Screening for Chronic Alcoholic Subjects Using Multiple Gamma Band EEG: A Pilot Study

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ABSTRACT

Electrophysiological impairments of alcoholism have been researched extensively. However, there is none or few reported research on screening methods for chronic alcoholic subjects. Since chronic alcoholics have serious brain dysfunction, a method to screen for them during specific job applications that require good memory, concentration and/or decision making would be useful. In this paper, a method is proposed to discriminate chronic alcoholic from non-alcoholic subjects while they are sober. Energies of electroencephalogram signals in multiple gamma bands recorded while the subjects performed a picture recognition task are used as features by a neural network to detect the chronic alcoholic subjects. Leave one out cross validation strategy reveals that alcoholics could be discriminated from non-alcoholics with accuracy of 94.55%. This pilot study has shown the potential of the method which could be further developed for use in automatic alcoholic screening procedures.

Keywords: Alcoholic subject discrimination, Electroencephalogram, Gamma band energy, Neural network

1. INTRODUCTION

Alcohol abuse is associated with many health and social problems and brings high economic costs. It is estimated that 9–20% of patients admitted to a primary healthcare service are screened positive for alcohol abuse [1]. Analyses on the brain dysfunction caused by alcoholism have been researched extensively. Chronic alcoholics, who have been drinking heavily for many years, have been shown to have problems with memory, attention and decision making even after a period of abstinence [2], [4], [10]. Therefore, screening for alcoholics could be of importance during certain job recruitments that need some of these skills (like machine operators requiring concentration).

However, there are not many reported studies on methods for detecting chronic alcoholics from the rest of the population when they are sober. This must not be confused with methods for detecting alcoholics under the influence of alcohol (using alcohol levels in blood, for example like the breath analyser test). The only related study to the one here was that by [8] who investigated a method to select optimal channels using genetic algorithm, where they particularly studied a two class problem using groups of alcoholics and non-alcoholics. Both the alcoholics and non-alcoholics were included in the training and testing data sets in this study and their objective was not on the individual discrimination of alcoholic subjects.

In this paper, an attempt is made to discriminate chronic alcoholic subjects from non-alcoholic subjects using features from brain signals. The validity of the method is shown through an analysis involving several stages of pre-processing, feature extraction and classification methodologies.

2. METHODOLOGY

In this study, electroencephalogram (EEG) data from ten alcoholics and ten non-alcoholics were used. This data set were recorded by the authors in [10], for their studies on establishing a marker to analyse the short-term visual memory deficits in alcoholics.

The subjects

The alcoholics tested had been abstinent for a minimum period of one month (through closed ward detention). Therefore, all alcoholics were fully detoxified and had no alcohol available for that period of hospitalisation. Alcoholic individuals were excluded from the study if they had history of drug dependence, major psychiatric illness, or other diseases related to overt liver, metabolic, vascular and neurological. Most of the alcoholics had been drinking heavily for a minimum of 15 years. The diagnosis of alcohol abuse was made by the intake psychiatrist of the Addictive Disease Hospital in Brooklyn, USA according to DSM-III criteria. The alcoholics were non-amnesics and also not substance abusers. They were also matched for socioeconomic status.

EEG data

The EEG signals were recorded non-invasively from 61 active plus 3 reference channels from the scalp. The positions of 19 electrodes were in conjunction with the 10-20 international system and additional electrodes were placed in between these to obtain the total of 61 electrodes, covering most of the recordable activity of the brain. Figure 1 shows the location of these electrodes.

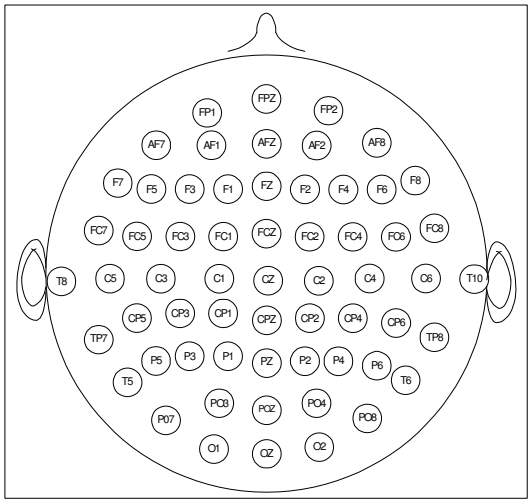

Figure 1. 61 active electrode system.

EEG signals are actually potentials exhibited by neuronal excitations in the cortex and these were recorded with the subjects observing drawings of common black and white objects from the Snodgrass and Vanderwart (SV) picture set [9]. The SV picture set represent common black and white objects, such as, for instance, airplane, banana, and ball. These were chosen according to a set of rules that provides consistency of pictorial contents. They have been standardised based on the variables of central relevance to memory and cognitive processing. These objects can be named i.e. they have definite verbal labels.

All the subjects were asked to remember or recognise the stimulus. Stimulus duration of every picture was 300 ms. All the stimuli were shown using a display located 1 meter away from the subjects. One-second EEG measurements (sampled at 256 Hz) after each stimulus onset were stored. Figure 2 shows some examples of the picture stimuli.

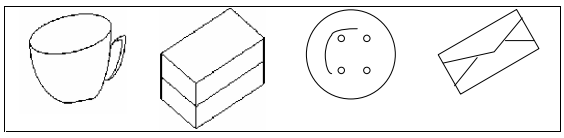

Figure 2. Examples of stimuli from SV set [9].

Pre-processing

EEG signals contaminated with eye blink artifacts were not considered in the approach, and were detected using a 100 μV threshold. This is a common threshold value in EEG studies, and is used since blinking produces 100-200 μV potential lasting 250 milliseconds [7]. A total of 40 artifact free trials were considered for every subject, to make a total 800 EEG signals.

Feature extraction

EEG signals were filtered using Elliptic filter. Filtering was performed twice; once forward and once reverse to remove the non-linear phase effects. Frequency range was from 20-70 Hz because of the reported existence of gamma band oscillations in this range [3].

This frequency range was split into 3 gamma bands: low-gamma (20-30 Hz), mid-gamma (30-50 Hz) and high-gamma (50-70 Hz). Order 5 was sufficient to obtain pass-bands of 20-30 Hz, 30-50 Hz and 50-70 Hz with minimum stop-band attenuation of 30 dB at 5 Hz below and above the pass-band ranges. The ripple in the pass-bands was kept below 0.1 dB. Energy of the filtered EEG signal in each low-gamma, mid-gamma and high-gamma bands from each channel were computed and normalised with the total energy in each band from 61 channels to form a total of 183 EEG features.

To reduce the number of features, a simple technique using t-test[1] analyses (with significance of 0.01) were used to obtain the most discriminant channels for each band. For each gamma band, the channels that gave significant difference between alcoholic features and non-alcoholic features were noted and only features from these channels for the particular gamma band were used in classification. There were 33 significant channels for low-gamma, 36 significant channels for mid-gamma and 54 significant channels for high-gamma, giving a total of 123 features for each EEG signal. There were only 21 common significant channels for the 3 gamma bands, the rest of the significant channels differed.

Neural network classification

Features from nine alcoholics and nine non-alcoholics (totalling 720 feature set, each with 123 features) were used in training the multilayer-perceptron (MLP) neural network (NN), while the rest of the features from the other alcoholic and other non-alcoholic (totalling 80 feature set) were used in the testing. The feature sets used in training and testing were whitened to remove correlation.

Signal whitening seeks to obtain the EEG matrix $\tilde{\mathbf{x}}$, such that the covariance of matrix $\tilde{\mathbf{x}}$ becomes the identity matrix

$$\mathbf{E}(\tilde{\mathbf{x}}\tilde{\mathbf{x}}^{\mathbf{T}}) = \mathbf{I}. \quad (1)$$

A common whitening method is via the eigenvalue decomposition of the covariance matrix $\mathbf{E}(\mathbf{x}\mathbf{x}^{\mathbf{T}}) = \mathbf{F}\mathbf{D}\mathbf{F}^{\mathbf{T}}$, where $\mathbf{F}$ is the orthogonal matrix of eigenvectors of $\mathbf{E}(\mathbf{x}\mathbf{x}^{\mathbf{T}})$ and $\mathbf{D}$ is the diagonal matrix of its eigenvalues, $\mathbf{D} = diag(d_1,.....,d_n)$. Whitening can now be performed using

[1] The features were assumed to be of normal distribution.

$$\tilde{\mathbf{x}} = \mathbf{F}\mathbf{D}^{-1/2}\mathbf{F}^{\mathrm{T}}\mathbf{x}\,. \quad (2)$$

These whitened features were then normalised to the range [-1,1], using maximum and minimum values of each feature, with the idea to improve the NN training;

MLP NN was trained by the backpropagation algorithm (BP) with adaptive learning rate to classify the features. The hidden units (HU) were varied from 20 to 100 in steps of 20. The number of input units was set at 123. The output units were set at two: one for each alcoholic or non-alcoholic category. One-hot encoding was used for the target values (either 0 or 1). The training was conducted until the mean-square error fell below a threshold of 0.01. The MLP-BP training and testing procedures were repeated for ten times but with training and testing feature sets from different alcoholics and different non-alcoholics for each time. In other words, feature sets from different nine alcoholics and nine different non-alcoholics were used for training, while feature sets from the other alcoholic and other non-alcoholic were used for testing each time. This procedure of repeating the training and testing is commonly referred as the leave one out cross validation, which is useful in increasing the reliability of the classification results.

3. RESULTS

Table 1 shows the MLP-BP NN training, testing times and the classification accuracies for varying HU sizes. Only the averaged values from the ten leave one out cross validation experiments are shown in the table. The execution times, rather than the number of iterations are listed. Since the experiments were run on the same code, using Matlab, this still provides a fair comparison of the measure of complexity caused by the varying HUs.

Table 1: NN classification results

MLP-BP HU	Training time (s)	Testing time (s)	Accuracy (%)
20	105.08	0.0148	94.55
40	151.63	0.0157	91.90
60	181.24	0.0157	89.75
80	220.39	0.0158	91.63
100	255.41	0.0159	87.75
Average	**182.75**	**0.0156**	**91.12**

The best classification accuracy of 94.55% was obtained for HU size of 20. Classification experiments were also tried with HUs lower than 20 but their performances were poor as the MLP-BP failed to converge and hence not reported here. The lower accuracies when using higher HUs could most probably be due to the overfitting phenomena. The training and testing times were also the shortest using 20 HUs. As such, it would be appropriate to use this HU size as the design complexity and computational time would be reduced in addition to giving the best classification accuracy.

4. DISCUSSION

Gamma band oscillations are evoked during visual perception especially when a stimulus is recognised and these oscillations contribute to feature binding process which is necessary during stimulus perception [3]. Another study [6] speculated that the function of gamma band oscillations is to provide a reference clock to control the firing of the excitatory neurons.

It is likely that long term use of alcohol causes irreversible damage to neuronal excitations leading to the difference in gamma band energies that discriminate alcoholics from non-alcoholics. Though the t-test gives significant difference between alcoholics and non-alcoholics for different gamma band energies for a few common channels; the significant difference for different channels for different gamma band energies show that electrophysiological deficits related to perception and gamma band oscillations occur differently at different areas of the brain.

5. CONCLUSION

In this paper, a method to discriminate alcoholic subjects is proposed using energy of multiple gamma bands of EEG signals. The recording procedure is simple as the EEG is recorded when subjects perceive a single picture. MLP-BP NN classifies the EEG features from 3 gamma band energies (20-30 Hz, 30-50 Hz, 50-70 Hz) from selected channels into either the alcoholics or non-alcoholics category. The good discrimination accuracy obtained in this study offers promise for the method to be developed further for use in alcoholic screening tests.

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