brain cells and central nervous system. The predisposition towards alcoholism can be pre detected to avoid it from taking adverse effects among youngsters who abuse alcohol. Objective: If the negative effects of alcoholism are explained to them clearly, with evidence, the habit of abuse can be positively eradicated. A simple visual exercise using pictures is used to extract the P300 component evoked in brain. The extracted P300 varies in dimension among healthy and alcoholic abusers. The Naïve bayes classifier, KNN clustering and SVM classifier were used on three sets of combinational features constructed by the Fourier features and fractal dimension; Fourier feature and singular value decomposition feature; as well as fractal dimension feature and singular value decomposition from the visual evoked potentials of brain to distinguish the controls from alcohol abusers. This experiment is aimed to take preventive, educative and corrective actions for the benefit of youngsters. The P300 component buried VEP represent in the combo features is expected to provide the substantiation for clustering. Result: It is proved by this research work that the combinational feature vector produced using FFT and FD along with a combination of FD and SVD, as well as FFT and SVD were effective in classifications than the similar classifiers used for simple feature in the previous studies. Conclusion: We proposed the use of combinational features for P300 classification with assorted combinations. This is done with the assurance obtained in classification results of P300 features when used in combination brings a better classification always than the individual feature usage. We concluded with a support to these findings, the trend analysis calculated by the Mean Absolute Percentage Error (MAPE) is also ensures and confirm the findings.

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INTRODUCTION

The ongoing electrical activity of brain can be measured precisely using Electroencephalogram (EEG). The impact on brain and central nervous system due to the long time abuse of alcohol can be detected using EEG signals that are derived from the brain scalp using the positional electrodes. Many studies proved that the continuous drinking may cause severe damage on brain nervous system and leads to loss of memory (Gupta, C.N. and R. Palaniappan, 2007). EEG includes Evoked Potentials (EP), which involves the presentation of a stimulus of visual, somatosensory and auditory (Palaniappan, R., 2004). The clinical use of EEG diagnosis the clear activity of abnormalities such as coma, encephalopathies, including brain death. The non-invasive method is mostly desirable to avoid surgical risks. One of the most important applications using EEG is analysis of brain electrical activity under various conditions such as sleep disorders, epilepsy, mania and depression (15.

Samraj Andrews, Ramaswamy Palaniappan, 2000). In this present work we set to prove that the use of Visual Evoked Potential signal, which is a type of ERP that is evoked by external visual stimulus, for investigating the electrophysiological differences between alcoholics and controls are a significant way. In this present work we compared the classification performance of Naïve Bayes classifier using features extracted from the VEP signal, by classifying various features of the same signal sets extracted using assorted feature extraction techniques. This is done to investigate the electrophysiological differences between alcoholics and

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controls for clinical and social purposes in an accurate way. The feature components were extracted by Fractal Dimension (FD), Singular Value Decomposition (SVD) and Fast Fourier Transformation (FFT). We used all these features and also their combinational features to analyze the strengths of P300 in the brain signals of alcoholics and controls. All the feature set values were calculated based on P300 strength and its temporal location which quantify the level and qualify of user concentration.

The P300 component originated as a reflection process involved in stimulus evaluation or categorization by means of systematically displayed picture set. P300 arises as the evoked component from EEG signal around 300ms after a visual stimulus onset. A communication protocol using this P300 component is used to identify the brain activity of alcoholic and non-alcoholics to measure the mental stability (Birbaumer, N., T. Hinterberger; Andrews, S. Ramaswamy Palaniappan, 2008). Significant growth using the P300-VEP based BCI have taken place since 1998 and in recent years, (Larry, M., Manevitz, Malik Yousef, 2001; Palaniappan, R., 2004; Samraj Andrews, Ramaswamy Palaniappan, 2000) many different variants of the oddball paradigm (to evoke P300) have been developed where P300 features could be classified into necessary codes for the purpose of BCI(Gupta, C.N., R. Palaniappan, 2012; Farewell, L.A. and E. Donchin, 1988).

Methods:

As a paradigm to extract the EEG signals using simple picture set displayed to the subjects in two phases. The EEG signals were recorded for one second from 64 electrodes placed on the scalp of the subject and was sampled at 256Hz when the pictures were shown as the stimulus, Hence, there are 256 data points were stored for each EEG signal from all the placed electrodes. The extracted VEP signals from 40 subjects (20 alcohols and 20 controls) are taken as the average of 5 trials for each subject. Therefore a total of 200 VEP signals (40 subjects x 5 trials) are stored in an array. The electrode placement system was used an extension of the 10-20 international positioning system (Burges, C.J.C. 1998). The time window based sampling points that we have selected here for P300 detection is from 77th to 154th data points from the sampling. The raw EEG signals extracted from the scalp were processed using MATLAB for the features like amplitude and latency of the P300 peak. Similarly, the signals were preprocessed using the 9th order butter worth filter to analyze the same feature components. Applying the FFT, SVD and FD functions on the amplitude and latency values corresponding to the CZ channel; selecting and combining features are the steps we have taken for constructing the combinational feature vectors for clustering. As a novel method the combination were done by portion of FFT feature combined with whole FD feature and SVD with FD and portion of FFT with SVD features to form a new hybrid feature vector for classification and results produced in this experiment.

a. P300 Responses using VEP:

This research work was done with the help of classical Snodgrass and Vanderwart's (SV) picture set, (1980) since these pictures have been used successfully in a large number of benchmark studies, and it is clear from the accumulated results that most of their stimuli are "good" stimulus (Angel Fernandez and Emiliano Diez, 2004). The VEP signals were recorded from both controls and alcoholics during separate experiments while being exposed to two types of stimuli, which were pictures of objects chosen from Snodgrass and Vanderwart picture set(Ramaswamy Palaniappan, Paramesran Raveendran, 1999; Andrews, S., Ramasamy Palaniappan). Figure 1 shows samples of these pictures, Figure 2 shows the position of the 64 electrodes used to record EEG during this experiment. The sample stimulus (S1) shown to the subjects was a randomly chosen picture from the set. The second type stimulus shown was chosen as either matching (S2M) or non-matching (S2N) relative to the initial stimulus S1. To reduce the possibility of ambiguity, S2N was chosen to be dissimilar from S1 not only in its visual manifestation but also in terms of the semantics. For example, if a picture of a knife is shown for S1, then S2N will not be a picture from the tool category. One-second duration of EEG measurements after each stimulus presentation was recorded. We selected a set of five trials from ten different subjects equally divided from both categories. The equal selection is made for the purpose of clustering them based on the P300 parameter due to the visual stimuli.

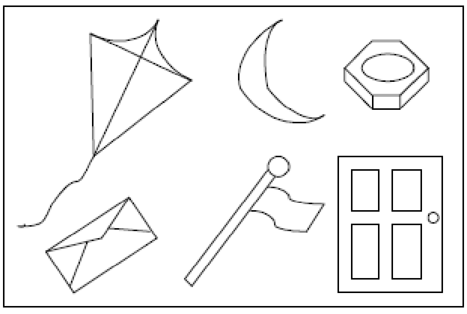

Fig. 1: Sample objects from the Snodgrass and Vanderwart picture set.

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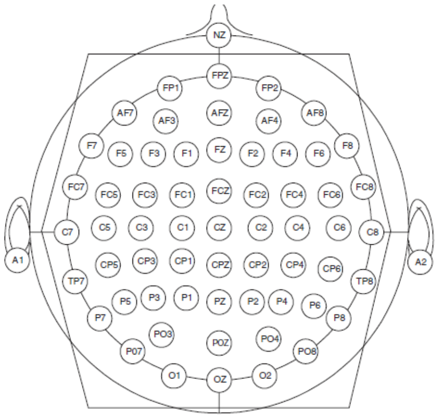

Fig. 2: Sixty-Four channel electrode positions.

b. Feature extraction by Fast Fourier Transformation and Fractal Dimension:

Feature extraction is the process of accurately simplifying the representation of input data by reducing its dimensionality while acquiring its relevant characteristics for the desired task. There are two types of features used in this experiment. They were chosen from the extracted signals of the CZ channel using the feature extraction methods. Here in this experiment, a novel idea of combining the features extracted by three different feature extraction algorithms to form three combinations of FFT-FD, FFT-SVD and SVD-FD features. The extracted VEP signals from 10 subjects (5 alcohols and 5 controls) were taken as the average of 5 trials for each subject. Therefore a total of 50 VEP signals (10 subjects x 5 trials) are stored in an array.

The application of FFT on these signals is to compute the Discrete Fourier Transform (DFT) and its inverse using the butterfly method shown in figure 3. It is much faster than the DFT and it supports for the huge datasets where N may be thousands or millions. The FFT is applied on the VEP signal components say the maximum amplitude and its corresponding latency of CZ and later compute the grouping with the clustering algorithms instead of the whole signal. Out of the 50 data samples from both alcoholics and controls FFT features were representing the highest amplitude value of the selected window and its latency. This is to represent the presence of P300 component and its strength. The channel CZ out of the 64 channels is chosen throughout this experiment.

Let x(j) be the N point sequence of samples.

$$X(k) = \sum_{j=1}^{N} x(j)\, \omega_N^{(j-1)(k-1)} \quad - \quad (1)$$

where, X(k)-DFT through FFT of x(j)

$\omega_N = e^{(-2\pi i)/N}$ is an Nth root of unity(twiddle factor).

Inverse DFT of X(k) through FFT is given by

$$x(j) = \left(\frac{1}{N}\right) \sum_{k=1}^{N} X(k)\omega_N^{-(j-1)(k-1)} \quad - \quad (2)$$

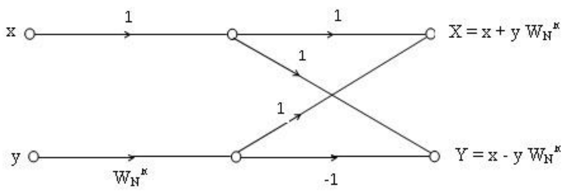

Fig. 3: Basic Butterfly or Flow graph of DIT-radix-2 FFT.

Where, x is the latency and y is the amplitude of the signal.

Fractal dimension is a very effective tool applied in many quantification processes which helps to evaluate feature spaces. Once such domain in which FD is efficient is the bio signals analysis. The results of FD in time domain depend on algorithm and window length (Chu Kiong Loo, Andrews Samraj; Andrews Samraj, Nasir, G., 2003; Truong Quang Dang Khoa, Vo Quang Ha, 2012). One of the advantages of fractal analysis is the ability to describe irregular and complex objects. Fractal analysis of EEG signals and the development and neurophysiologically realistic models of EEG generation may produce new successful avenues in automated

EEG analysis techniques and can have important diagnostic implications. The FD used in this experiment follows the Katz's method [19-11] variant of FD throughout the experiment.

Katz's Method:

Katz's method calculates the fractal dimension of a sample as follows: The sum and average of the Euclidean distances between the successive points of the sample (L and a, respectively) are calculated as well as the maximum distance between the first point and any other point of the sample (d). The fractal dimension of the sample (D) then becomes:

$$D = \frac{\log\ (L/a)}{\log\ (\mathrm{d}/\mathrm{a})} = \frac{\log\ (n)}{\log\ (\mathrm{n}) + \log\ (\mathrm{d}/\mathrm{L})} \tag{3}$$

where n is L divided by a.

c. Singular Value Decomposition:

SVD is a matrix factorization technique commonly used for producing low-rank approximations. Usually SVD calculated for a matrix results in a feature vector of reduced dimension. Given an m×n matrix A, with rank r, the singular value decomposition, *SVD (A)*, is defined as

$$SVD(A) = USV^T \tag{4}$$

where U, S and V are of dimensions m × m, m × n, and n × n, respectively. Matrix S is a diagonal matrix having only r nonzero entries, which makes the effective dimensions of these three matrices m × r, r × r, and r × n, respectively. U and V are two orthogonal matrices and S is a diagonal matrix, called the singular matrix [1]. The SVD method is used to reduce the overlapping spectral EEG and other noise artifacts. The use of SVD also reduces the feature size and simple distance based classifier (with two thresholds) is capable of availing this reduced feature set(Ramaswamy Palaniappan, Paramesran Raveendran, 1999). The SVD is applied firstly on the amplitude and latency calculated on raw signals and secondly on the amplitude and latency derived out of filtered VEP signals from the CZ channel, and is classified by Naïve Bayes.

d. Combo feature;

As a novel approach to enhance the uniqueness of the signal representation, we formed three different types of combinational feature for every signal by adopting the fusion technique to form the new features. The components of the first type combo feature are FFT and FD as given in equation 5. The next combinational feature is formed with the components of SVD and FD is shown in equation 6 and at finally the third combinational feature FFT and SVD is given in the equation 7.

$$f_c = \{ f_{\frac{1}{2}}, f_2 \} \tag{5}$$

Where, $f_{1/2}$ is the feature of the signal by FFT and f_2 is the feature through FD.

$$f_x = \{ f_1, f_2 \} \tag{6}$$

Where, f_1 is the feature of the signal by SVD and f_2 is the feature through FD

$$f_k = \{ f_{\frac{1}{2}}, f_2 \} \tag{7}$$

Where, $f_{1/2}$ is the feature of the signal by FFT and f_2 is the feature through SVD.

So the, f_c , f_x and f_k are the combinational feature used for clustering in this experiment.

To make it simple the filtered signals were used to form the combo features since we found advantage of filtering as a preprocessing in our preliminary tests.

e. Naive bayes classification:

The Naive bayes classifier combines this model with a decision rule. One common rule is to pick the hypothesis that is most probable; this is known as the maximum a posteriori or MAPE decision rule (Gupta, C.N., R. Palaniappan, 2012). The advantage of Naïve Bayes classification is that the precise number of features falls under both the categories can be found. The corresponding classifier, a Bayes classifier, is the function Classify defined as follows:

$$Classify(x_1, x_2, \dots, x_n) = \arg\max_c p(C = c) \prod_{i=1}^{n} p(X_i = x_i | C = c) \tag{8}$$

Where C is a dependent class variable and x_i is a feature variables

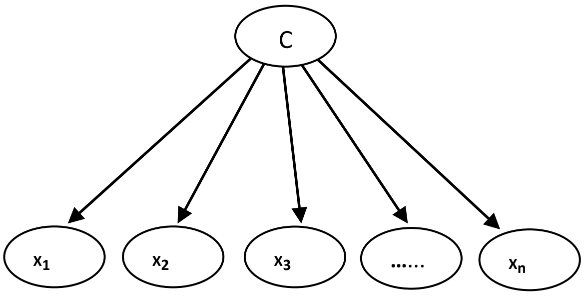

Fig. 4: Naïve Bayes Classifier.

The simple structure of Naïve Bayes is shown in Figure 4.Where, the root node C represents different classes and the child nodes are X1, X2,….Xn represent different components or features of a sample. NB assumes all the feature nodes are independent of each other given the class, and typically, the feature variables are assumed to have Gaussian distribution if they are continuous. NB has worked quite well in many complex real-world situations. Compared to other complex graphical models, it requires smaller amount of training data to accurately estimate the parameters necessary for the classification.

f. Classification by K-Nearest Neighbor Algorithm (K-NN):

The *k*-nearest neighbor algorithm (*k*-NN) is a non-parametric method for classifying objects based on closest similarity objects in the feature space (Aydemir, O., T. Kayikcioglu, 2009). It also stands as an example for instance-based learning, in which the training data set is stored, so that a classification for a new unclassified feature may be found simply by comparing it to the most similar features of the training set. Here in this experiment the FFT-FD, FFT-SVD and SVD-FD Combo features were clustered using *k*-NN. The distance between features were calculated by using the Euclidean function as

$$d_{Euclidean}\ (X,Y) = \sum_i (x_i - y_i)^2 \qquad (9)$$

If k = 1, then the object is simply assigned to the class of its nearest neighbor. The value of k is for all time selected to be an odd number to avoid tie. With the combinational features of FFT-FD, FFT-SVD and SVD-FD Combo for all the trials, the k-NN splits the data into two classes as sample and training. The training phase of the algorithm consists only of storing the feature vectors and assign class labels of the training samples. Where the P300 signals comprises the alcoholics in data1 and the data2 contains controls. While classifying k-NN assigns features to either clusters of alcohol or controls that closely fit in to the respective cluster centre. However, some of the alcoholic data features also misclassified to the control group. The k-NN classifier shows that the alcoholic abusers have less realization capability than the controls.

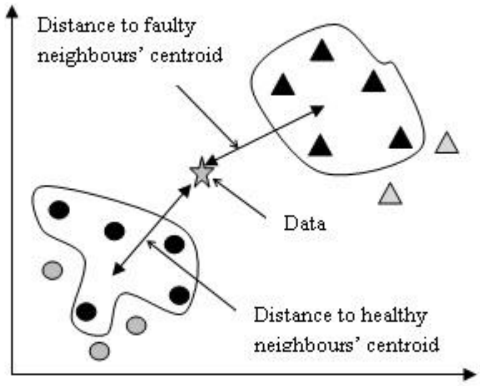

Fig. 5: k-NN-Classifier.

g. Classification by Support Vector Machine (SVM):

A supervised learning model Support Vector Machines (SVM) with associated learning algorithms that analyze data and recognize patterns is used for classification and regression analysis. The major processes of SVM are the construction of hyper lanes to classify various features in a multidimensional space to separates features. The classification task usually involves separating features into training and testing sets. The SVM takes the set of input features and predict the given input and it forms the two possible output classes by defining the values -1 and 1 for the two classes to identify the support vectors present in the two classes(Jasper, H.H., 1958). The data used for training and testing samples comprises of 10 samples from 5 alcoholics and 10 samples from 5 controls of Fourier transformation values. The SVM algorithm generates a separating hyper plane in the original space of n coordinates between two distinct classes (1 and −1). The SVM always tries to maximize the generalization of features by maximizing the margin and also supports nonlinear separation using advanced kernels, by which SVMs try to avoid over fitting and under fitting (Larry, M., Manevitz, Malik Yousef, 2001). The distances +d and –d in figure 5 are representing the hyper plane separation of two classes of elements with respect to the support vectors. Here in this work we used the Radial Basis Function kernel (RBF) which is the most popular kernel function used in support vector machine classification. The below RBF function were used to find the classification results given in the table1and table2.

The RBF kernel on two samples $\boldsymbol{x}$ and $\boldsymbol{x'}$ represented as feature vectors in some input space, is defined as

$$K(\boldsymbol{x},\ \boldsymbol{x'}) = exp\left(-\frac{\|x-x'\|_2^2}{2\sigma^2}\right) \tag{10}$$

The squared Euclidean distance between the two feature vectors is

$$\|\boldsymbol{x} - \boldsymbol{x}'\|_2^2 \tag{11}$$

where, σ is a free parameter. An equivalent, but simpler, definition involves a parameter

$$\gamma = -\frac{1}{2\sigma^2} \tag{12}$$

$$K(\boldsymbol{x},\ \boldsymbol{x'}) = exp(\gamma\|\boldsymbol{x} - \boldsymbol{x}'\|_2^2) \tag{13}$$

Since the value of the RBF kernel decreases with distance and ranges between zero (in the limit) and one (when $x = x'$), it has a ready interpretation as a similarity measure of dimensions; for $\sigma = 1$, its expansion is given in (13) . The feature space of the kernel has an infinite number.

$$exp\left(-\frac{1}{2}\|\boldsymbol{x} - \boldsymbol{x}'\|_2^2\right) = \sum_{j=0}^{\infty}\frac{\left(\boldsymbol{x}^T\boldsymbol{x}'\right)^j}{j!} exp\left(-\frac{1}{2}\|\boldsymbol{x}\|_2^2\right) exp\left(-\frac{1}{2}\|\boldsymbol{x'}\|_2^2\right) \tag{14}$$

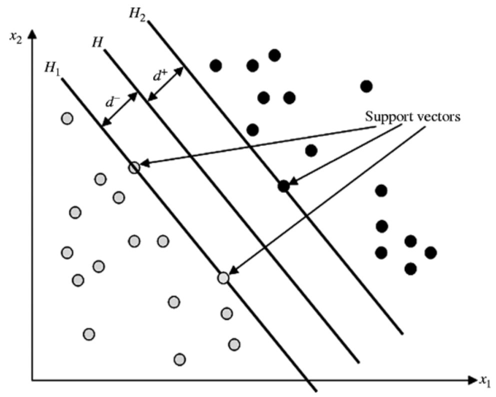

Fig. 6: SVM Classification Diagram.

h. MAPE trend analysis:

The Mean Absolute Percentage Error (MAPE) is a measure of accuracy of a method for constructing fitted time series values in statistics, specifically in trend estimation. It usually expresses accuracy as a percentage, and is defined by the formula:

$$M = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \tag{15}$$

where A_t is the actual value and F_t is the forecast value.

Measuring the actual points from the patient's brain samples were used to forecast the accuracy of the trend error in the samples. In this experiment the total numbers of samples (n) were taken for 10 subjects out of 5 from alcohol and 5 from control signals. Where, A_t is the actual value of naïve bayes classifier point value and F_t is the forecast value which is always taken as 100% to calculate the trend error rate.

Results:

The results of FD-SVD, FFT-FD and FFT-SVD combo features based classification of alcoholics and controls are shown in table1. In table1 the results are from FD-SVD, FFT-FD and FFT-SVD combo features that were classified through Naive bayes, KNN and SVM. It can be observed from this table that the performance of FFT-FD is strongly consistent. Another important point that is to be worth noted is the strong presence of P300 in controls identified in this work too which helps the classification accuracy to be better than the alcoholics (Andrews, S., A. Teoh, L.C., 2007). More over in general the intra distance among the alcoholics is wider when compared to the intra distance among the controls. The intact grouping of control features which can be seen from figure 10 caused the controls to achieve 100% classification in both the combo feature classification where as alcoholics can achieve only 80% of classification in FD-SVD combo features.

Similarly, the results of feature sets FFT, FFT-FD, FFT-SVD, FD and FD-SVD combo features based classification of alcoholics and controls are shown in table2. The results are from individual and the other combinational features that were classified through Naïve Bayes Classifier. It is found and shown in table 2, that the performance of FFT-SVD is better than all the other four features. Another important point that is to be worth noted is the MAPE which measures the trend values for the controls and alcoholics that helps to find the accuracy over the features. As compared with the naïve bayes classification percentage error and the predicted trend values taken as percentage of classification showing that the classification rate is increased in the combinational feature FFT-SVD and this is the best result as compared to the other features set.

Table1: FFT, FD and SVD Combo Classification.

Combo Features	Matching	Naïve Bayes%	KNN%	SVM%
FD-SVD	Alcohol	76.4	80	100
	Control	76.6	100	100
FFT-FD	Alcohol	76.5	100	100
	Control	76.6	100	100
FFT-SVD	Alcohol	79.8	100	100
	Control	80	100	100

Table 2: Actual Classification Percentage with Forecasting Errors of MAPE.

Feature Set	Points	Naïve Bayes % of classification	MAPE	Trend Values
FFT	46	76.6	37.6	62.4
FFT&FD	46	76.6	19.1	80.9
FFT&SVD	48	80	17.8	82.2
FD	48	80	27.8	72.2
FD&SVD	46	76.6	19.1	80.9

Since the MAPE expresses the forecasting errors from different measurement units into percentage errors on actual observations, it is unit free; therefore, the MAPE is probably the most widely used forecasting accuracy measurement of this kind and followed by us in this analysis. In the below figure 7 the trend analysis graph of all the five feature sets which compared the results with NB classifier to predict the trend error rate between the alcoholics and controls are shown for comparison.

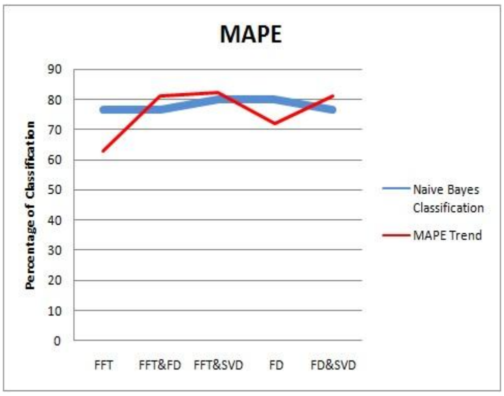

Fig. 7: Trend Analysis Graph.

Figure8 shows the result of k-NN classification of two groups namely control and alcoholics on their FFT-FD features. Similarly, in figure9 the classification of alcoholics and controls using FD-SVD features by k-NN can be seen. But in figure 9, the average inter distance among both the classes are reduced. This may be due to the resemblance of P300 component and its latency overlaps among both the classes. Figure 10 shows the SVM classification and the support vectors of alcoholics and control classes of FFT-FD combo features for 20 samples. Similarly, Figure 11 shows the SVM classification and the support vectors of alcoholics and controls of FFT-FD combo features for 10 samples. The classification of SVM for 10 and 20 samples of FD-SVD features were shown in figure 12 and 13 respectively. Figure 14 shows the KNN classification of FFT-SVD combination features of alcoholics and controls, similarly figure 15 shows the SVM classification of FFT-SVD combo features.

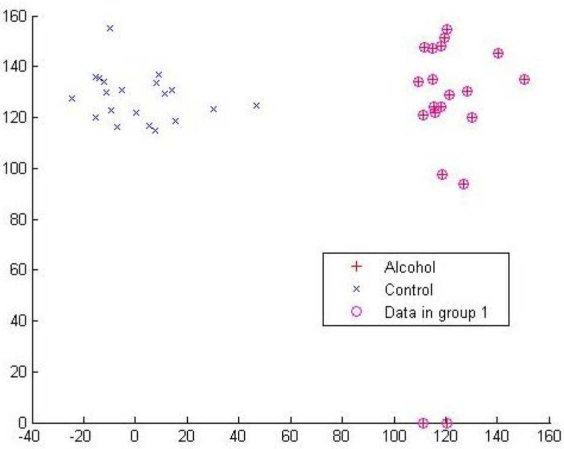

Fig. 8: k-NN application on FFT with FD features of filtered signals.

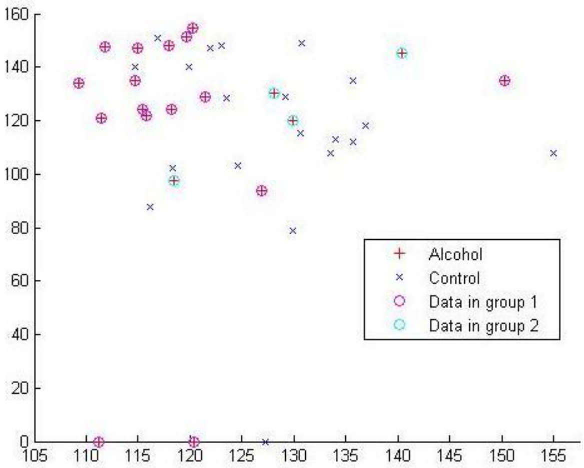

Fig. 9: k-NN application on FD and SVD features of filtered signals.

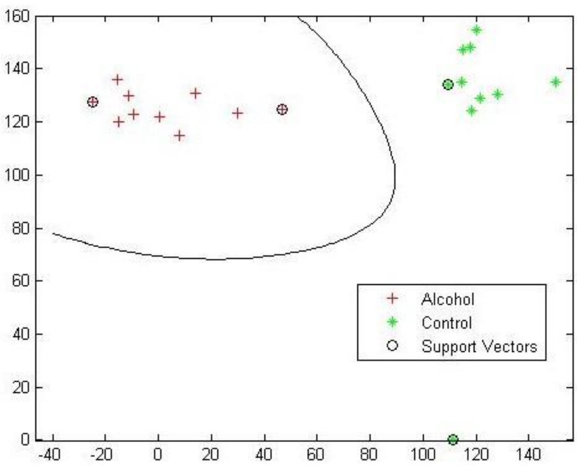

Fig. 10: Application of SVM on FFT-FD combo features.

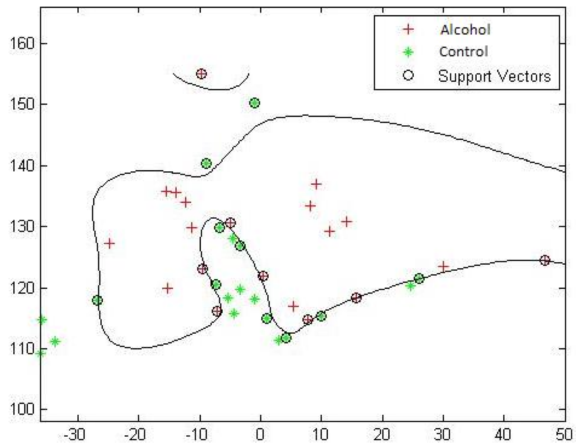

Fig. 11: Application of SVM on FFT-FD combo features.

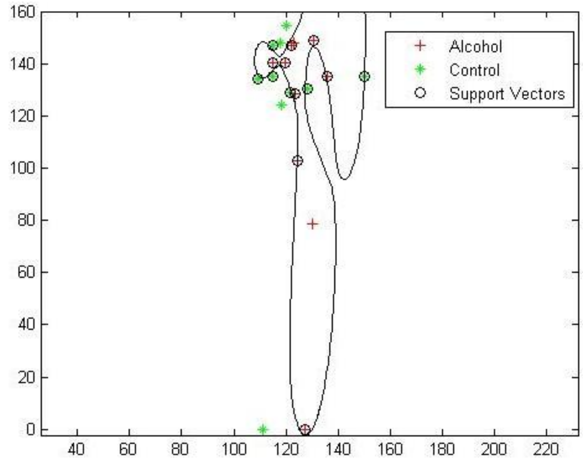

Fig. 12: Application of SVM on FD-SVD combo features.

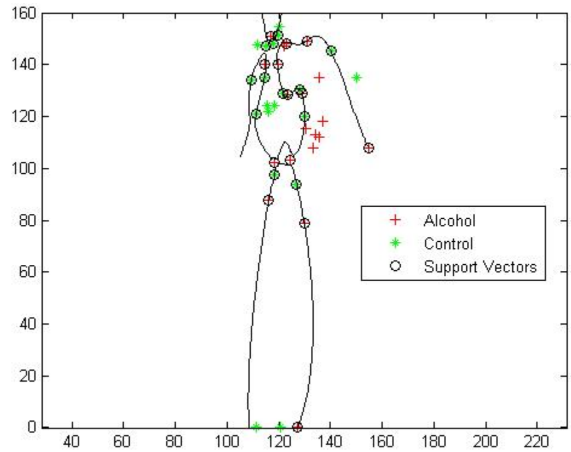

Fig. 13: Application of SVM on FD-SVD combo features.

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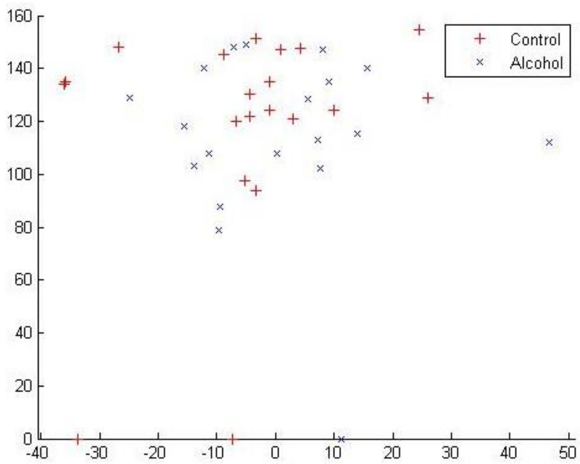

Fig. 14: k-NN application on FFT and SVD features of filtered signals.

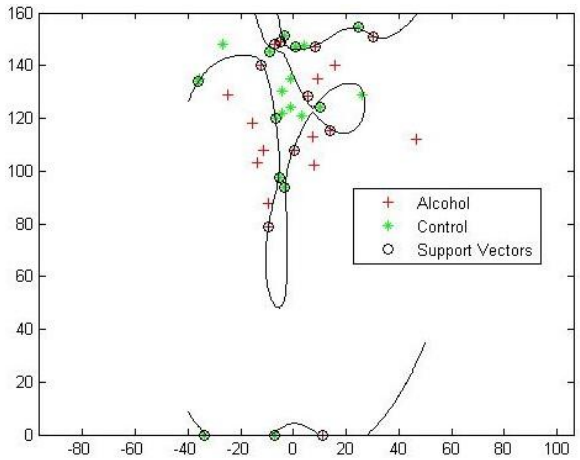

Fig. 15: Application of SVM on FFT-SVD combo features.

Discussion:

The motivation behind the combinational features is due to the continuous enhancements we tried on the classification results. When using SVD features and FD features, separately for k-NN and SVM classifications resulted in poor percentage of results. Hence the FFT features were used to augment the feature to improve the classification performance as feature enrichment. The classifications including SVM produced most distinguished results for all the combo feature vector. The classification accuracy found from the tables using different combinations of feature vectors reflects the amplitude and latency of the maximum positive peak found in the optimal window of the extracted VEP from alcoholics and controls. The cause of the less accuracy in alcoholics is due to the failure of producing strong P300 for the visual responses shown against the stimuli. The whole experiment is conducted on randomly selected signals of both the stimuli S2N and S2M from alcoholics and controls. It is found consistently that the combinational features are reliable for accuracy in classification but with the slightly higher computational complexity.

Conclusion:

The controls exhibited more accurate and consistent responses to the visual stimuli than the alcoholics by producing stronger and timely P300 responses. KNN and SVM classification on all the combinational features of FFT-FD, FFT-SVD and FD-SVD performed well but the FFT-FD combination is strongly consistent in both the cases of alcoholics and controls. The results given here are from the signals that were preprocessed using butterworth filter, since we found the features extracted from the preprocessed signals were better classified than the raw signals.

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