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Adaptive estimation of EEG-rhythms for optimal band identification in BCI

Kalyana C. Veluvolu*, Yubo Wang, Swathi S. Kavuri

School of Electronics Engineering, College of IT Engineering, Kyungpook National University, Daegu 702-701, Republic of Korea

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ABSTRACT

The amplitude of EEG μ-rhythm is large when the subject does not perform or imagine movement and attenuates when the subject either performs or imagines movement. The knowledge of EEG individual frequency components in the time-domain provides useful insight into the classification process. Identification of subject-specific reactive band is crucial for accurate event classification in brain–computer interfaces (BCI). This work develops a simple time-frequency decomposition method for EEG μ rhythm by adaptive modeling. With the time-domain decomposition of the signal, subject-specific reactive band identification method is proposed. Study is conducted on 30 subjects for optimal band selection for four movement classes. Our results show that over 93% the subjects have an optimal band and selection of this band improves the relative power spectral density by 200% with respect to normalized power.

1. Introduction

The brain–computer interface (BCI) is an emergent technology that provides a new pathway for communication by allowing the brain to control a computer directly, without any physical movement achieved through normal neuromuscular pathways (Wolpaw et al., 2000; Comment, 2006). Non-invasive EEG-based BCIs for neuroprosthesis control has been an attractive control method for various applications ranging from cursor control to robotic neuroprosthesis (Wolpaw et al., 2000; Graimann et al., 2010; Schalk and Mellinger, 2010; Mueller-Putz et al., 2006, 2000; Sun et al., 2000). Among the various ways to acquire brain signals, EEG still remains as the most viable option (Wolpaw et al., 2000; Curran and Strokes, 2003; Vaughan, 2000). The analysis for EEG signal can be performed in both time and frequency domains. Both forms of analysis can be used for EEG-based communication (Wolpaw et al., 2000).

Spatial filters (Blankertz et al., 2008) that match the spatial frequencies of the users μ or β rhythms, autoregressive frequency analysis (McFarland et al., 2008; McFarland and Wolpaw, 2008) that gives higher resolution than fast Fourier transform (FFT) analysis for short time segments to permit rapid device control are popular for BCI applications. Frequency-domain control based on μ and β rhythms can be combined with time-domain control based on slow potentials to yield better EEG-based communication (McFarland et al., 1997; Krusienski et al., 2007; Brunner et al., 2010; Guger et al., 2003). If the data is available for short time segments, the frequency domain classification via band-power may not accurate.

In Neuper et al. (2000), it was shown that by estimating the band power in the frequency band (15–19 Hz) and by applying simple threshold classification, the foot motor imagery related brain pattern could be detected with 100% accuracy. The amplitude of the μ rhythm is largest when the subject is not moving or not imagining any movement, and attenuates when the subject is moving or imagines movement (Wolpaw et al., 2000; Birbaumer et al., 1999; Pfurtscheller et al., 2000; Pineda et al., 2000; Lotte et al., 2007). Movement-based BCI's recognize changes in the human μ rhythm from the central region of the scalp overlying the sensorimotor cortices (Comment, 2006; Mueller-Putz et al., 2006; Pineda et al., 2000). The free-running EEG shows characteristic changes in μ-activity, which are unique for the movement of different limbs (Pfurtscheller and Neuper, 2000). Studies that show that people can learn to regulate EEG μ-rhythm (Mueller-Putz et al., 2000; Pfurtscheller and Neuper, 2000; McFarland et al., 1997).

In general, the collected EEG signal is then divided into small segments, and the μ (8–13 Hz) and β (18–27 Hz) powers in each segment are calculated using frequency domain methods such as fast-Fourier-transform (FFT), autoregressive spectral analysis to calculate band-power for event classification. These methods rely on band power to classify the μ rhythm in the range of 8–13 Hz. A threshold is set for classifying the type of activity based on the rhythm (Guger et al., 2003; Neuper et al., 2000). As the band remains fixed for all subjects, large data sets are required for setting the threshold for classification.

Instead of using the complete μ or β spectral bands, narrowed subject-specific frequency bands are selected to achieve higher accuracy in classification (McFarland and Wolpaw, 2008; McFarland et al., 2010; Royer et al., 2000; Schalk and Mellinger, 2010). In McFarland and Wolpaw (2008), spectral bands with multiple 3 Hz-bins are selected for feature extraction to control cursor

* Corresponding author. Tel.: +82 539507232.
E-mail address: veluvolu@ee.knu.ac.kr (K.C. Veluvolu).

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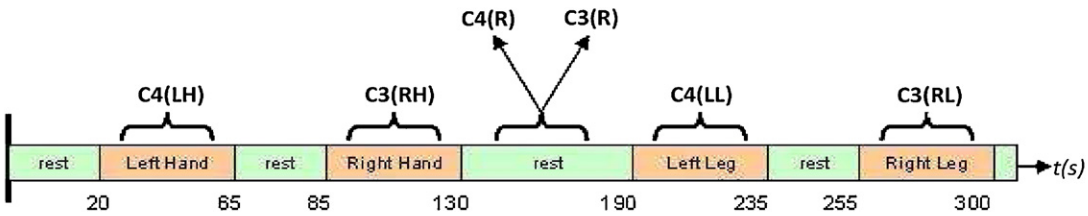

Fig. 1. EEG recording sequence and timings of the 5 classes in each trial.

movements. Recently, similar approach was adopted for three-dimensional movement in virtual space (McFarland et al., 2010; Royer et al., 2000). Tools to customize frequency band for subjects are readily available with BCI2000 (Schalk and Mellinger, 2010). However, in order to identify the subject specific reactive bands, large number of trials/training sessions are needed to identify the bands for electrode locations. These methods rely on higher-order (e.g. 16-order McFarland et al., 2010; Royer et al., 2000) autoregressive algorithm to model the EEG data. The data in short-time segments is processed and logarithmic amplitudes are employed as commands for control. In Blankertz et al. (2008), a heuristic approach was adopted for selection of discriminative spectral band. Methods that on auto-regressive spectral analysis or FFT based spectral estimation methods that does not provide temporal information. Time-domain (temporal) information of the dominant spectral bands is necessary for customizing subject-specific reactive band for a given electrode location.

Several time-frequency decomposition methods, such as band-pass filtering, short time Fourier transform and continuous wavelet transform, are analyzed for EEG analysis (Allen and MacKinnon, 2010; McFarland et al., 2008). In the band-pass filtering approach, the temporal resolution mainly depends on the filter type and the filter complexity increases with the spectral resolution. In the short time Fourier transform, the spectral and temporal resolution is pair of contradictory which depends on the time window selection. Recently, it was demonstrated in Allen and MacKinnon (2010) that continuous wavelet transform (CWT) is not superior to the STFT in terms of spectral and temporal resolution. Also its high-computation requirement remains as a barrier for real-time BCI applications. Auto-regressive methods (McFarland and Wolpaw, 2008; Bashashati et al., 2007) and Fourier transform (FFT) are popular for EEG spectral analysis that only provides spectral information but lack temporal resolution.

A simple and efficient method that provides optimal temporal and spectral resolution is required for real-time feature extraction in BCI. This paper develops a time-domain analysis method by estimation of bandlimited EEG μ-rhythm through adaptive filtering (Veluvolu and Ang, 2000). The method developed in (Veluvolu and Ang, 2000) is adopted to model the EEG signal through multiple Fourier series as individual frequency components with LMS algorithm. Compared to FFT, the proposed method does not rely on transformation and provides the individual frequency components in time-domain with optimal temporal resolution and user-defined frequency resolution.

With time-frequency decomposition obtained, a study is conducted on 30 subjects for optimal band identification that demonstrates the significant change in amplitude for accurate event classification. The study also aims to identify the characteristics of reactive band for different electrode locations for various movement classes. The time-domain characteristics of subjects reactive band for different movement classes will be crucial to identify an optimal band (common reactive band) for the subject. A measure is formulated based on the average energy distribution in the reactive band for 30 subjects with different movement classes. With this measure, a procedure to automatically identify the optimal band is presented. The study shows that selecting the optimal band for the subject increased the relative power spectral density by 200%.

2. Methods

Three channels EEG data were recorded monopolarly from C3, C4 and Cz corresponding to the international 10/20 system (Jasper, 1958), with the right mastoid as ground and left mastoid as reference. Analog-to-digital conversion and amplification of the EEG data was done by LXE3204 of LAXTHA (www.laxtha.com) which can provide 4 channels EEG data recording with one reference and one ground additionally. The data was sampled at 512 Hz.

34 subjects (12 female, 22 male) aged between 22 and 27 participated in the research study. All of the subjects are healthy and none of them has prior knowledge about EEG data collection. The subjects sat on a comfortable chair to make sure their limbs were in rest position. All participants gave written informed consent prior to study procedures. The study was approved by the Kyungpook National University Ethical Committee.

Four trials were recorded for each subject in one session. During the trial, 5 classes of movement were carried out: resting, left hand movement, right hand movement, left leg movement, and right leg movement. The sequence of each trial is shown in Fig. 1. Subjects were not informed of the sequence and the interval of each activity in order to minimize anticipatory actions. Each action began with an acoustic stimulus lasted 0.5 s followed by a picture and textual description shown on 26′′ computer screen to indicate the appropriate limb movement. The experiment setup is shown in Fig. 2. The data used for the comparison between various classes lasted 25 s, starting 10 s after the start of each class. For e.g. data in the segment C4(LH) (shown in Fig. 1) from 30 s to 55 s is considered for analysis. For rest, C4(R) or C3(R) segment data from time 140 s to 165 s is considered. Among 34 subjects, only 30 subjects (10 female, 20 male) data was used in the study. An observer stationed behind the

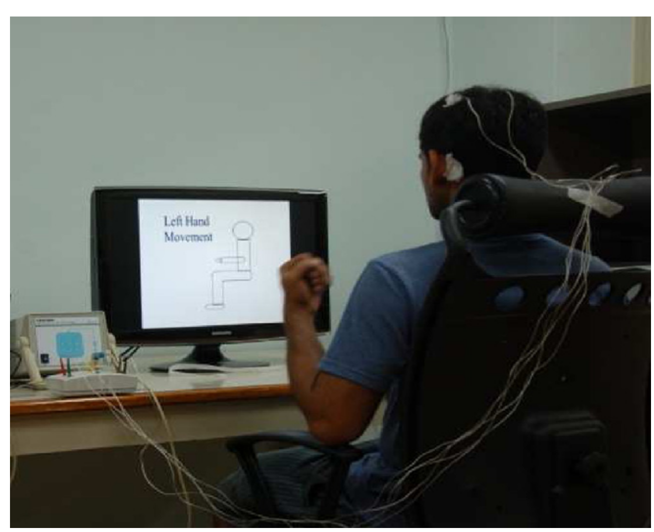

Fig. 2. Recording of EEG from a subject.