An Exponential Power Ratio Index based Algorithm for Analysis of Alcoholic EEG Signal

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Abstract—**This paper presents a new Algorithm to analyze the Electroencephalography (EEG) signal, which is regarded as an important way to analyze the alcoholism. In order to distinguish the nonlinear characteristics of EEG with alcoholic people and the control, an exponential power ratio index (EPRI) is proposed to quantify the slow wave and fast wave power features of the EEG signal, and the Independent Component Analysis (ICA) and Support Vector Machine (SVM) are combined for analysis. The proposed method is implemented on the real data sets acquired from UCI common databases, which have been studied by some research groups. The results suggest that the proposed method is valid for analysis of EEG signal in alcoholism.**

Index Terms—**Electroencephalography (EEG), Independent Component Analysis (ICA), Support Vector Machine (SVM), Time Series, Feature Analysis**

I. INTRODUCTION

Since ancient times, the great interest on the Human brain has been generated and lots of researches have been held. However, there are many unresolved issues and difficulties to be overcome because of the complexity and uncertainty of the brain system. Electroencephalography (EEG), the electrical activity of cerebral cortex, exhibits the brain function and the status of the whole body, which is as a kind of effective means to study the brain [1]. As is known to all, Hans Berger (1873-1941), the one is as the electroencephalographers, who discovered the existence of human EEG signals. Since Berger studied EEG in 1920 [2], the analysis of EEG signal plays a more and more important role in clinical medicine, biology, psychology and other areas. It provides the motivation to apply advanced digital signal processing methods to the EEG signals measured from the brain of a human subject, and thereby underpins the later section of the paper [3-4]. Analysis of the Electroencephalography (EEG) is proved valid to monitoring the patient state [5] among various methods, and it is an effective tool to research and analyze the feature of alcoholism.

There are a lot of algorithms and parameters proposed to judge whether the brain performance be abnormal or not. In England, W. Gray Walter firstly discovers the foci of slow brain activity (delta waves), which initiates enormous clinical interest in the diagnosis of brain abnormalities. In North America, Hallowell Davis starts research activities related to EEG and illustrates a good alpha rhythm for himself. A cathode ray oscilloscope is used around this date by the group in St Louis University in Washington, in the study of peripheral nerve potentials [3]. Since Berger and Dietch apply Fourier analysis to EEG sequences, it is rapidly developed. Nagata proposes the power ratio index (PRI) to study topographic electroencephalographic and applies to the research of malignant brain tumors [6]. Claassen lists twelve parameters including total power (TP, 1-30Hz), alpha power (AP, 8-13Hz), delta power (DP, 1-4 Hz), beta power (BP, 14-30Hz), fast power (FP, 8-30Hz), alpha/total power (RA, 8-13/1-30Hz), delta/total power (RD, 1-4/1-30Hz), alpha/delta power (AD, 8-13/1-4Hz), fast/delta power (FD, 8-30/1-4Hz), alpha power (CA, 8-13Hz left vs. 8-13Hz right), delta power (CD, 1-4Hz left vs. 1-4Hz right), average frequency total (AF, average FFT frequency 1-30) [7]. On these bases, Finnigan changes AD to DAR and combines it with PRI and NIHSS to study the EEG signal in sub-acute stroke [8]. Nowadays, the features of different frequency waves are always the important points of the clinical interest. Besides the traditional indices, nonlinear parameters are increasingly developed and widely used to analyze the EEG signal, such as correlation dimension, Lyapunov exponent[9], approximate entropy[10], and so on. Modern research methods, for example, principal component analysis (PCA), independent component analysis (ICA), wavelet transformation analysis, support vector machine (SVM), hidden Markov models (HMM), dynamic Bayesian networks, artificial neural networks (ANN), etc.[11-18] are also used to study the EEG sequences. The research of EEG has brought daily development of clinical, experimental, and computational studies for discovery, recognition, diagnosis, and treatment of a great number of neurological and physiological abnormalities of the brain and the rest of the central nervous system (CNS) of human beings.

This paper proposes a new method for analysis of EEG in alcoholism. Firstly, the Independent Component Analysis (ICA) is used to separate EEG sequences into independent signals. Then, an index based on the existing parameters describes the nonlinear characteristics of EEG signals by quantifying the slow wave and fast wave power features, which is proved viable in distinguishing

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the alcoholic people and the control. For a change, it is not derived from a simple ratio of different frequency power bounds but introduces the exponential function in accord with customary practice. Then, support vector machine (SVM) is as the method of classification algorithm.

The paper is organized as follows: Section 2 proposes the new methodology which extracts the features of EEG in alcoholic. The exponential power ratio index (EPRI) and the discriminant analysis method of EEG signals are proposed in this part. Section 3 gives the experimental results which are over real public datasets. Section 4 is the conclusion.

II. Methodology

A. Independent Component Analysis

Independent Component Analysis (ICA) is a feature extraction analysis tool derived from the "source separation" signal processing techniques, and its characteristic is to decompose mixed signals into independent components. Some research results show that ICA algorithm can extract the multi-channel EEG signals from the interference of other biological electrical signals, and can also separate the basic rhythms of the EEG signals (such as alpha waves, beta waves etc.) into different independent components respectively.

Let $S_i\left(1 \le i \le M\right)$ be the original signals and $X_j\left(1 \le j \le N\right)$ be the observations, where each observation is a mixture of the original signals. Under the assumption that the original signals are statistically independent and it is possible to recover the original signals from the observations under mild conditions on the mixture. This technique making this task possible is often called ICA, as they factorize the observations as a combination of original sources. For the linear mixture, ICA estimates the inverse of the mixing matrix. It is worth noting that the number of observations *N* must be at least equal to the number of original signals *M*. Generally, it is assumed that *N*=*M*. It is not necessary to have signals X to consider using ICA: X may also be multidimensional vectors. Assuming that each X_j is an unknown, different combination of original "source vectors" S_i, ICA will expand each signal X_j into a weighted sum of source vectors S_i (ICA estimates both the source vectors S and the coefficients of the weighted sum) [19].

Suppose that the original vector is observed at each moment,

$$X = A \cdot S \tag{1}$$

where A is a $M \times N$ scalar matrix, and below we shall require $M \le N$. The task of independent component analysis is to recover the source signals from the observed signals. More specifically, a real matrix *W* is required as

$$S' = W \cdot X = W \cdot A \cdot S \tag{2}$$

where S' is the estimate of the sources S. Obviously, if $W = A^{-1}$, the estimated signals will be just equal to the original signals. However, neither *A* nor its inverse *W* are known to us. To solve this problem, matrix *A* could be determined by maximum-likelihood techniques. We use an estimate of the density, parameterized by $\hat{p}\left(x;a\right)$ and seek the parameter vector a that minimizes the difference between the source distribution and the estimate. That is, a is the basis vector of *A* and thus $\hat{p}\left(x;a\right)$ is an estimate of the *p*(*x*) [20]. Details are given in [21].

B. Exponential Power Ratio Index

Brain patterns from wave shapes are commonly sinusoidal. Usually, they are measured from peak to peak and normally range from 0.5 to 100 μV in amplitude. By means of fast Fourier transform (FFT) power spectrum from the row EEG signal is derived. In Power spectrum contribution of sine waves with different frequencies are visible. Although the spectrum is continuous, ranging from 0 Hz up to one half of sampling frequency, the brain state of the individual may make certain frequencies more dominate. As a general rule, the brain waves over all channels have been categorized into four basic groups: δ (0.5-3.5Hz), θ (4-7.5Hz), α (8-13Hz), β (14-30) and γ (>30 Hz) [22]. Normally, the delta waves and theta waves are collectively known as slow waves, while the alpha waves and beta waves are called fast waves. As a measure for the power ratio, we consider the spectral density of the right and left hemisphere in the frequency range from 1 to 30 Hz. A new definition of slow-fast wave power ratio is defined as the exponential power ratio index (EPRI):

$$EPRI = e^{-\frac{\lambda}{TM}\sum_{i=1}^{M}\frac{p_s(i)}{p_f(i)}} \tag{3}$$

where λ is a constant, *M* is the number of the channels and *T* is the length of time which specified in seconds. The p_s and p_f represent power spectral density of slow waves ($\delta + \theta$) and that of fast waves ($\alpha + \beta$), respectively. According to the above formula, the range of EPRI is 0 to 1, and it can be deduced that EPRI =1 means entire fast waves no slow waves and EPRI=0 means the reverse case.

C. Support Vector Machine

Support Vector Machine (SVM) is a popular classification algorithm which uses a discriminant hyperplane to identify classes. As shown in Fig. 1, the selected hyperplane is the one that maximizes the distance from the nearest training points which is so called margins. It is known that maximizing the margins is to increase the generalization capabilities. SVM uses a regularization parameter that enables accommodation to outliers and allows errors on the training set.

As shown in Fig. 1, the SVM classification with linear decision boundaries is known as linear SVM [23-24]. However, there are many ways to create all kinds of nonlinear decision boundaries, with only a low increase of the complexity, by using the "kernel trick". It consists in implicitly mapping the data to another space, generally of much higher dimensionality, using a kernel function $K(x,y)$. Among all the kind of kernel functions, the most commonly used is the Gaussian kernel, which is also named Radial Basis Function (RBF) kernel. The corresponding SVM is known as Gaussian SVM or RBF SVM, and it gives very good results for EEG signal analysis. The kernel function can be calculated as:

$$K(x,y) = e^{-\frac{\|x-y\|^2}{\sigma^2}} \tag{4}$$

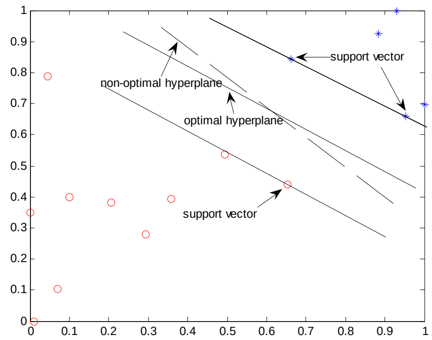

Figure 1. SVM find the optimal hyperplane for generalization.

D. Discriminant Analysis

A discriminant analysis method of EEG signal in alcoholism is proposed in this paper, where the ICA algorithm, SVM classification and the EPRI mentioned above are introduced to analyze the alcoholic EEG features.

The analysis steps of this discriminant method as follows:

Step1 Partition each subject's multi-dimensional EEG signal into a data matrix in per second, where the rows represent the sampling points and the columns represent the channels;

Step2 Decompose each mixed matrix of multi-channel signals and seek the source matrices by ICA;

Step3 Compute the EPRI of each processed matrix;

Step4 Use SVM classification algorithm to distinguish the alcoholic subjects from the controls.

It can be seen that the clearest characteristic of this discriminant analysis method is series segmentation in Step 1. That is to say, maybe not every EEG signal in per second shows same characteristics.

It is worth noting that the Step 4 is not limited to the particular SVM classification algorithm. We can choose such as the classification tree method, Linear Discriminant Analysis (LDA), Neural Networks (NN), Bayesian classifier and any other proper methods to perform the classification step. If it is possible, we can even set a threshold to distinguish the two cases under some circumstances. It depends entirely on the data and the application environment.

III. Experiments and Main Results

A. Subjects and Datasets

The experimental data in this paper are multi-electrode EEG time series under a variety of conditions, which are obtained from University of California (UC) Irvine Machine Learning Repository and sponsored by the National Institute on Alcohol Abuse and Alcoholism (NIAAA) project. This data arises from a large study to examine EEG correlates of genetic predisposition to alcoholism. It contains measurements from 64 electrodes placed on subject's scalps which are sampled at 256 Hz (3.9-msec epoch) for 1 second. The positions of 64 electrodes are shown as Fig. 2.

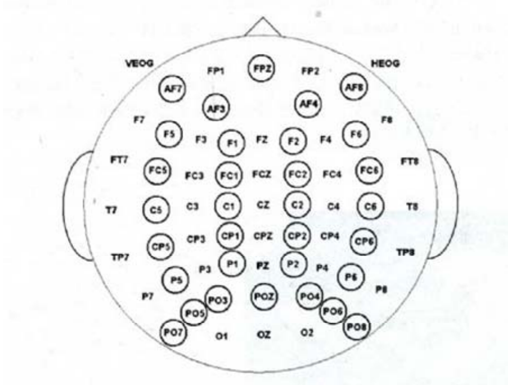

Figure 2. Positions of 64 electrodes.

There are two groups of subjects: alcoholic people and the control. Each subject is exposed to either a single stimulus (S1) or to two stimuli (S1 and S2) which are pictures of objects chosen from the 1980 Snodgrass and Vander wart picture set. When two stimuli are shown, they are presented in either a matched condition where S1 is identical to S2 or in a non-matched condition where S1 differed from S2.

There are two data sets used here. One is a small data set which contains data for the 2 subjects: alcoholic and control. For each of the 3 matching paradigms, one presentation only, match to previous presentation and no-match to previous presentation, 10 runs are shown. The other is a large data set which contains data for 10 alcoholic and 10 control subjects, with 10 runs per subject per paradigm. The test data used the same 10 alcoholic and 10 control subjects as with the training data, but with 10 out-of-sample runs per subject per paradigm.

B. Experiments and Main Results

This section presents the experimental results on the above-motioned EEG datasets. All procedures are written and implemented by adopting Matlab7.0 combined with EEG Anywhere 2.1 on the windows platform in the microcomputer equipped with Pentium (R) Core Dual-Core CPU E5800 @3.20GHz 3.20GHz and 2GB RAM.

1) The small data set which contains data for the 2 subjects: the alcoholic people and the control.

According to section 2, transform each subject's EEG signals into 10 scalar matrices with 256 rows and 64 columns. Each matrix refers to one second, a row channel. The discriminant analysis method of EEG signal is executed. In equation 3, the constant T equals to 1 (each matrix refer to a second) and M equals to 64 (64 electrodes). We set another constant $\lambda = 0.001$.

In order to display the importance and necessity of ICA, the experimental results without including ICA are given as the comparison to those of including ICA. The results without including ICA are shown as Fig. 3-Fig. 5, represents a sampling point and a column represents a and those under the case of including ICA are shown as Fig. 6- Fig. 8.

Concerning Fig. 3-Fig. 5, it is can be seen that the red lines of the alcoholic and the blue lines of the control twist together especially under two matched stimuli trials. The advantages of both the fast waves and the slow waves of the alcoholic subject are not obviously. It is difficult to distinguish the alcoholic EEG EPRI from the normal.

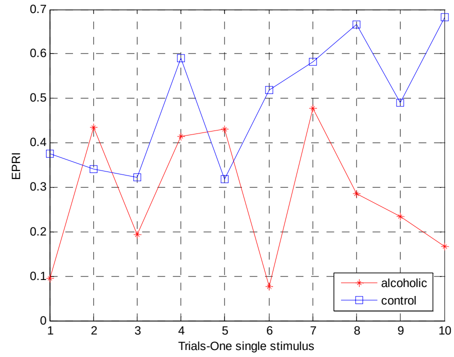

Figure 3. One single stimulus in 10 seconds (not including ICA).

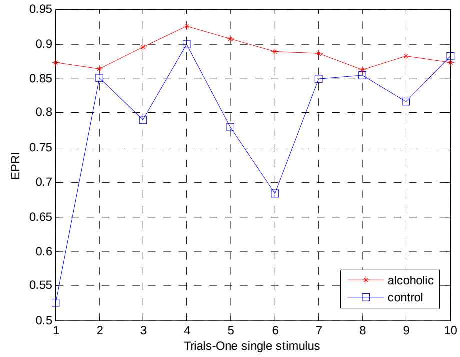

Figure 6. One single stimulus in 10 seconds (including ICA).

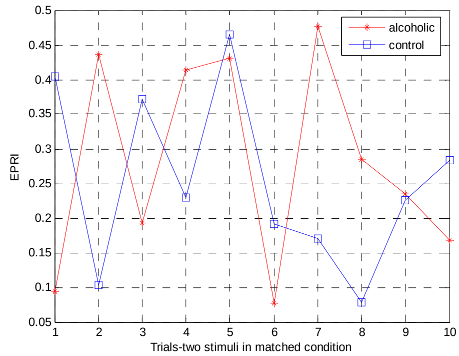

Figure 4. Two matched stimuli in 10 seconds (not including ICA).

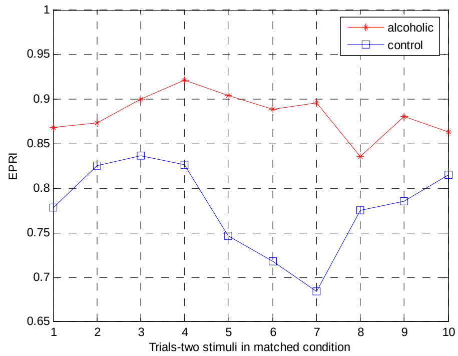

Figure 7. Two matched stimuli in 10 seconds (including ICA).

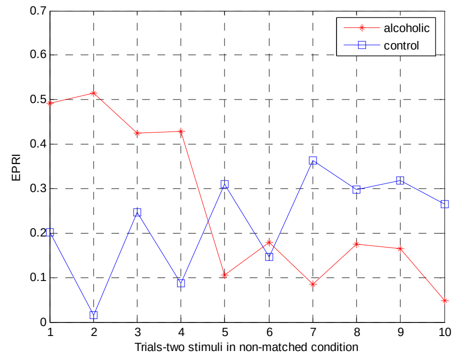

Figure 5. Two non-matched stimuli in 10 seconds (not including ICA).

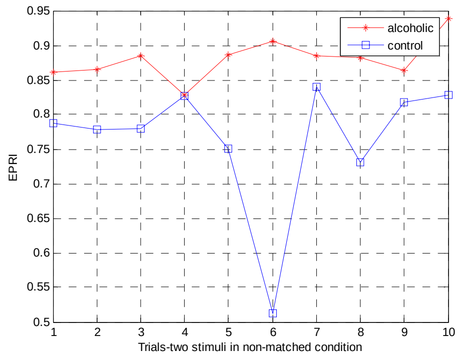

Figure 8. Two non-matched stimuli in 10 seconds (including ICA).

Comparing with the above mentioned three figures, the results of Fig. 6-Fig. 8 show another case. The results of the alcoholic subject are clearly separated from those of the control subject. The function of ICA is to find the latent variables which are assumed to be statistically independent. The features of the independent components are more separable than those of dependent. So it can be known that the decomposing step with ICA is necessary for this discriminant analysis method.

Fig. 6-Fig. 8 are results of one single stimulus, two stimuli in matched condition and two stimuli in non-matched condition respectively. From those three figures, it is shown that the EPRI of the alcoholic people is usually higher than that of the control, no matter how many stimuli there are and no matter whether the stimuli are matched or not. The higher EPRI indicates the more fast waves and less slow waves in alcoholic cases. Combined with the clinical manifestation, alcohol is a stimulant and causes mental excited within a short time, and then causes mental depression and dehydration. During the excitement, the EEG signal of the subject becomes active than usual, and the fast wave increases accordingly. That keeps with the experimental results in this section.

Now that we obtain the results of two groups in three kinds of conditions, it may be more interesting whether there is a borderline between the alcoholic people and the control. If we set threshold EPRI=0.85, it will be quite easy to distinguish the alcoholic subjects from the controls. That is to say, EPRI does not be affected by the number of stimulus.

2) The large data set which contains data for the 20 subjects: the alcoholic people and the control.

There are 10 alcoholic people and 10 matched control subjects. Each subject's EEG signals are corresponding to 10 scalar matrices with 256 rows and 64 columns.

For the discriminant analysis method in section 2, Step 1 to Step 3 are executed and the parameters are set as same as the previous experiment: T=1, M=64 and $\lambda = 0.001$. We work out the EPRI of each matrix and obtain the averages of every subject in 10 trials. For all practical purposes, another index, sample entropy, is also taken as the association indications to study the subjects' condition. The research suggests that the alcoholic people tend to have higher entropy than the controls. The computational method of sample entropy is detailed in paper [25]. With respect to Step 4, support vector machine (SVM) algorithm is used here and the typical Gaussian RBF kernel with $\sigma = 1$ is adopted [26].

From Fig. 9-Fig. 11, it shows the classification results between the two groups in the above-mentioned experiments. Those figures illustrate that the two groups of EEG signal could be distinguished by the proposed method entirely.

The experiments on the small data set and the existing related studies implement the comparison and analysis between the alcoholic people and the controls and the results suggest that the former subjects tend to have higher EPRI and entropy than the latter ones. Judging from the experiments on the large data set, it provides a new characterization method. The experiment results show that the proposed method could effectively distinguish the state of brain activity between an alcoholic person and a normal.

According to the results in previous experiments, the number of stimulus does not much affect the discriminant analysis in alcoholism, so we can analyze any condition of them (one single stimulus, two matched stimuli and two non-matched stimuli) to discuss in the real applications.

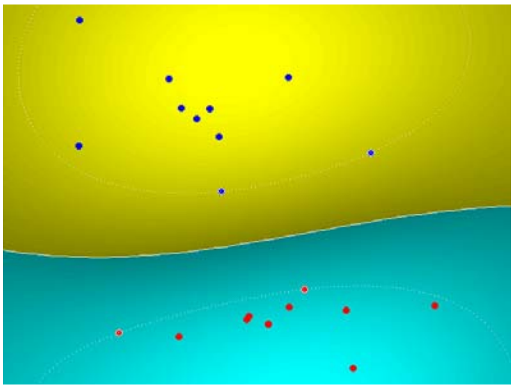

Figure 9. Classification result of 20 subjects in one stimulus trials (blue points refer to the alcoholic people and red ones refer to the controls).

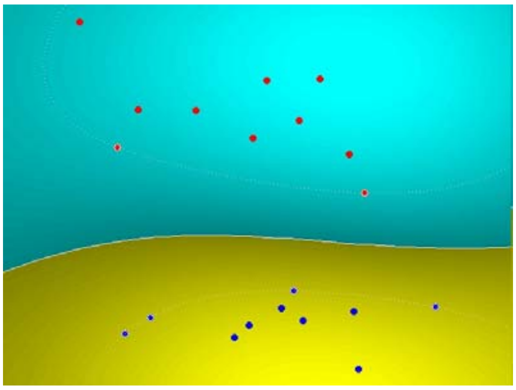

Figure 10. Classification result of 20 subjects in two matched stimuli trials (blue points refer to the alcoholic people and red ones refer to the controls).

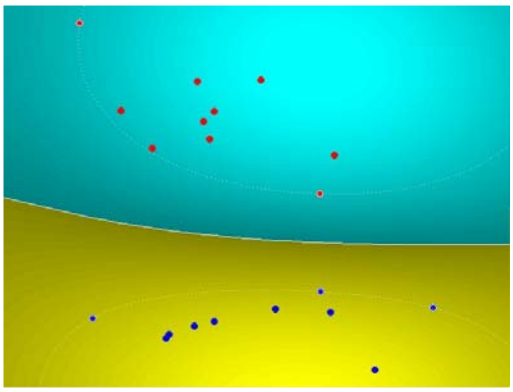

Figure 11. Classification result of 20 subjects in two non-matched stimuli trials (blue points refer to the alcoholic people and red ones refer to the controls).

IV. Discussion and Conclusion

This paper proposes an exponential power ratio index and a discriminant analysis method to analysis the characteristic of EEG signal, which makes use of the Independent Component Analysis for decomposing the mixed matrix and the Support Vector Machine for classifying the different data groups. The method could be seen as a general frame for the study of EEG time series. In the case of SVM algorithm, the experimental results reflect the validity of the proposed method but it is not limited to the particular SVM. In future work, other classification algorithms such as Neural Networks would be explored in the Step 4 to make the best experimental results.

As a new developed methodology, it can be used to the detection of drunk driving for the traffic management department.

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