BCI-Based Alcohol Patient Detection

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***Abstract*—This paper reviews the classification of Electroencephalogram (EEG) signals correlated with alcoholic and non-alcoholic subjects. EEG signals, which record the electrical activity in the brain, are useful for assessing the current mental status of a person. Alcohol consumption of people became a social problem as well as health hazards. Nowadays, more and more people wanted to travel back and forth to various places, With increasing of vehicular population and their movements on the roads, accidents are steadily increasing. Many road accidents are reported due to the consumption of alcohol by drivers and driving vehicles. This study investigates about the difference between drunked and non-drunked peoples brain signal using Electroencephalogram (EEG). EEG data is used for 20 alcoholic and 20 non-alcoholic subjects. Support Vector Machines were used for classifying EEG signals.**

Keywords*—*Electroencephalogram, Alcohol Detection, Electrodes, Brain Computer Interfaces

I. Introduction

Brain computer Interface (BCI) is a relatively new technology which aims to build a direct interface between the human brain and the computer. BCI is a powerful tool for communication between users and systems. It does not use devices or muscular activities for issuing orders and full interaction[20]. Initially BCI systems were developed for biomedical applications in mind, leading to the formation of devices [16] that created a medium to communicate and restore mobility to physically challenged or locked in patients[3].

However new researches have been done targeting non-medical application of BCIs. BCIs used in novel human computer interaction methods such as mind controlled computer that perceives input through brain signals and hands-free applications[20], [16]. In addition, researches on BCI are also done in various fields such as smart industry, education, advertising, entertainment, and smart transportation. Nowadays it is used in brain based authentication, alcohol detection, credibility assessments, drowsiness, alertness & vigilance detection, emotion detection, usability assessment, market assessment, advertising, virtual reality applications, games, robotic controlling and many other areas.

Approximately there are 76.3 million people are diagnosed with alcohol disorders in the world. High consumption of alcohol not only affects the human brain but also damages other vital organs of the human body and affects their social life. People who drink excessive alcohol suffer from blurred vision, imbalanced walking, impaired driving, slurred speech, memory slips, impaired sleep and slow reaction. Long-term alcohol abuse can be called alcoholism. Alcoholism is a common neurological disease which may not only lead to cognitive impairments but also damage the human brain systems [15].

Alcoholism causes huge socio-cultural and economic effects on the person who drink, the environment and society as a whole. Indeed, increase in traffic accidents, accidents while operating machines or even violence are also a consequence of alcoholism. Consumption of alcohol can be detected conventionally using blood sample, urine, breathalyzer or saliva[6]. These conventional alcohol detection tests were performed mostly in laboratories and are complicated and expensive to use by a motor traffic police officer to examine a drunken driver for example.

Neuroscience research of the last century of has greatly increased our knowledge about the brain and particularly, the electrical signals emitted by neurons firing in the brain. The patterns and frequencies of these electrical signals can be measured by placing a sensor on the scalp. Electroencephalogram (EEG) is a technology that used to capture the brain signals by placing electrodes in a standard order. EEG recording procedure is either invasive or non-invasive. Non-invasive EEG recordings obtained from electrodes attached to the scalp surface and Invasive EEG recorded from implanted electrodes inside the brain which requires surgery. Non invasive EEG devices become more popular among researchers and it is one of the widely used brain signal recording methods due to portability, ease and comfort of use, low cost setup and low risky. In non-invasive EEG electrodes were placed at standard scalp electrode positions according to the 10-20 system as recommended by the American EEG Society as shown in figure 1.

The EEG signals displays some special patterns during psychiatric phenotypes such as body movement, epilepsy, and movement imagination, etc.. These signals can be used for brain computer interfacing or clinical diagnosis. EEG applications increasingly developed in evaluating brains dynamic models, diagnosis of anomalies like epilepsy [17], mapping discovered disorders to a location in brain[4], classification of mental states[1], brain computer interfacing[12] and designing of emulators for some motor-sensory functions.

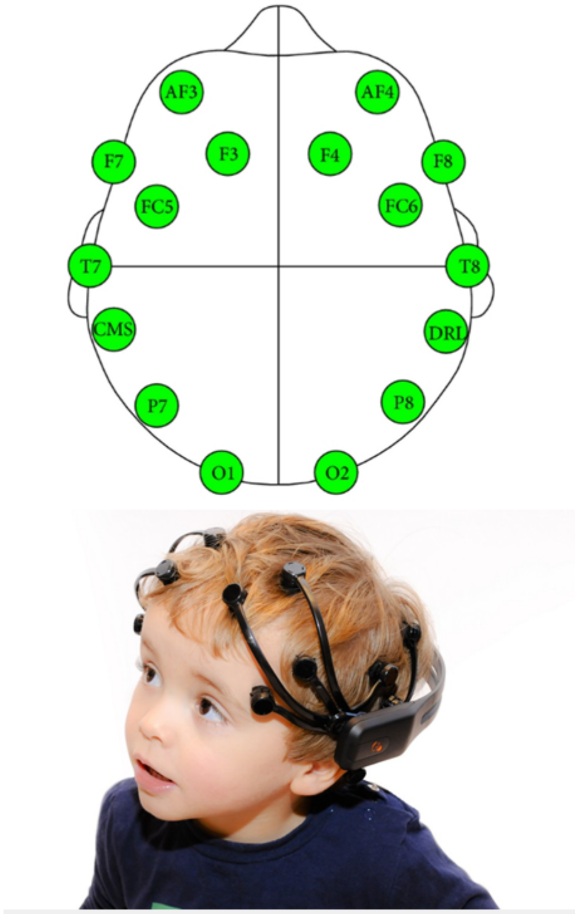


Fig. 1: Brain signal recording using Emotive EEG headset, 10-20 electrode positioning (image curtesy: www.emotive.com & https://lucid.me/blog/wed-love-try-emotiv-epoc/)

TABLE I: EEG frequency sub bands

Rhythmic waves	Frequency band
Delta (δ)	0.5 to 3 Hz
Theta (θ)	4 to 7 Hz
Alpha (α)	8 to 13 Hz
Beta (β)	14 to 31 Hz
Gama (γ)	$>$ 32 Hz

The amplitude of EEG signals varies between 1-100 μV as well as their frequency spectrum lies between 0.5Hz to 100 Hz. The rhythmic activity divided into five frequency bands as listed in table I.

These frequency bands were depending on peoples instant mental attitudes. Delta waves were observed in babies, adults when deep sleep, and during some continuous-attention tasks. Theta waves were observed in young children, during drowsiness in adults and teens, and also associated with inhibition of elicited responses. Alpha waves were observed in normal, calm and relaxed people and also associated with inhibition control. Beta waves were observed usually in cases of stress, active thinking, and anxious. Gama waves were observed during short-term memory matching of recognized objects, sounds, or tactile sensations.

Alcohol consumption can be detected by using brain signals. There are various studies have been done on alcohol detection using EEG based BCIs. Yazdani & Setarehdan (2007)) have used 4 EEG datasets to classify alcoholic and control subjects with four different classifiers, k-nearest neighbor (with k=5) yielded 79.17% accuracy [22]. Power spectrum analysis with wavelet transformation of brain signals on alcoholic and non-alcoholic subjects were employed by Sun et al (2006), where power of alcoholics in delta and theta band were greater than controls comparing to other bands[11]. Malar et al[18] also used a similar approach using the Power Spectral Density Analysis of EEG and using wavelet transform. Ziya Eki, et al used artificial neural networks with yule-walker power spectral densities for classification[6]. Kohji Murata et al used the frequency time series analysis to attempt to distinguish between normal and intoxicated states of a person[13]. Jiufu Liu et al.[10] have used wavelet entropy to classify drunken and control subjects. Wang et al[21] have proposed a method using principle component analysis based on graph entropy and J48 decision tree on EEG signals to predict whether a person is alcoholic or not. For this experiment they have used K-nearest neighbor (KNN) and support vector machine (SVM) for feature comparison. Faust et al have developed a Computer-based identification of normal and alcoholic EEG signals using wavelet packets and energy measures, where they used 10-fold cross-validated analysis of six classification algorithms. Such as k-nearest neighbor (k-NN) algorithm, Naive Bayes classification (NBC), fuzzy Sugeno classifier (FSC), probabilistic neural network (PNN), Gaussian mixture model (GMM), and decision tree (DT).

In this paper we analyse the possibilities of detecting the alcohol consumed people from controls using EEG signals. The rest of the paper is organised as follows: Material and methods described in Section II. Section III discusses about the Results obtained from the experiments and some concluding remarks were given in Section IV.

II. MATERIALS AND METHODS

The EEG data for the analysis were downloaded from an open EEG database by Lester Ingber from State University of New York health center [2], [19]. It has data recorded from 122 subject and each subject completed 120 trials. In the experiment, the subject heads were placed with 64 electrodes, the sampling frequency was set to 256Hz and recording data period was 1 second and each epocs were 3.9 milliseconds in every experiment. According to the data owners description, some experiment data are not in the database, therefore, for the purpose of analysis and to ensure the comparability of results, 20 alcoholic and 20 control EEG data were was randomly chosen for this study as training data and another 20 alcoholic and 20 control EEG data were chosen randomly to test the system.

The downloaded EEG signals were processed both in time and frequency domain. It is required to analyze the signal in both time as well as frequency domain since EEG signal is non-stationary and brain rhythms exist in time domain. The data analysis for this research work was done in MATLAB software.

As the long term intention of the study is to create a real-time portable alcohol detection system using emotive epoc headset with 14 electrodes, the particular 14 electrode were selected to analyse the brain data with alcoholic and control subjects.

EEG data were filtered using a high pass filter at 0.5Hz in order to remove 0Hz offset and suppress the very low frequency noise. It also passed through a low pass filter at 50 Hz in order to remove 50Hz line noise as well as suppress the high frequency noises.

Band power, power spectral density and mean frequency were extracted from the data as features. The frequency domain analysis was done using the Fast Fourier Transform (FFT) algorithm to calculate absolute band power, power spectral density and mean frequency (Hz) within each of the sub-bands. The absolute power of a band is the integral of all of the power values within its frequency range. Mean frequency was calculated using a formula published by [5].

Support vector machines were used to classify different class of data. The block diagram of the experimental model is given in figure 2.

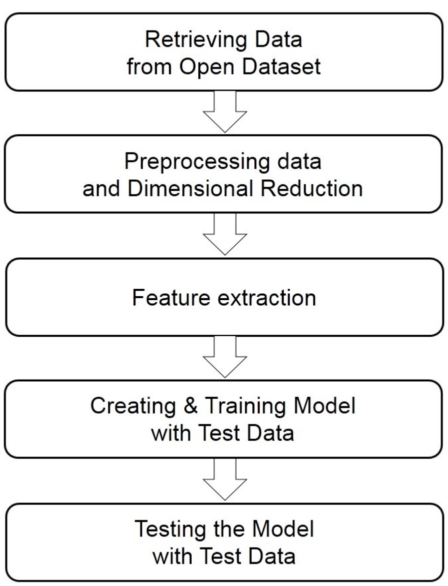


Fig. 2: Block diagram of experimental model

A. Support Vector Machines

Support Vector Machine(SVM) classifiers are very popular in EEG classification problems. The following section provides a brief review of the theory behind SVM algorithm. The SVM maps the points into a feature space and finds a separating hyperplane which maximizes the margin between the two groups in this feature space as seen in figure 3. Finding a hyperplane by maximizing the margin is a quadratic programming problem (QP) and can be solved by using Lagrange multipliers. SVM uses the kernels, a dot product function in feature space, to the optimal hyperplane without any knowledge of the mapping. The solution of the optimal hyperplane can be written as a combination of a few input points that are called support vectors[9].

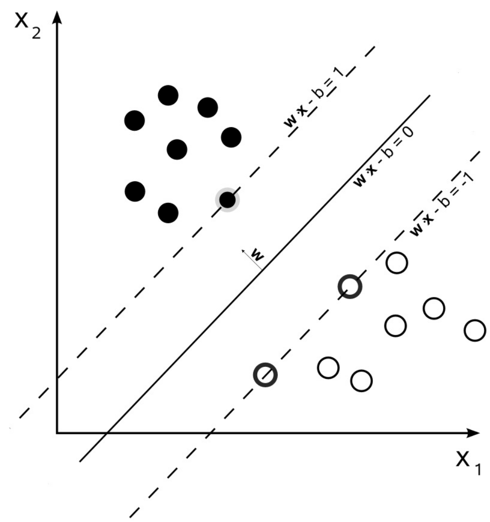


Fig. 3: SVM trained with samples from two classes and maximum margin hyperplane

Consider the problem of separating the set of training data

$$(x_1, y_1), (x_2, y_2), ...(x_m, y_m)$$

into two classes, where x_i is a feature vector and y_i are either $+1$ or -1, indicating the class to which the point x_i belongs to. If we assume that the two classes can be separated by a hyperplane

$$wz + b = 0 \tag{1}$$

and no prior knowledge about the data distribution, then the optimal hyperplane is the one which maximizes the margin. The optimal hyperplane separates the point x_i according to the function

$$f(x_i) = sign(w.z_i + b) = \begin{cases} \text{+1}, & \text{if } y_i = 1 \\ \text{-1}, & \text{if } y_i = -1 \end{cases} \tag{2}$$

The optimal values for w and b can be found by solving a constrained minimization problem, using Lagrange multipliers $\alpha_i (i = 1, ...m)$.

$$\text{maximise } W(\alpha) = \sum_{i=1}^{m} \alpha_i - \frac{1}{2} \sum_{i=1}^{m} \sum_{j=1}^{m} \alpha_i \alpha_j y_i y_j z_i.z_j$$

$$\text{subject to } \sum_{i=1}^{m} y_i \alpha_i = 0 \quad 0 \le \alpha_i \le C, i = 1, ..., m \tag{3}$$

where C is a regularisation parameter. Tuning this parameter can make balance between margin maximization and classification violation. So the decision function can de solves as,

$$f(x) = sign(w.z + b) = sign\left(\sum_{i=1}^{m} \alpha_i y_i K(x_i, x) + b\right) \quad (4)$$

B. Power Spectral Density

The Power Spectral Density (PSD) function was used to assess the spectral characteristics of EEG activity of each epoch. It is computed as Fourier transform of its autocorrelation function. The PSD is normalized by the total power in the frequency range of 0.5 Hz -50 Hz to obtain a normalized PSD. The following equation was used for calculating the power in each band of the signal[8].

$$PSD_n(f) = \frac{PSD(f)}{\sum_{f=1Hz}^{50Hz} PSD(f)} \quad (5)$$

so that:

$$\sum_{f=1Hz}^{50Hz} PSD(f) = 1 \quad (6)$$

then the Relative Power is calculated for each band using the equation:

$$RP = \sum_{f=f_{low}}^{f_{high}} PSD(f) \quad (7)$$

where f_{low} and f_{high} are the low and high cut-off frequencies of each band (e.g., f_{low}=8Hz and f_{high}=13Hz for alpha band)

III. RESULTS AND DISCUSSIONS

The analysis focused on 14 electrode locations of interest: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and AF4 respectively, because the analysing all 64 electrodes in the data set is a huge processing task and the plan is to propose a portable alcohol detection instrument with emotive epoc headset with above listed electrodes.

To evaluate the performance of the proposed model, it was tested with 20 alcoholic and 20 control EEG data. The classification results based on different EEG channels are displayed in figure 4.

The SVM classifier accuracy for the EEG sub bands against the electrodes presented in figure 5.

The SVM classifier classifies the data with more than 94.70 % accuracy as seen in figure 4. Moreover the data recorded from electrodes AF3, F7, F3, FC5, F4, F8 and AF4 were classified with 100% classification accuracy.

The classification accuracy of EEG signal sub bands also greater than 98.83% in average which is a higher figure when considering an ordinary classification problem.

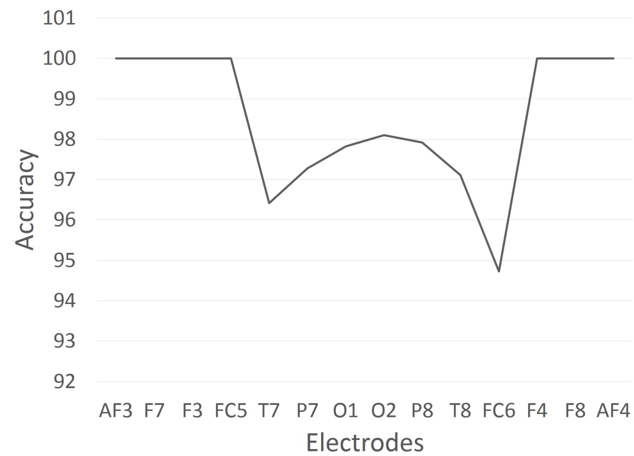


Fig. 4: Classification accuracy of SVM classifier for whole EEG signal

TABLE II: Summary: Classification Accuracy for whole EEG data and single electrode AF4

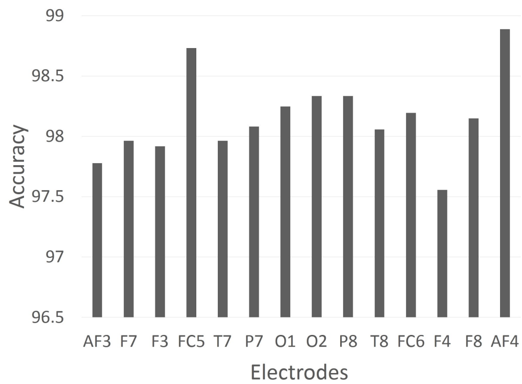
Test	Accuracy
Whole channels	98.52 %
Electrode AF4	98.83 %

The classification result presented in table II shows the accuracy when the experiment done considering the entire electrodes and a single electrode AF4. When considering individual electrodes, electrode AF4 classifies with highest accuracy in all bands with average of 98.83%. The electrode AF4 is located at the upper part of the eyes. As this table clearly depicts that the result is so significant as a single electrode (AF4) can be used to detect alcohol consumption with highest accuracy comparing the work done earlier. The table III describes the summary of the research work done on alcohol detection and our study also listed in it for easy reference.

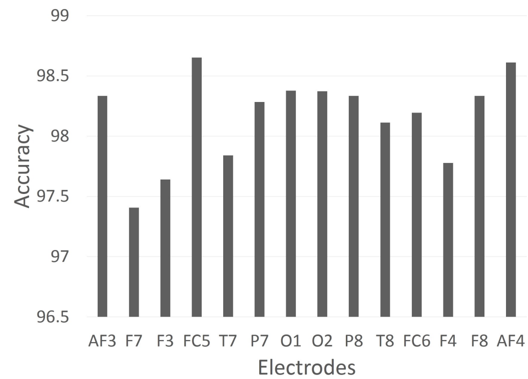
Some of the factors that influence the extent to which alcohol affect the brain are: a) the volume and the number of times a person drinks b) the age at when he started to drink and number of years continued c), education, gender and genetic predisposition, family history of alcohol dependence d) possibility of prenatal exposure and the overall health condition[14]. These factors were not considered when experiment was conducted as the data were downloaded from open EEG data bases.

IV. CONCLUSION

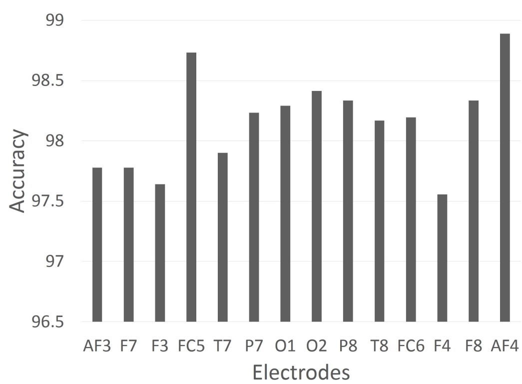
It is clear evident that there is a huge influence in brain signal of alcoholic subject when compare to control subjects. SVM classifiers are very efficient in classifying the signals with highest accuracy. Also detection of alcohol consumption can be done using EEG signals much easily and low cost by using portable EEG devices.



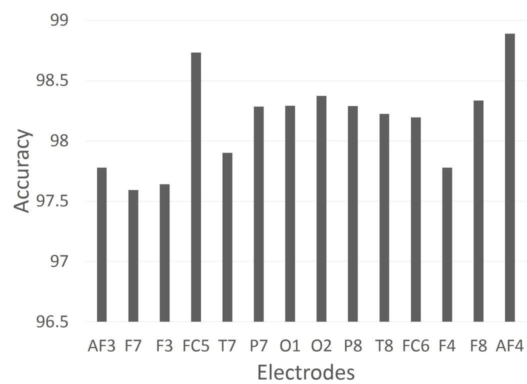
(a) Delta Band



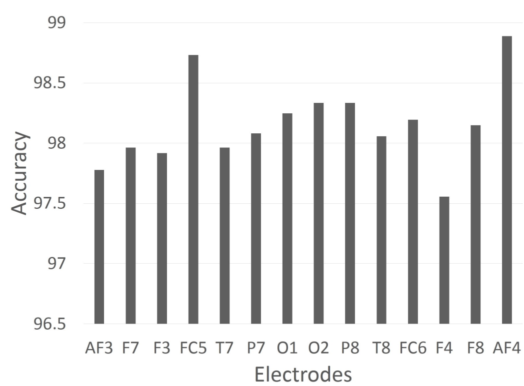
(b) Theta Band



(c) Alpha Band



(d) Beta Band



(e) Gamma Band

Fig. 5: Classification accuracy of EEG sub bands

TABLE III: Comparison of selected research work on alcohol detection and EEG signals

		E. Malar et al.	Ziya eki et al.	Jiufu liu et.al	Ashkan yazdani et.al	Shuaifang wang, et.al	Oliver faust et.al	This Study
Year		2011	2013	2012	2007	2016	2013	
References		[11]	[6]	[10]	[22]	[21]	[7]	
Model	Stationary waveletTransform	✓		✓				
	Yule-walker method		✓					
	Artificial neural network (ANN)		✓					
	Wavelet entropy			✓				
	PCA via SVD of separability matrix				✓			
	Naive Bayesian classifier				✓		✓	
	K-nearest neighbor (KNN)				✓	✓	✓	
	Bayesian with,KNN estimation				✓			
	Minimum mean, Distance				✓			
	Support vector machine(SVN)					✓		✓
	Fuzzy sugeno classifier (FSC)						✓	
	Probabilistic neural network (PNN)						✓	
	Gaussian mixture model(GMM)						✓	
	Decision tree (DT)						✓	
No of Electrodes used		6	-	-	1, 64	1, 2, 19, 64	64	1, 14
Accuracy			95%		79.17%	87.5%	95.8%	98.83 %

Since Electrode AF4 provide maximum of 98.83% classification accuracy, it is possible to build a portable alcohol detection system even with single electrode placed just above the right eye. Hence portable Emotive EEG headsets with 14 electrodes or even Emotive insight Brainwear with 4 electrodes can be used as a portable alcohol detection systems.

Further researches can be done to minimise the size of the alcohol detecting device using highly portable arduino or raspberry-pi based computers coupled with portable dry non-invasive EEG headsets.

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