Proceedings of the 2nd International IEEE EMBS
Conference on Neural Engineering
Arlington, Virginia · March 16 - 19, 2005

Tracking of the Mu Rhythm using an Empirically Derived Matched Filter

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***Abstract*-This paper introduces a method for improved detection and tracking of cortical mu rhythm modulation for the purpose of a Brain-Computer Interface (BCI). The cortical mu rhythm found in the EEG is of particular interest in BCIs because it can be modulated through motor imagery and can be monitored via noninvasive techniques. With proper training, a disabled person can learn to control the mu rhythm to operate a communication device. This paper discusses the extraction of the empirical mu rhythm, proposes a synthetic model for the mu rhythm, and examines the effectiveness of the synthetic model as a matched filter on two-dimensional cursor control data recorded from a BCI.**

I. Introduction

Brain-Computer Interfaces (BCI) are devices that allow individuals with severe motor disabilities to communicate or perform ordinary tasks exclusively via brain waves [4]. A BCI monitors the electroencephalogram (EEG) either invasively or noninvasively and translates the predetermined EEG features, corresponding to the individual's intentions, into device commands. The first step in developing a successful BCI paradigm is determining suitable control signals from the EEG. An effective control signal will have the following attributes: it can be precisely characterized in an individual, it can be readily modulated and/or translated to express intent, and it can be detected and tracked consistently and reliably. Standard control signals used for BCIs fall under two basic categories: stimulus evoked potentials and event related synchronizations. Stimulus evoked potentials are phase locked to a stimulus; however, many of the known evoked potentials are discrete responses that cannot be reasonably modulated for continuous control. On the other hand, event related synchronizations are responses that attenuate or intensify in a continuous fashion and hence are well suited for real-time control. The cortical mu rhythm is an example of an event related desynchronization.

The cortical mu rhythm is an idling rhythm that is evident in the scalp recorded EEG of most healthy adults [2]. It is prominent over the primary sensory motor cortical areas and is characterized by an arch-shaped 8-12 Hz rhythmical pattern. The mu rhythm is typically blocked by contralateral movement, tactile stimulation, and movement imagery. The foci of the responses over the left and right hemispheres are not synchronous, but the relative attenuation can be correlated as a result of jointly dependent sensorimotor activity. With adequate training, an individual can develop significant control over the independent mu rhythm modulation for each hemisphere, as demonstrated in [1].

II. Methodology

As mentioned previously, two of the keys to realizing an effective BCI control signal are precise characterization and reliable detection of the signal. The mu rhythm is known for its distinctive arch shaped pattern, but the presence of this feature in on-line recording is often obscured by noise. Because of its characteristic 8-12 Hz spectral localization, spectral analysis methods that resolve sinusoidal components such as the Fast Fourier Transform (FFT) and autoregressive (AR) models are the traditional techniques employed for continuous tracking of the mu rhythm in BCIs. Although these spectral methods are efficient and often effective in this context, there are two fundamental problems with these approaches. First, the visual alpha rhythm is prominent in normal EEG and occupies the same frequency band. Although the alpha rhythm is comparatively more sinusoidal and typically most prominent in the occipital regions, it is also detectable over the motor cortex. Because the exact relation between the mu and alpha rhythm is not clear, it is difficult to distinguish or isolate the two rhythms with spectral information alone. The second drawback of traditional spectral estimation techniques is that they are incapable of accurately modeling the sharp, peaking discontinuities characteristic of the mu rhythm. Both of these issues can be improved upon by harnessing the canonical mu rhythm and exploiting it as a template for a matched filter analysis. Matched filters are known to be particularly effective for waveform detection in the presence of noise, specific to responses with consistent temporal characteristics such as the sinus rhythm in the electrocardiogram, for instance.

In ongoing two-dimensional cursor control studies [5], subjects achieving the greatest accuracy are able to accurately modulate 8-12 Hz (mu) and 18-25 Hz (beta) spectral components over the motor cortex to move a cursor toward a randomly positioned target on a monitor. In order to examine the nature of the purported mu rhythm for a particular subject, first, the spectral component that provided the highest correlation with the task was determined using features generated by a 16th order AR model, although any similar spectral technique would suffice. This spectral component was assumed to be the fundamental frequency of the subject's mu rhythm. Next, the data from each trial (approximately 5-30s) for a particular target was cross-correlated with a sinusoid at the fundamental frequency and 1s segments having the maximum correlation were collected. These segments were then phase aligned and averaged to expose the prevailing characteristics of the control signal.

As expected, the averaging revealed the distinctive arch shape of the mu rhythm (Figure 1), which proved very similar across subjects. Because the resulting waveforms maintain a relatively constant amplitude envelope and no significant temporal variations were evident, other than that attributed to noise, it is feasible to derive a synthetic model of the mu rhythm that could be generalized between individuals as a matched filter template.

In order to produce the sharp negative peaks characteristic of the empirical mu rhythms, a rectified sinusoid was selected as an initial model. To further shape the waveform, a parameterized logsigmoid function (equation 2) was varied until a reasonable fit was achieved. The resulting model is provided below:

$$w_m(n) = h\left[\left|\sin\left(\frac{n\pi f_F}{f_S} + \frac{m\pi}{K}\right)\right|\right], \qquad m = 0,1,\ldots,K \qquad (1)$$

$$h_{ls}[x] = \frac{1}{1+e^{-Ax+B}} \qquad (2)$$

where n is the template sample number, f_S is the sampling frequency , f_F is the fundamental frequency of the mu rhythm template, K is the number of discrete phase shifts to evaluate, m is the phase shifted template index, and A and B are the slope and offset shaping parameters for the logsigmoid respectively. The slope and offset parameters can be used to adjust the relative sharpness of the peaks of the template waveform.

The values of A and B providing the best empirical fit for the data were found to be 5 and 2, respectively. Because this fit was sufficiently close from visual inspection of the empirical mu rhythms from both hemispherical channels over several subjects' responses, the accuracy of fit was not further quantified. Figure 1 depicts a representative empirical mu rhythm superimposed over the synthetic mu rhythm.

To use the synthetic model as a matched filter, an appropriate segment width was selected, the segment was normalized to have unit amplitude and the mean was subtracted. Multiple templates of the normalized, zero-mean waveform were generated comprising the K discrete phase shifts (equation 1) for one mu wave period. A type of matched filter bank was constructed using the phase shifted templates to produce a continuous FFT-like output for comparison purposes. The maximum output of these filters for a particular data segment was selected as the feature for that segment.

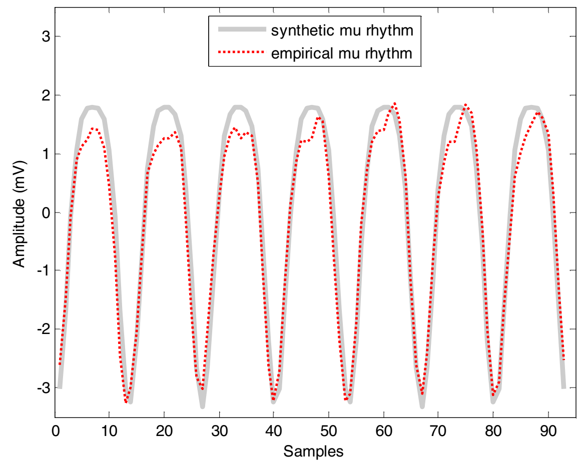

Figure 1. Empirical vs. Synthetic Mu Rhythm

III. Simulations

To test the performance of the synthetic mu rhythm as a matched filter for tracking the actual mu rhythm, the results were assessed against three comparable spectral estimation techniques for offline analysis of a two-dimensional cursor control BCI task.

Data were collected from 5 consenting subjects, 3 male, 2 female, two with spinal cord injury. The subjects ranged in age from 23-41 and all had significant training on the task. For the task, the subjects were presented a random target at one of eight locations along the periphery of a monitor. The subjects' goal was to move the cursor from the center of the screen toward the target. A new trial began when either the target was hit or a fixed amount of time expired. The trials continued in 3-minute runs, with a 1-minute break given between runs. The data set used for offline analysis consists of seven sessions of 8 runs for each of the 5 subjects. Further details about the data collection can be found in [5].

The details of the data collection and analysis are as follows: The EEG activity was collected using 64 channels at standard locations distributed around the scalp using BCI2000[1] [3]. All 64 channels were referenced to the right ear, bandpass filtered .1-60 Hz and digitized at 160 Hz. A large Laplacian spatial filter was applied to the two opposing hemispherical electrode locations over the sensorimotor cortex and a narrow frequency band at each of these locations was selected to generate the two control features. The electrode locations and frequency band were selected based on those determined optimal for the subjects in previous studies.

For the analysis, the features were calculated every 50 ms on 400 ms of data using the following techniques: a 128 point

[1] www.bci2000.org

standard FFT (zero padded), a 128 point FFT (zero padded) with a Hamming window applied to the data, a 16th order AR model derived using the maximum entropy method (MEM), and the mu matched filter with K = 10 and a Hamming window applied to the data. The Hamming window was used in conjunction with the mu matched filter because it provided marginally better results than the standard rectangular windowed data. For the spectral techniques, frequency bin widths equaling approximately 1 Hz were used for each method. The bins were chosen to be relatively narrow to provide a more level comparison to the fundamental frequency of the mu templates. The frequency bin corresponding to the fundamental mu frequency was selected as the control signal for each of the two channels.

The optimum linear regression coefficients for the two features generated by each technique were determined to predict the horizontal and vertical target locations independently. The predictions generated by the linearly transformed features were then averaged for each trial and correlated with the respective horizontal and vertical target locations. The results obtained from the 4 techniques are summarized in Figure 2, where each bar indicates the average R^2 of the horizontal and vertical directions.

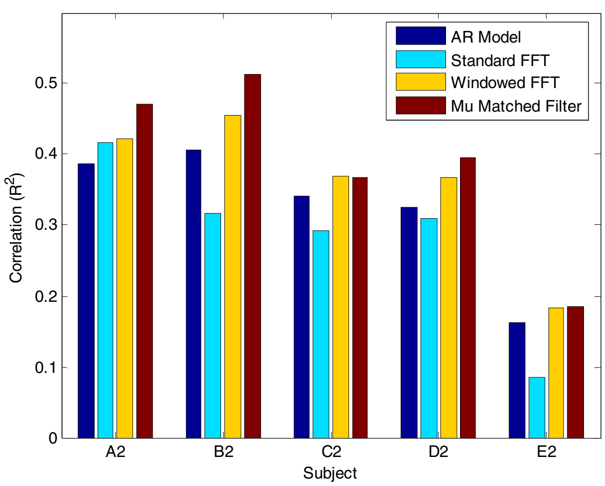

Figure 2. R^2 Results

IV. Results

As Figure 2 indicates, the mu-matched filter achieves the best overall performance. There are several possible reasons for this improvement. The matched filter features are not corrupted by the additional, non mu-like, components tracked by the sinusoidal, Fourier based methods. Along the same lines, the mu matched filter may be discriminating the mu rhythm from the visual alpha rhythm. However, for the subjects (C & E) whose strong rhythmic component was more sinusoidal than the prototypical mu, the windowed FFT produced similar results to the matched filter. The most highly trained subjects (A & B) achieve the best control and are found to have the strongest, most characteristic mu rhythm. Subject A has achieved very accurate narrow-band control, which is evident because the standard FFT performs as well as the windowed version, indicating that there is not much sidelobe interference from adjacent spectral bins. Interestingly, the fact that the mu-matched filter in conjunction with the Hamming window provided marginally better than the standard rectangular window seems to indicate that either a shorter window may be optimal for mu matched filtering, or the Hamming window is exploiting the packet-like nature of the mu rhythm.

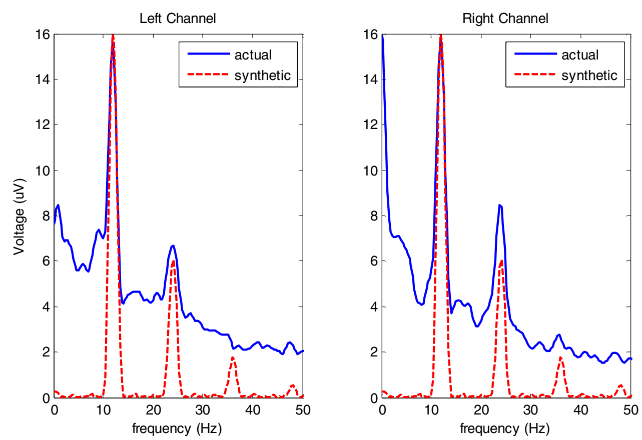

Figure 3. Synthetic vs. actual spectra

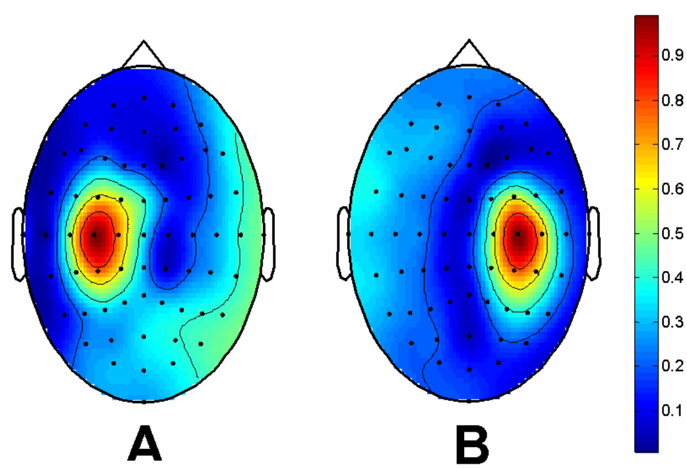

Figure 4. 12 Hz signal amplitude over the left (A) and right (B) sensorimotor cortex

Figure 3 depicts the averaged windowed FFT spectra of the selected data segments verses the spectra of the synthetic mu rhythm. Notice the higher order harmonics of the fundamental frequency, specifically the second harmonic in both spectra. This significant spectral component lies in the beta frequency band, and can be mistakenly characterized as an independent beta rhythm. Incorporating this beta band component into the regression model will tend to improve the correlation [6]. However, the entire spectrum is needed to accurately model the sharp negative peaks of the mu rhythm, making the results sensitive to spectral noise in the lower power spectral bands. This is not the case for the matched filter analysis, which effectively models the signal without explicitly evaluating the entire spectrum.

Figure 4 illustrates the topographies of the signals when the collected responses are time locked over the left (A) and right (B) channels. Notice that the power is considerably localized over these channels, indicating that the lateral mu rhythms do not appear to be phase locked. This, however, does not provide evidence that the blocking of the lateral mu rhythms is not synchronized.

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