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Pattern recognition of motor imagery EEG using wavelet transform

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ABSTRACT

Brain-computer interface (BCI) provides new communication and control channels that do not depend on the brain's normal output of peripheral nerves and muscles. In this paper, we report on results of developing a single trial online motor imagery feature extraction method for BCI. The wavelet coefficients and autoregressive parameter model was used to extract the features from the motor imagery EEG and the linear discriminant analysis based on mahalanobis distance was utilized to classify the pattern of left and right hand movement imagery. The performance was tested by the Graz dataset for BCI competition 2003 and the satisfactory results are obtained with an error rate as low as 10.0%.

Keywords: Brain-computer interface (BCI); Motor imagery; Wavelet coefficients; Autoregressive model

1. INTRODUCTION

Left and right hand movement imagery can modify the neuronal activity in the primary sensorimotor areas, leading to the changes of the mu rhythm and beta rhythm. BCI requires effective online processing method to classify these EEG signals in order to construct a system enabling severely physically disabled patients to communication with their surroundings [1-4].

This paper presents a novel effective method for feature extraction of motor imaginary. We combine the discrete wavelet transform (DWT) with autoregressive model (AR) to extract more useful information for non-stationary EEG signals. Applying this method to analyze the Graz dataset for BCI competition 2003, we achieved the classification accuracy of 90.0%.

2. METHODOLOGY

2.1. Experimental paradigm

The data set was provided by department of medical informatics, institute for biomedical engineering, university of technology Graz [5]. It was recorded from a normal subject (female, 25y) during a feedback session. The subject sat in a relaxing chair with armrests. The task was to control a feedback bar by means of imagery left or right hand movements. The order of left and right cues was random.

Figure 1 shows the timing of the experiment. The first 2s was quite; at t=2s an acoustic stimulus indicated the beginning of the trial; the trigger channel (#4) went from low to high, and a cross "+" was displayed for 1s; then at t=3s, an arrow (left or right) was displayed as cue. At the same time the subject was asked to move a bar into the direction of the cue. The feedback was based on AAR parameters of channel #1 (C3) and #3 (C4), the AAR parameters were combined with a discriminant analysis into one output parameter.

The recording was made using a G.tec amplifier and a Ag/AgCl electrodes. Three bipolar EEG chan-

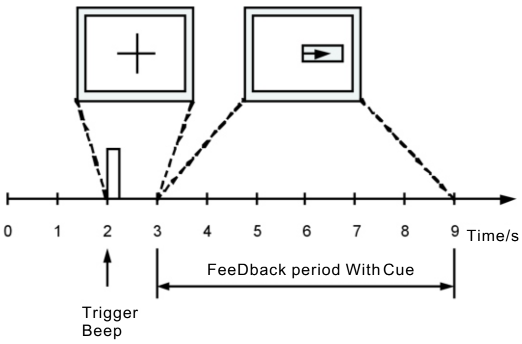

Figure1. Timing scheme.

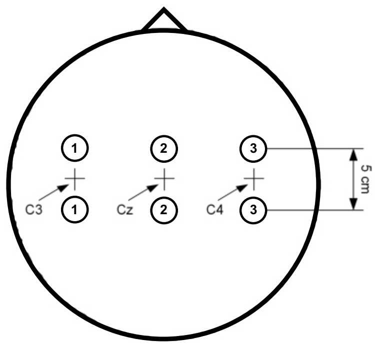

Figure 2. Electrode positions.

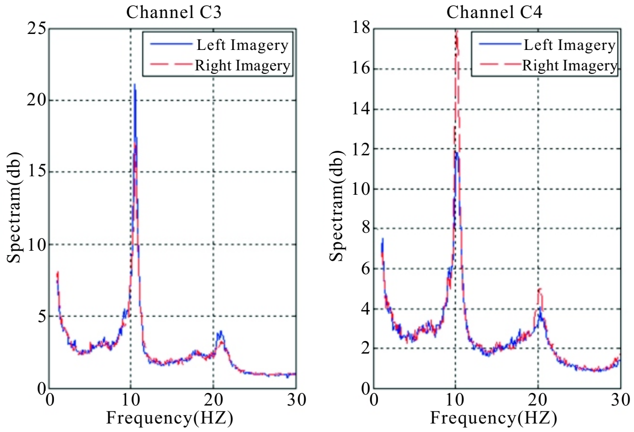

Figure 3. Average power spectrums on channel C3 and C4.

nels (anterior '+', posterior '-') were measured over C3, Cz and C4 [**Figure 2**]. The EEG was sampled with 128Hz, it was filtered between 0.5 and 30Hz. Similar experiments are described in [6].

The experiment consists of 7 runs with 40 trials each. All runs were conducted on the same day with several minutes break durrng experiment. One half of the datasets are provided for training; others are for evaluating the performance of the system.

2.2. Feature consideration

Central brain oscillations in the mu rhythm in the range of 7-12Hz and beta above 13Hz bands are strongly related to sensorimotor tasks. Sensory stimulation, motor behavior, mental imagery can change the functional connectivity cortex which results in an amplitude suppression or in an amplitude enhancement .This phenomenon was also called event-related desynchronization (ERD) and event-related synchronization (ERS) [7, 8]. Left and right hand movement imagery is typically accompanied with ERD in the mu and beta rhythms and has the characteristic of contralateral dominance.

The power spectrums on C3 and C4 of the training set are shown in **Figure 3**. It indicates that the power spectrums mainly distribute in the range of 8-13Hz and 19-24Hz.In addition, the power of mu and beta rhythms evoked by right hand movement imagery is lower than that of left hand movement imagery for channel C3, and it is contrary for channel C4 which is consistent with the principle of contralateral dominance. This led us to use wavelet decomposition to extract the differences between the two motor imagery tasks.

2.3. Procedure

The flow chart of processing single-trial motor imagery EEG is shown as in **Figure 4**. First, the time window was used to filter the data in temporal domain in order to get the segment that contained the most obvious difference between the two motor imagery tasks. Then EEG signals were decomposed into the frequency sub-bands using DWT and a set for statistical features was extracted from the sub-bands to represent the distribution of wavelet coefficients according to the characteristics of motor imagery EEG signals. Also the sixth-order AR coefficients of segmentation EEG signals were estimated using Burg's algorithm. Next, the combination features of wavelet coefficients and the AR coefficients were used as an input vector. Finally linear discriminant analysis (LDA) based on mahalanobis distance was utilized to classify computed features into different categories that represent the left or right hand movement imagery.

2.4. Feature extraction using discrete wavelet transforms

Classic Fourier transform has succeeded in stationary signals processing. However, EEG signal contains non-stationary or transitory characteristics. Thus it is not suitable to directly apply Fourier transform to such signals. The wavelet transform decomposes a signal into a set of functions obtained by shifting and dilating one single function called mother wavelet [10, 11]. Continuous wavelet transform is given by

$$W_f(a,\tau) = \frac{1}{\sqrt{a}} \int_R f(t)\Psi^*\left(\frac{t-\tau}{a}\right)dt \qquad (1)$$

Where $\Psi(t)$ is the mother wavelet, a is the scale parameter and τ is the shift parameter. In principle the CWT produced an infinite number of coefficients, thus it provides a redundant representation of the signal.

The DWT provides a highly efficient wavelet representation that can be implemented with a simple recursive filter scheme and the original signal reconstruction can be obtained by an inverse filter. The pro-

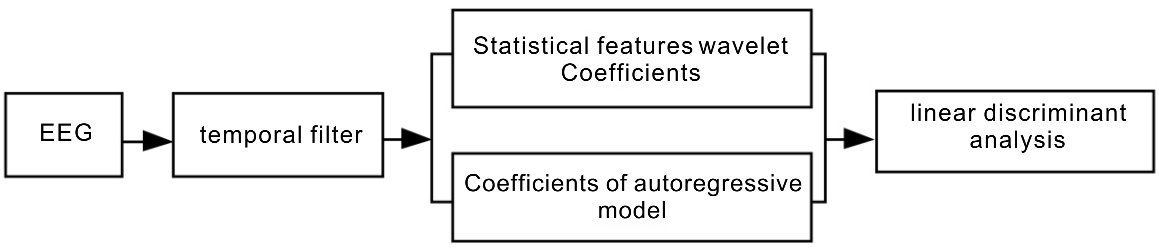

Figure 4. Flow chart of the data processing.

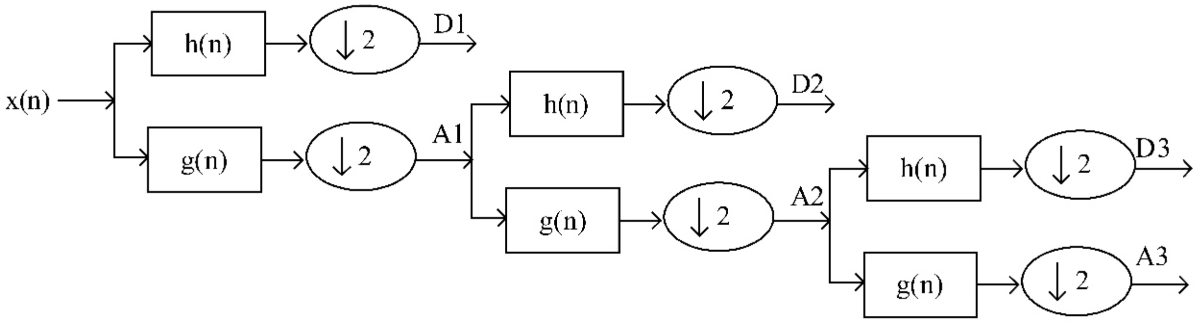

Figure 5. Decomposition of DWT; h[n] is the high-pass filter; g[n] is the low-pass filter.

cedure of multi-resolution decomposition of a signal x[n] is schematically shown in **Figure 5.**

The number of levels of decomposition is chosen on the basis of the dominant frequency components of the signal. According to the motor imagery EEG signals itself, we chose the level of 4 and the wavelet of Daubechies order 10.As a result, the EEG signal is decomposed into the details D1-D3 and approximation A3. The ranges of different frequency band are shown in **Table 1**.

The extracted wavelet coefficients show the distribution of the motor imagery signal in time and frequency. It can be seen from the table that the component D3 decomposition is within the mu rhythm, D2 is within the beta rhythm. Statistics over the set of wavelet coefficients were computed so as to reduce the total dimension of the feature vectors. The statistical features of each sub-band are as follows:

(1) Mean of the absolute values of the coefficients.
(2) Standard deviation of the coefficients.
(3) Average power of the wavelet coefficients.

These features represent the frequency distribution and the amount of changes in frequency distribution. Thus 12 statistical features of wavelet coefficients are obtained for two channels.

2.5. Feature extraction using autoregressive model

EEG signal can be considered as the output of a linear filter driven by a white noise. This filter, referred to as AR, is a linear combination of the previous output itself. A zero-mean, stationary autoregressive process of order p is given by

$$x(n) = -\sum_{i=1}^{p} a_p(i)x(n-i) + \varepsilon(n) \qquad (2)$$

Where p is the model order, $x(n)$ is the signal at the sampled point n, $a_p(i)$ *is* the AR coefficients and $\varepsilon(n)$ is a zero-mean white noise. In application, the values of the $a_p(i)$ have to be estimated from the finite samples of data $x(1), x(2), x(3), \ldots, x(N)$.

The first important things involved in using AR model is determining the optimal AR model order since too low a model order tends to smooth the spectrum and too high tends to introduce spurious peaks. Here order six was used based on the suggestions [9].

Then the Burg's method was used to estimate the AR coefficients. This method is more accurate and yields better resolution without the problem of spectral 'leakage' as compared to other methods such as Levison-Durbin as it uses the data points directly. In addition, the Burg's method can minimize both forward and backward error.

Next the AR coefficients were computed and we got six coefficients for each channel, giving a total of 12 AR coefficients features for each EEG segment for a motor imagery task.

2.6. Linear discriminant analysis (LDA)

LDA is one of the most effective linear classification methods for brain-computer interface, and it requires fewer examples for obtaining a reliable classifier output [12].

As to the LDA method, assume that each data element s_i has m features. Then, an element s_i is one point in a dimensional feature space. The number of examples is n , each example is assigned to one of two classes $C=\{0,1\}$; Then, S is a matrix of size $n\times m$, and C is a vector of size $n.N_0$. And N_1 are the number of elements for class 0 and 1, respectively.

The mean μ_c of each class c is the mean over all s_i with i being all elements with in class c . The total mean of the data is

$$\mu_c = \left(\frac{N_0\mu_0 + N_1\mu_1}{N_0 + N_1}\right) \qquad (3)$$

Table 1. Frequencies correspond to different levels of deposition for daubechies order 10 wavelet with a sample rate 128HZ.

Decomposed signal	Frequency range (Hz)	Level
D1	32-64	1
D2	16-32	2
D3	8-16	3
A3	0-8	3

Table 2 . Dirrerent wavelet used for extracting features.

Wavelet	Recognition rate
Daubechies order 10	90%
Discrete Meyer	90%
Coiflets order 5	89.29%
Rbio1.3	87.86%

The covariance matrix C of the data is the expectation value for

$$C=E<(s-\mu)^T(s-\mu)> \quad (4)$$

Then, the weight vector w and the offset w_0 are

$$w=C^{-1}(\mu_1-\mu_0)^T \quad (5)$$

$$w_0=-\mu w \quad (6)$$

The weight vector w determines a separating hyperplane in the m -dimensional feature space. The normal distance $D(x)$ of any element x is

$$D(x)=xw+w_0=(x-\mu)C^{-1}(\mu_1-\mu_0)^T \quad (7)$$

If $D(x)$ is larger than 0, x is assigned to class 1, while if $D(x)$ is smaller than 0, x is assigned to class 0. However, $D(x)=0$ indicates that all elements x are part of the separating hyperplane.

3. EXPERIMENT RESULTS

Here, we have had 6 statistical wavelet coefficients and 6 AR coefficients for each channel, giving a total of 24 features for a motor imagery task. These parameters were selected as inputs of LDA classifier. **Table 2** compared the classification performances among four different wavelets. The results show the Daubechies order 10 gave the best performance and the recognition rate is as high as 90.0%. Also the results indicate that method of combining DWT with AR model are capable of extracting more useful information from the simultaneously acquired motor imagery EEG. Furthermore, when the window of 384 samples with a shift of 1 sample was used, maximum classification accuracy of 92.1% is achieved.

4. CONCLUSION AND FUTURE WORK

In this paper, a novel single-trial motor imagery EEG classification method is proposed. The pattern classification techniques as described in this work make possible the development of a fully automated motor imagery EEG signals analysis system which is accurate, simple and reliable enough to use in brain-computer interface. Future work will utilize the algorithms developed in this study to directly control the embedded rehabilitation robot so as to help the patient with severed paralysis to solve the problem of environment control and provide a new communication and channel to outside world.

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