ASSESSING FEATURES FOR ELECTROENCEPHALOGRAPHIC SIGNAL CATEGORIZATION

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ABSTRACT

The classification of electroencephalographic (EEG) signals is an important issue in the ongoing research of brain-computer interface (BCI) technology. One such BCI uses slow cortical potential measures to infer user intent from the original brain activity. In the paper seven features based on the standard low-level signal properties are evaluated in their ability to classify brain activities, and thus make up for the scarcity of signal features for the current EEG signal categorization. In addition, a paradigm is proposed to select effective low-level features for EEG signal classification. Combining the features selected by the paradigm with the DC value of slow cortical potentials for categorization based on a Bayesian classifier, we obtained significant improvement on classification accuracy for data set Ia of BCI competition 2003, which is a typical representative of one kind of BCI data.

1. INTRODUCTION

Over the past decades, many laboratories have begun to explore brain-computer interface (BCI) technology which gives its users communication and control routes that do not depend on the brain's normal output channels of peripheral nerves and muscles [1][2][3]. In-depth BCI research would also contribute to the study of brain cognition behaviors. Current interest in BCI development comes mainly from the hope that this technology could be a valuable new augmentative communication option for those with severe motor disabilities—disabilities that prevent them from using conventional augmentative technologies, all of which require some voluntary muscle control [1].

Among the variety of methods for monitoring brain activity, electroencephalography (EEG) provides a practical way for BCI study. However, in the current research of EEG-based BCI, the signal features presented up to the present are very limited. Some BCI systems use rhythm features reflecting oscillations in particular neuronal circuits (e.g. mu or beta rhythms from sensorimotor cortex). Other systems use potentials evoked from particular brain regions by particular stimuli, e.g. P300 event-related potential, or slow cortical potentials, as the BCI control signal [4] [5].

The existing BCIs often use the following information present in the signal to assess the state of the subject's brain and thus to category different EEG signals: frequency-domain information as with mu- and/or beta-rhythm amplitude, time-domain waveforms such as the P300, or DC potentials [6]. Although with several different classification methods, their error rates are often a little high [7]. In some cases, the classification scheme does not significantly influence the classification accuracy, suggesting that the topology of the feature space is relatively simple. Perhaps further advances could be made by developing more powerful features or at least understanding the feature space. This is the direct motivation of the research presented in our paper. We explore the applicability of standard low-level features used in audio/speech signal processing to the problem of EEG signal classification.

The main contribution of our paper would be that we extend the choice of features for EEG signal categorization to a large extent, and provide a general paradigm for feature selection of EEG signal. Using the complemented features with DC potentials for categorization, we obtained much better classification results than that of only based on DC potentials, and even get a better result than the best method for BCI competition 2003—data set Ia [7].

2. METHODS

The biological signals (e.g. EEG signals) being used in a BCI are typically non-stationary. In addition, they change due to subject fatigue and attention, due to disease progression, and/or with user training [2]. Therefore, feature selection for EEG signals is a challenging topic, and categorization based on EEG signal features is also a hard task. Because BCI is an interdisciplinary project, many neuroscientists, psychologists and rehabilitation specialists might not be accustomed to adopt the features widely used by audio/speech signal processing specialists. However, on the other hand, the general features used to describe an audio/speech signal have not been thoroughly evaluated in their capability for EEG signal categorization to this day. In this article, we concentrate on assessing the applicability and effectiveness of standard low-level signal features for EEG signal categorization, and propose a paradigm for EEG signal feature selection.

2.1. Data set description

The data set used to interpret our approach is from BCI competition 2003—data set Ia [7]. The purpose of BCI 2003 competition is to stimulate improvements in the signal-processing component of BCIs. In the competition, several data sets of different types were made publicly available for analysis by research groups worldwide. Each of the data sets is very typical for BCI research.

All data in data set Ia were taken from a single healthy subject at the university of Tuebingen, Germany. The subject was asked to move a cursor up (class "0") and down (class "1") on a computer screen. Trials consisted of three phases: a 1-s rest phase, a 1.5-s cue-presentation phase, and a 3.5-s feedback phase. Six EEG recording electrodes were all referenced to the vertex electrode C_z (International 10-20 system) as follows: channels 1 and 2, left and right mastoids; channels 3-6, anterior (ch. 3, 5) or posterior (ch. 4, 6) to position C_3 (ch. 3, 4) or C_4 (ch. 5, 6). These EEG potentials were sampled at 256 Hz.

All the trials were separated into a training set (268 trials, 135 for class "0", 133 for class "1") and a test set (293 trials), both of which contained EEG data from only the 3.5-s feedback phase of each trial. The purpose is to categorize the trials in the test set into class "0" or class "1".

2.2. Feature extraction

The standard low-level signal features are widely used in general audio data classification [8]. To describe the EEG signal, we introduce the standard low-level signal properties to the field of EEG signal analysis. These features include: (1) root-mean-square (RMS) level; (2) spectral centroid; (3) bandwidth; (4) zero-crossing rate; (5) spectral roll-off frequency; (6) band energy ratio; (7) delta spectrum magnitude [9]. The computational details of the features can be referred to [8]. Due to space limitation, we omit their descriptions here.

For every training trial, the feature extraction process is illustrated in Fig. 1. The standard low-level features are calculated for every 0.5-s subframe in the 3.5-s signal waveform of each channel. Thus for every 0.5-s subframe, seven low-level features described above are obtained as candidate features.

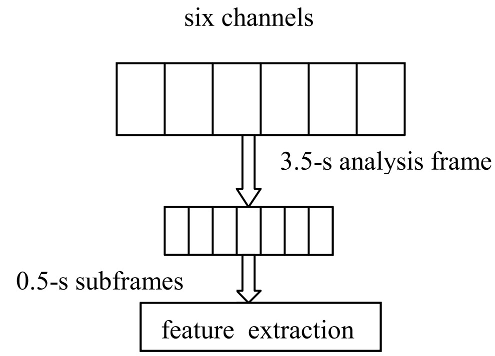

Fig. 1. Feature extraction method.

Step 1:
— Eligible feature selection and eligible channel selection between two categories.

Step 2:
— Effective feature selection across eligible channels.

Fig. 2. Paradigm for feature selection of EEG signals.

2.3. Feature selection

Following the before-mentioned feature extraction procedure, we can then select the effective features on effective channels for subsequent EEG signal classification. Whereas, for biological signal processing, the population of sample is usually very small. As a result, we can only select a few features to represent each sample in order to avoid the over-fitting problem. So in the paper, we concentrate on how to select one best feature from the standard low-level signal properties. Our paradigm for feature selection of EEG signals is illustrated in Fig. 2.

In step 1, for each category we average the features across every training trial. And then based on the difference between these two classes, we can find the eligible features and the eligible channels which are discriminative for classification. Now, although we know some features might be useful for classification, but we still do not know their relative performance. In step 2, for every eligible feature (averaged across each subframe), we average its classification accuracy rates on training set across eligible channels. Thus, we exclude the inter-channel influence, and can obtain a performance rank of eligible features. Therefore, the best feature could be identified. Finally we can combine the distinguished feature found in step 2 with other useful features (e.g. the DC value in the potential waveform) to improve the classification of EEG signals. In the experimental section, we would display the progress of feature selection of EEG signals in detail.

3. EXPERIMENTS

In this section, we carry out classification of the given data set using our feature selection paradigm and the standard low-level signal parameters. A normal density distribution is fit to each class with means and covariances estimated from the training set. The class of a test trial was then predicted based on which distribution had higher density at the corresponding point in the feature space.

3.1. Evaluating the classification ability of standard low-level EEG signal parameters

In the first step of our feature selection paradigm, we compare the discriminative performance among seven standard low-level signal parameters and select eligible features for classification. Fig.3 shows the RMS measurements between two averaged curves of two classes. We concatenated the six channels from channel 1 to channel 6 to get a subframe series from 1 to 42. Every seven subframes belong to one channel. From the figure, we can judge that RMS is not a valid feature for EEG signal categorization of our data set, since the two curves interweaves severely (significant level p=0.19). This candidate feature can be reject-ed automatically through computer codes.

However, from Fig. 4 we can identify that the spectral centroid might be a valuable feature, since for every channel the value of the spectral centroid of class 0 on the first five subframes is almost always superior to that of class 1 (p<10^{-8}). Following this strategy, finally, we can find the eligible features and eligible channels, which are: (1) spectral centroid on each channel; (2) band width on each channel; (3) zero-crossing rate on each channel; (4) roll off frequency on the first five channels; (5) band energy ratio on each channel.

Then, for every trial we average their feature value on different subframes to obtain a scalar measurement of the corresponding feature on each channel to evaluate its classification capability. The measurement is made on the average of all eligible channels. We take the DC potentials from channel 1 and channel 2 as the baseline feature (which is represented as SCP in [6]). The classification accuracy rates on the training set and the test set are given in Table 1. From Table 1, we can find that all the classification accuracy rates are higher than 60%, implying that the eligible features are beneficial for EEG signal categorization.

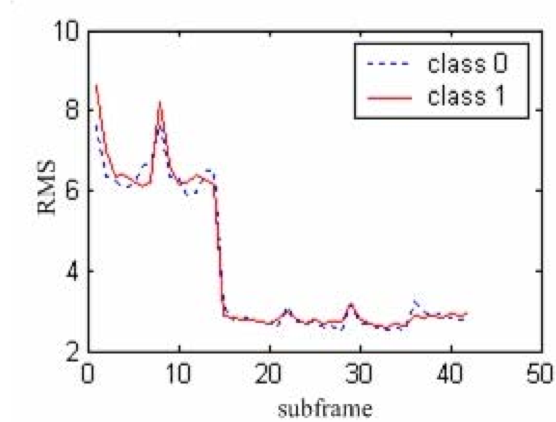

Fig. 3. RMS measurements, training set.

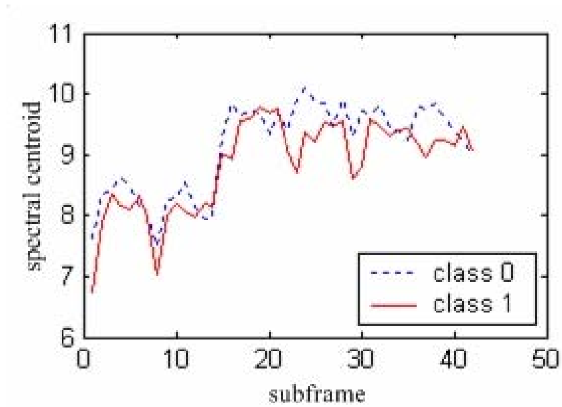

Fig. 4. Spectral centroid measurements, training set.

Table 1. Average classification performance of single feature.

Features	Training Set (% correct)	Test Set (% correct)
single SCP	69.78 ± 0.00	66.72 ± 3.62
spectral centroid	61.38 ± 1.41	61.04 ± 4.08
band width	61.01 ± 2.79	61.60 ± 5.66
zero-crossing rate	61.01 ± 1.27	61.21 ± 3.54
roll off frequency	61.87 ± 6.32	64.44 ± 4.28
band energy ratio	60.70 ± 3.65	63.25 ± 5.95

3.2. Categorization using selected features and DC potentials (SCP)

As article [6] reports, DC potentials (SCP) are good features for EEG signal classification. We now explore whether the standard low-level features combining with the SCP can further improve the final classification performance. First of all, we combine SCP with every eligible feature on each eligible channel to carry out categorization on the training set in order to find which

Table 2. Average classification performance of multiple features.

Features	Training Set (% correct)
SCP	70.9
SCP+spectral centroid	**76.68** ± 1.84
SCP+band width	71.89 ± 2.01
SCP+zero-crossing rate	75.25 ± 1.45
SCP+roll off frequency	73.96 ± 3.91
SCP+band energy ratio	72.33 ± 2.65

Table 3. Classification performance by combing SCP with the best spectral centroid feature.

Features	Training Set (% correct)	Test Set (% correct)
SCP	70.9	82.6
SCP+spectral centroid on channel 4	76.49	**90.44**
SCP+one principal component of spectral centroid features	**80.60**	87.37

eligible feature is the most effective in combining SCPs. Table 2 gives the averaged classification results across each eligible channel on the training set. From Table 2, we can see that by adding eligible features, the classification performance is improved. This suggests us that we might be able to gain better results on test set by combining SCP with standard low-level signal parameters (e.g. spectral centroid) on some channel.

In succession, we would like to find the best channel for denoting the spectral centroid feature or select one component by PCA for all the eligible channels. By calculating the difference of all six eligible channels of Fig. 4, the difference for spectral centroid between class 0 and class 1 is obtained. Channel 4 ranks No.1, implying the spectral centroid on this channel might be a best feature. So we combine SCP with spectral centroid on channel 4 to carry out classification. The final results are shown in Table 3. Besides, we also carry out Principal Component Analysis (PCA) on the six channels with their spectral centroid features, and combine SCP with one principal component to carry out classification. The result is given in Table 3. From Table 3, we can see that we improve the classification results significantly, and even gain a better results than the best result (88.7% correct on test set) of BCI competition 2003—data set Ia.

4. DISCUSSIONS AND FUTURE WORK

In this paper, we evaluated several standard low-level signal features for EEG signal classification. Through comprehensive experiments, we demonstrate their applicability and effectiveness. Besides, we proposed a paradigm to deal with the feature selection problem of EEG signals. Combining SCP with the selected features found by our feature selection paradigm, we significantly improved the classification accuracy rate and even overtop the best performance of the method of BCI competition 2003 on the same data set.

However, since our main purpose is assessing the features for EEG signal categorization, we did not elaborately select the classification method. In the future, exploring better classification method would be a valuable direction.

5. ACKNOWLEDGEMENT

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