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EEG feature extraction based on wavelet packet decomposition for brain computer interface

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Abstract

In the study of brain computer interfaces, a novel method was proposed in this paper for the feature extraction of electroencephalogram (EEG). It was based on wavelet packet decomposition (WPD). The energy of special sub-bands and corresponding coefficients of wavelet packet decomposition were selected as features which have maximal separability according to the Fisher distance criterion. The eigenvector was obtained for classification by combining the effective features from different channels; its performance was evaluated by separability and pattern recognition accuracy using the datasets of BCI 2003 Competition. The classification results have proved the effectiveness of the proposed method. This technology provides another useful way to EEG feature extraction in BCIs.

Keywords: Brain computer interface (BCI); Wavelet packet decomposition (WPD); Feature extraction; Energy of sub-band

1. Introduction

Brain computer interfaces (BCIs) are devices intended to help disabled people to communicate with a computer using the brains' electrical activity. The electrical activity can be measured by electroencephalogram (EEG) [1,2]. BCIs include two kinds, one is based on spontaneous EEG and the other is based on evoked EEG. The evoked EEG is produced by the neural stimulation of inside and outside. For example, P300 and SSVEP (steady-state visual evoked potential) belong to the evoked EEG [3,4]. The spontaneous EEG is produced by human specific thoughts, such as ERD/ERS (event-related desynchronization/event-related synchronization), SCP (slow cortical potention) and some EEG rhythm waves (α rhythm, β rhythm, γ rhythm) [5–7] . Most BCIs make use of spontaneous mental activities (e.g., imagining moving a finger, the hand, or the whole arm, etc.) to produce distinguishable electroencephalogram (EEG) signals [8,9]. The distinguishable EEG signals are then transformed into external actions. Over the past years a variety of evidences have evaluated the possibility to recognize a few mental tasks from EEG signals [10–12]. However, how to improve the recognition performance of EEG signals in signal processing is still a key problem. The recognition procedure mainly includes the feature extraction and the

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classification, in which the feature extraction plays an important role for the classification. This paper mainly focuses on the feature extraction.

At present, feature extraction methods for the motor imagery EEG mainly include the following methods: (1) *Fast Fourier transform* (FFT): In [13] and [14], the Fourier spectral features were computed with the Welch method using windowed Fourier transforms of signal segments. The main disadvantage of this method is that it only uses the frequency information and doesn't use time domain information. However, the research shows that the combination of frequency information and time domain information can improve the classification performance of EEG signal [15]. (2) *Autoregressive* (AR) *model*: From the AR spectrum, band power is calculated in several frequency bands and the power sum is used as independent variables [16]. In addition, the AR model coefficients or multivariate autoregressive (MVAR) model coefficients are used as features [17,18]. (3) *Time–frequency* (TF) *analysis*: Wang et al. use the TF analysis as a useful tool for oscillatory EEG components during motor imagery [19]. As we all know, oscillatory EEG components produced during motor imagery are both time and frequency related, therefore, the method obtained promising results. However, oscillatory EEG components may cause simultaneous shifts in slow cortical potentials. A combination of two correlated signals might be used to increase extracted information. The TF method only considers oscillatory EEG components. (4) Utilizing coefficients of wavelet transform, i.e., extracting coefficients of wavelet transform at the useful frequency band according to transcendent information [20]. However, the production mechanism of EEG is rather complex, thus, it is difficult to get accurate transcendent information and it is rather inflexible.

Due to the non-stationary property of EEG signals, traditional analysis methods such as the Fourier transform are not very suitable for this work. This paper discusses a feature extraction method based on the wavelet packet decomposition. It used the coefficients mean of wavelet transform (information in time-domain) and power at special subsets as the initial features whose separabilities were measured by the Fisher criteria, in which the features that had a higher separability were considered effective and were formed the final feature vector. This approach accorded with the result that the energies of EEG frequency range are different during subjects' having different imaging tasks, at the same time, some statistical information in time-domain had some changes [21]. The energy of special subbands and corresponding coefficients of wavelet packet decomposition were selected as features which have maximal separability according to the Fisher distance criterion. The performance and effectiveness of this method have been proved by classification results using the datasets of BCI 2003 competition.

2. Wavelet packet decomposition

Wavelet packet decomposition (WPD) is extended from the wavelet decomposition (WD). It includes multiple bases and different basis will result in different classification performance and cover the shortage of fixed time–frequency decomposition in DWT [22]. The wavelet decomposition splits the original signal into two subspaces, V and W, which are orthonormally? Complementary to each other, with V being the space that includes the low frequency information about the original signal and W includes the high frequency information. As shown in Fig. 1, the decomposition of the low frequency subspace V was repeated. WD only partitions the frequency axis finely toward low frequency, and WPD is a generalized version, which also decomposes the high frequency bands that are kept intact in wavelet decomposition. WPD leads to a complete wavelet packet tree, which is shown in Fig. 2, where $U_{j,n}$ is the nth (n is the frequency factor, $n = 0, 1, 2, \ldots, 2j-1$) subspace of wavelet packet at the jth scale, and $U^n_{j,k}(t)$ is its corresponding orthonormal basis, where $U^n_{j,k}(t) = 2^{-j/2}u^n\ (2^{-j}t-k)$ (k is the shift factor) , it satisfies with (1) and (2)

$$u^n_{j,0}(t) = \sum_k h_0(k) u^i_{j-1,k} \quad (n \text{ is even}) \tag{1}$$

$$u^n_{j,0}(t) = \sum_k h_1(k) u^i_{j-1,k} \quad (n \text{ is odd}) \tag{2}$$

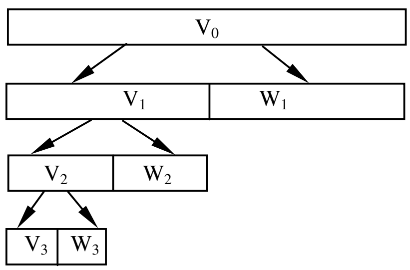

Fig. 1. The structures of wavelet decomposition.