Single-trial Event-Related Potential Emotional Classification Based on Compressed Sensing

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***Abstract*—In this study, a robust classification method for emotional speech single-trial event-related potential (ERP) signal was developed. The classification method based on compression sensing (CS) theory. First, we use CS theory to reduce the dimensionality of the ERP signal. Second, the ERP signal was reconstructed by using K-SVD method to construct the over-complete redundant dictionary. Finally, the ERP signal was classified by calculating the residuals between the reconstructed samples and the test samples. The experimental results show that the proposed algorithm can effectively classify the noisy ERP signal and avoid the feature extraction process in the signal recognition.**

Keywords- Compression Sensing; EEG; Event-related Potential; Signal Classification

I. INTRODUCTION

Recently, Compressed sensing (CS) is a novel approach for efficiently reconstructing a sparse signal, which has attracted considerable attention in area of signal processing. CS method can solve the traditional limits of sampling theory, which can reconstruct the signals from far fewer samples than what is achieved using the number of Nyquist-rate samples. It has also been used to signal classification applications. For example, Wang [1] used the sparse representation of CS in the human face recognition classification. Ren [2] used the CS for solving genetic data classification problem, and achieved better recognition rate than traditional classification methods such as the support vector machines(SVM), decision trees and K-means clustering. In addition, the use of CS theory can also avoid the feature extraction steps compared to traditional classification methods. Fira [3] combined CS and K-nearest neighbor (KNN) algorithm for ECG signal classification, the results show high recognition rate. In this paper, the electroencephalography (EEG) signal will be compressed and identified by CS method.

In general, EEG was recorded at a 1000 Hz sampling rate, which include abundant useful information in EEG signal. However, EEG is the high dimension signal, which need to been down sampled for further signal classification and recognition. And the down sampling will lose some of the useful information in the signal. In addition, to obtain clean ERP waveforms, a classical and typical approach is to average EEG signal over multiple event (trials), which will also lead to the loss of effective information for the event-related potential (ERP) study. For example, the brain computer interface (BCI) application that critically depend on online decoding of brain activity during a single events (trials). Therefore, it is necessary to study a single-trial ERP signal for classification.

In general, CS classification mainly focus on signal sparse representation. For multi-dimensional data, compressed sampling strategy can be used to classify the signals, which can significantly reduce the computational costs of signal processing.

In this study, we focus on single-trial ERP emotional classification using the CS method. Our proposed method can not only effectively simplify the ERP signal recognition process and improve the ERP emotion signal classification accurate but also can avoid the signal noise reduction and feature extraction issue.

II. SPARSE CLASSIFICATION

Sparse classification can usually be simplified as a linear programming. Assuming that the signal can be divided into i types, if $\mathbf{A}=[\mathbf{A}_1,\mathbf{A}_2,......,\mathbf{A}_i]$ is a sparse dictionary consisting of i -class training samples, where $\mathbf{A}_i$ is the sparse dictionary of the i -th class of training samples. For any test sample x , it can be reconstructed by the sparse matrix $\mathbf{A}$ .The sparse representation of test sample x is $x=\mathbf{A}\theta_i$. Where θ_i is the sparse coefficient of the i -th sample. That is, if the result of (1) is less than ε , then x is the i -th class data.

$$\min \| x - \mathbf{A}\theta_i \|_F^2 < \varepsilon \quad (1)$$

Therefore, it can be seen from that, in order to correctly classify the signal, the correct sparse classification dictionary needs to be constructed. In particular, it is necessary to construct a over-complete redundancy sparse dictionary.

III. COMPRESSION SENSING CLASSIFICATION

Sparse classification is usually used for efficient classification of low-dimensional signals. For high-dimensional signals, it is sometimes difficult to classify the signals directly by using sparse dictionaries. Compressed perception classification approach combines the signal compression and sparse classification, which will significantly simplify the calculation of high-dimensional signal classification process. Thus, this study adopted CS theory to classify the single-trial ERP signal. Its mathematical model can be described as follows.

A. Signal compression

For the signal X ($N \times 1$), in the compression of the signal, if the observation matrix $\mathbf{\Phi} = \sum_i^N \phi_i$ (ϕ_i is the $M \times 1$ -dimensional column vector) of $M \times N$ -dimension and the perceptual matrix $\mathbf{\Psi}$ are irrelevancies, and $K < M << N$, then the observed value Y of the signal is:

$$Y = \mathbf{\Phi}X = \mathbf{\Phi}\mathbf{\Psi}^{-1}\theta = \mathbf{A}_{\mathrm{CS}}\theta \quad (2)$$

where $\mathbf{A}_{\mathrm{CS}} = \mathbf{\Phi}\mathbf{\Psi}^{-1}$ is the sensing matrix, the signal X is compressed into M -dimensional in (2). This achieves the signal compression sampling. The signal compression ratio formula is:

$$R = M / N \quad (3)$$

B. Signal reconstruction and classification

The reconstruction of the signal is actually the process of solving the inverse operation of formula (2). If the K is known, then the sparse coefficient θ in (5) is obtained.

$$\min \| \theta \|_0 \quad (4)$$

$$\hat{X} = \mathbf{\Psi}^{-1}\theta \quad (5)$$

With the help of (5), the original signal $\hat{X} \approx X$ can be estimated. The more sparsity signal is, the more accurate signal reconstructed. Therefore, it is possible to reconstruct the signal using the over-complete redundancy dictionary to achieve the lossless recovery of the signal.

In the CS theory, the commonly used reconstruction algorithm is based on the l_0 -norm. For example, orthogonal matching pursuit (OMP) [4] algorithm and sparsity adaptive matching pursuit[5](SAMP) algorithm. The iterative speed of the OMP algorithm is fast, but the reconstruction error is large, while the reconstruction error of SAMP algorithm is small, but because of its iteration step number is larger than OMP algorithm, it makes it run at a low speed.

In the signal classification, the compressed signal X as the need to classify the signal, and then sparse classification, The classification signal is the parameter x in (1), and its classification process is similar to that of sparse classification. Let $X' = Y$, then X' in the $S \times M$ ($S > N \gg M$) dimension of the over-complete redundant dictionary D sparse expressed as:

$$\theta' = \mathbf{\Psi}' X' = \mathbf{\Psi}' Y \quad (6)$$

Where θ' is the sparse matrix of S dimension. According to (6) as long as X' sparseness is greatest for a certain category of over-complete dictionary, then the category of the dictionary is the type of signal to be measured. That is, (7) is the smallest, then the compressed signal can be classified.

$$\min \| \hat{X}' - \hat{\theta}' \mathbf{\Psi}'^{-1} \|_2^2 < \varepsilon \quad (7)$$

From the above description, it can be seen that both the CS classification and the sparse classification can directly classify the signal without extracting the signal characteristics. In this study, K-SVD method was used to construct and train the sparse dictionary of signals. In general, K-SVD algorithm includes two steps, the first step is the dictionary initialization phase, the second step is the dictionary update. The specific method will be described in the following experiment.

IV. METHODS

A. Dataset

In this study, the EEG data was obtained from the prior Ref. [6]. The stimuli were induced by emotional speech and non-speech, where the emotion-induced materials were selected from mandarin emotional speech (happy, sad, and Neutral) in TYUT2.0, non-speech emotional voice (positive and negative) in TYUT2.1, and German emotional speech (happy, sad and neutral) in EMO-DB.

12 electrode positions (FC1, FC2, FC3, FC4, C1, C2, C4, CP1, CP2, CP4) of 1000 Hz sampling rate EEG signals were selected as experimental data. For the off-line analysis, data was referenced to average reference by Curry software (Neuroscan. USA) and were selected at the time range between stimulus onset and 1000 ms after stimulus onset. All EEG signals were preprocessing of baseline correction and artifact removal.

B. The recognition method of single-Trial ERP signal based on compressed sensing

For the single-trial ERP signal recognition, this paper proposed a classification recognition method based on compressed sensing, which adopted K-SVD algorithm to construct over-complete redundant sparse classification dictionaries, which can be used to identify EEG signals in different emotional states. The specific experimental steps were as follows: