Connectivity network analysis of EEG signals for detecting deception

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Abstract. In this paper, we proposed a novel deception detection (authenticity monitoring) method based on functional connectivity of different brain regions. 12-channels EEG signals were recorded. A mutual information analysis method was used to describe and quantify the connectivity information (correlation) of different regions. Following that, we analysed the statistical difference in the connectivity values between the guilty and innocent groups, and the electrode pairs on which there was statistical difference between two groups were selected. Finally, those connectivity values on selected electrode pairs were combined into the feature vector that was then fed into support vector machine classifier to identify the liars and the truth-telling subjects. Experimental results shows that the classification accuracy of 99.85% is obtained. This study proves that the mutual information method is an effective method of feature extraction for EEG signals, which provides a new way for deception detection based on EEG signals.

1. Introduction

Current authenticity and deception monitoring is different from the polygraph method and often used brain cognitive signals to detect liars. Most of the researchers used EEG [1-2], fMRI [3] and fNIRS [4] signals to identify the liars, To date, with the development of network analysis methods, increasing number of LD methods have focused on using functional or effective connectivity [5-6] to explore the difference between the guilty and the innocent subjects.

With the development of non-linear dynamics, many researchers has paid more attention to use the related methods of non-linear dynamics in the field of brain cognitive science, and they began to focus on the interdependence of brain signals between different brain regions [7]. Compared with the linear analysis method, the non-linear analysis method is more suitable for the analysis and processing of non-stationary EEG signals, which has been demonstrated that it can describe the behavior of complex systems with high effectivity. In recent years the feature extraction of EEG signals by non-linear analysis method has attracted the attention of many researchers. Common non-linear analysis methods include entropy analysis method [8], Lyapunov index [8] and mutual information methods [10].

Mutual information (MI) analysis method is based on the theory of entropy and quantifies the relationship between different signals. Compared with sample entropy and approximate entropy, it can measure the interaction between two signals and the dynamic characteristics of information transmission. Up to date, MI method has been gradually applied to the analysis of information
transmission in many brain diseases. Huang et al. [11] used MI method to study schizophrenia. Ken applied this method to explore epilepsy, and found that the brain information exchange activities of epilepsy patients were more frequent than the healthy subjects. Jeong et al. [12] and Liu et al. [13] investigated Alzheimer’s disease using MI method. Both studies found that the mutual information of frontal and parietal lobes in patients with Alzheimer’s disease was lower than that in healthy subjects. Ken et al. [14] applied MI analysis to study epilepsy disease. In sum, current research using MI in brain cognitive field shows that MI analysis method has significant advantages in exploring brain information exchange and functional brain network. Unfortunately, MI analysis method has not applied in detecting the deception and hence it deserves to deeply investigate. In this study we applied MI method first in the field of EEG-based lie detection, and reports on the application of the concept of MI to biological time series of the brain electrical activity during deception. The functional network of brain is constructed by the connection information from MI to study human mechanism underlying deception.

2. Method

2.1. Subjects and experimental protocol

Fifty healthy subjects (10 males, age range 21-23 years, mean age 22.2 years) with no history of neurological or psychiatric disease were recruited. The participants signed the informed consent before the beginning of the experiment, after we had explained the nature and possible consequences of the study. They were randomly divided into two groups: guilty group and innocent group. The standard three stimuli protocol was employed in this study [5]. Six images of jewelry with different characteristics were prepared. A box containing two jewelry was given to the guilty. Then, the guilty were instructed to steal it that was served as the probe (P) stimuli. The other objects in box are the Target (T) stimulus. The remaining four objects are irrelevant (I) stimuli. The innocent only saw one jewelry in the box that served as T stimuli (stole nothing). The other details about experimental protocol can be referred previous work [5].

2.2. EEG recording and preprocessing

All of the subjects observe a video screen that was approximately 1m away from their eyes. The stimuli pictures were presented randomly at the screen. Each picture remained 1 s with 30 iterations for one session; each session lasted for about 5 min. The inter-stimulus interval was 1.5 s. Each subject was instructed to perform 5 sessions. One push button was given to each subject and he/she was asked to press “Yes” or “No” button when facing with familiar or unknown items, respectively.

Electrodes were was recorded on 12 channels according to the International 10-20 System. Vertical EOG (VEOG) and horizontal EOG (HEOG) were also recorded. The VEOG signal was recorded from the right eye, and the HEOG was recorded from the outer canthus. Amplifiers used were Neuroscan Synamps. The sampling frequency was 500Hz and the bandwidths of amplifiers were 0.05-30 Hz One earlobe was served as reference.

Based on prior experience, P responses were selected for further processing. Using EEGLAB toolbox, the continuous EEG signals was first segmented into epochs from 0.3 s before to 1.3 s after the stimuli onset. The artifact removal criterion was $±80\mu V$. Then all the P responses (from P stimuli) were baseline-corrected based on the pre-stimulus interval. Each 4 single trials were then averaged within each subject.

2.3. MI algorithm

Mutual information [15] is a measure to measure that one variable of two random variables carries another variable. The larger the value, the more correlated the two signals are. Assuming that a discrete random variable $X$ has $N$ different random states, dividing these values into $M$ regions and calculating the distribution density in each region, the probability of the variable $X$ can be obtained in each region, that is, the probability of the event $\{X=x_i\}$ $P_i$, $i = 1, 2, \cdots, M$, and $P_i \geq 0$. Then we can define the information entropy of the discrete sequence $X$, as shown in
\[ H_i = -\sum_{i=1}^{y} P_i \log(P_i) \]  

Similarly, we can define the probability that the discrete random variables \( X \) and \( Y \) are located in \( N \) \( \times \) \( N \) regions, i.e. the probability of events \( \{ X = x_i, Y = y_j \} \) is \( P_{ij}, j = 1, 2, \ldots, M \), and the joint entropy of the two variables is shown in equation (2):

\[ H_{xy} = -\sum_{i,j=1}^{y} P_{ij} \log(P_{ij}) \]  

Then the mutual information definitions of \( X \) and \( Y \) is calculated in equation (3):

\[ I_{xy} = H_x + H_y - H_{xy} \]  

This formula expresses how much information is transmitted to \( Y \) when \( X \) is known. When applied to EEG analysis, \( X \) and \( Y \) represent EEG signals of any two leads, the formula can measure the amount of information from one lead to another. In special cases, if the EEGs of the two leads are independent of each other, the mutual information is 0.

2.4. Feature extraction and classification

The mutual information values of EEG signals of each brain region pair in the P response datasets were calculated, and 600 mutual information adjacency matrices of 10 \( \times \) 10 (channel number \( \times \) channel number) were generated on the two groups. Because the false connection will produce some errors, it is necessary to set a threshold to reduce the error, which is finally set as 0.2. Based on the new adjacency matrix, two sets of mutual information values of each pair of connections are tested by t-test statistics. Bonferroni multiple correction is used to classify the mutual information values of adjacent edges with significant differences. The F_score values of each feature are calculated by F_score method [16], and sorted in descending order to form a new feature set. A 10-fold cross-validation method was performed, of which 9 samples were used as training sets and the remaining samples were used as testing sets. In this process, different parameter combinations are used to train the classifier with sub-training sets using LIBSVM toolbox [17]. In this study, support vector machine (SVM) [17] with radial basis function (RBF) as the kernel function is chosen as the classifier. The test set is then fed into the classifier to obtain the test accuracy (mean of sensitivity and specificity, hereinafter referred to as average test accuracy).

3. Results

By the MI calculation, the group mean of the adjacency matrices is presented in Fig. 1. As the figure shown, there are remarkable difference between most of the connectivity information between different brain regions. The connectivity values (see the right panel) in guilty group are bigger than the innocent group (see the left panel) at nearly all the region pairs.
By statistical analysis, totally 41 pairs MI values have significant difference between the two groups. The mean (± standard deviation, SD) were given in Fig. 2. Using these MI values to construct feature vector. The classification accuracy is shown in Fig.3. In this figure, note that the accuracy is the balanced accuracy (average on the specificity and sensitivity on two groups). The accuracy result shows that the classification performance reaches the highest (99.85%) when total 23 connectivity information are used the features in classification system.

4. Discussion

Mutual information has been used in brain cognitive field for many years including for the patients with some diseases and the healthy subjects. It has been demonstrated effectiveness for non-stationary brain signals such as EEG signals. In the present study, we have applied the concept of mutual information to time series of brain electrical activity recorded from the experiment samples to investigate whether non-linear dynamics from the brain activity can be related to the cognitive mechanism of deception.

Our results indicate that MI method is beneficial to recognize brain electrical activity of guilty from innocent subjects. Note that although MI method improves the effectiveness of lie detection, it is still susceptible to volume-conduction of source activity. Hence, the analysis of MI on source space in brain cortex, removing the effect of volume-conduction, is one of the research works in the future. In addition, although we have found there are 23 brain regions’ connectivity that could provide the highest classification performance, their deep physiological significance deserves further study. Due to the limited space, it is not discussed in this study and will be explored in future.

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