Addressing Low Frequency Movement Artifacts in EEG Signals Recorded During Center-Out Reaching Tasks

Gavin R. Philips, Mehrnaz Kh. Hazrati, Janis J. Daly, and Jose C. Principe

Abstract— **The successful application of noninvasive brain-computer interfaces (BCI) to neurological rehabilitation requires examination of low frequency movement artifacts and development of accurate new methods for their correction. To this end, this study applies an adaptive trend extraction method to electroencephalogram (EEG) signals recorded during active and passive center-out reaching tasks. Distinct patterns are discovered, which correlate to arm kinematics, but are shown to be largely artifactual in nature. Notably, these patterns are found to be similar to features currently used for discrimination of movement direction, indicating a necessity for caution and precise signal processing methods when utilizing low frequency content of EEG signals in such applications.**

I. INTRODUCTION

In recent years, significant progress has been made toward successfully decoding the direction of human arm movement from neural signals acquired by noninvasive means, such as magnetoencephalography (MEG) and electroencephalography (EEG). Such capabilities would prove exceedingly advantageous in a wide variety of brain-computer interface (BCI) applications.

One such application, which has thus far received little attention, is neurological rehabilitation. People who have been affected by stroke or other traumatic brain disorders might regain some degree of motor function through the proper application of BCI technology. A BCI could aid in activity-dependent brain plasticity by providing neural feedback to the user, reinforcing desirable neural activity, and discouraging abnormal activity [1], [2].

Because motor recovery is the goal, movement of the subject is desired. EEG is plagued by artifact contamination, and typical methods for reducing the effect of artifacts are by minimizing any movement, and discarding trials which contain movement artifacts [3], [4], [5]. Clearly this is not practical in such a motor learning application, necessitating deeper examination of the nature of such artifacts, and improved methods for correcting them.

Of particular interest are low frequency ($< 1Hz$) movement artifacts, due to the fact that many of the more successful methods of discriminating arm kinematics utilize event-related potentials (ERP) and similar features derived from low frequency bands [6], [7], [8], [9]. Digital filters are often employed in EEG processing to reduce noise in this frequency range. However, in order to attenuate such slow trends, a finite impulse response (FIR) filter must be of such a high order that it causes significant group delay. (In testing, a 50th order FIR filter was found insufficient.) Alternatively, the phase distortion of an infinite impulse response filter can be corrected by zero-phase filtering, but such methods are noncausal and cannot be implemented online.

For these reasons, a single parameter least mean squares (LMS) adaptive filter is proposed as a tool for extraction and examination of low frequency movement artifacts in EEG signals. This method is applied to a center-out reaching task, similar to those performed with joysticks [6], [8], touch screens [9], arrays of tactile buttons [10], and the same robot system utilized in this study [2], [1], [7].

II. METHOD

A. Preprocessing

Prior to processing, each trial was visually inspected, and those possessing extreme artifacts (signifying temporary, drastic changes in electrode impedance) were removed. No other preprocessing was performed, in order to examine the true effects of motion artifacts on raw EEG signals. The adaptive filtering described below is intended as an online preprocessing step for various feature extraction and classification algorithms.

B. LMS Algorithm

The LMS algorithm is considered a standard among adaptive filters, and possesses a simplicity that makes it a very efficient method for minimizing the mean squared error (MSE) cost function. It recursively updates filter weights, based on the gradient of the performance surface (the MSE in the weight space). At each time step, the instantaneous gradient is estimated from the output of the filter at the previous time step, and the current reference input. Thus, the weights are updated in the opposite direction of this gradient using the following equation:

$$\mathbf{W}_{k+1} = \mathbf{W}_k + \mu \varepsilon_k \mathbf{X}_k \quad (1)$$

Where $\mathbf{W}$ is the weight vector, μ is the step size parameter, ε is the error, and $\mathbf{X}$ is the input signal at the last M time steps (where M is the filter order) [11]. The error ε is the difference between the reference signal and the output of the filter at the previous time step:

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$$\varepsilon_k = \mathbf{D}_k - \mathbf{W}_k^T \mathbf{X}_k \tag{2}$$

Where $\mathbf{D}$ is the reference signal at the last M time steps.

In exchange for its favorable properties, the LMS algorithm incorporates a free parameter μ, which is known as the step size, and controls the speed of adaptation. This parameter must be carefully selected for the application, with attention to the compromise between speed of adaptation and misadjustment, the amount by which the iterative solution varies from the optimal solution.

C. Adaptive Trend Extraction

The LMS algorithm may be further simplified for the purpose of adaptive trend extraction, as shown in Fig. 1 [12].

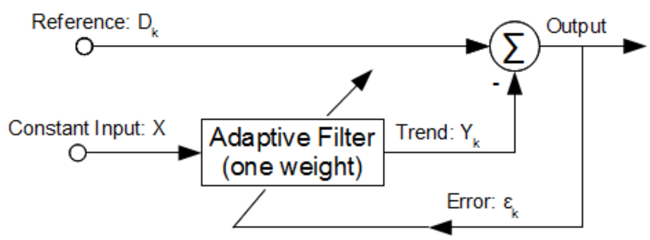

Fig. 1. Modified LMS adaptive filter for trend extraction. Input X is a constant value, and reference D_k is the raw EEG signal.

In this special case, the input of the adaptive filter is set to a constant value, ideally 1 for convenience. Because the filter includes only one coefficient, and the input is equal to 1, the output is simply the filter coefficient. Thus, Eq. (1) can be rewritten as:

$$W_{k+1} = W_k + \mu(D_k - W_k) \tag{3}$$

Because the input is a constant 1, the output Y_k is simply the current weight W_k, and the frequency response from the reference to the extracted trend is defined as follows:

$$\frac{Y(\mathrm{e}^{j\omega})}{D(\mathrm{e}^{j\omega})} = \frac{\mu}{\mathrm{e}^{j\omega} - (1-\mu)} \tag{4}$$

This enables analysis of filter performance as a function of step size μ. This single free parameter controls the speed of adaptation, which in this case effectively controls the cutoff frequency of the filter.

For this study, a step size of $\mu = 0.02$ is selected, low pass filtering the raw signal with a $3dB$ cutoff frequency of $0.8Hz$ to produce the trend, and subtracting that trend from the EEG signal.

III. EXPERIMENT

For this study, EEG data was recorded from human subjects at the Brain Rehabilitation Research Center (BRRC) of the Malcolm Randall VA Medical center, located in Gainesville, Florida. A protocol was developed to guide subjects in a center-out reaching task, during which each subject moved his or her dominant hand in eight different directions, as prompted by a visual display.

A. Setup

For each subject, an appropriately sized Electro-Cap International (ECI) Electro-Cap was used, which incorporated 58 pure tin electrodes, distributed over the entire scalp. The cap was secured in place using a chest strap, and referenced to the left earlobe. Recordings were performed using a 64 channel NeuroScan SynAmps RT EEG amplifier, sampling at 250 Hz, with 24 bit analog to digital conversion.

The tasks and recordings were coordinated using BCI2000 software, which communicated by local network with the InMotion ARM Interactive Therapy System (also known as the MIT-Manus robot). The ARM system recorded kinematic data in parallel with EEG, including position, velocity, and force of the end effector.

Each subject was secured in an upright, seated position with a chest harness. Each subject's forearm was secured to, and supported by the end effector of the ARM system. Movements were performed in a horizontal plane, extending in a 15 cm radius from the center point. The screen, which provided visual prompts, was placed 60 cm from the tip of the subject's nose. This configuration is shown in Fig. 2.

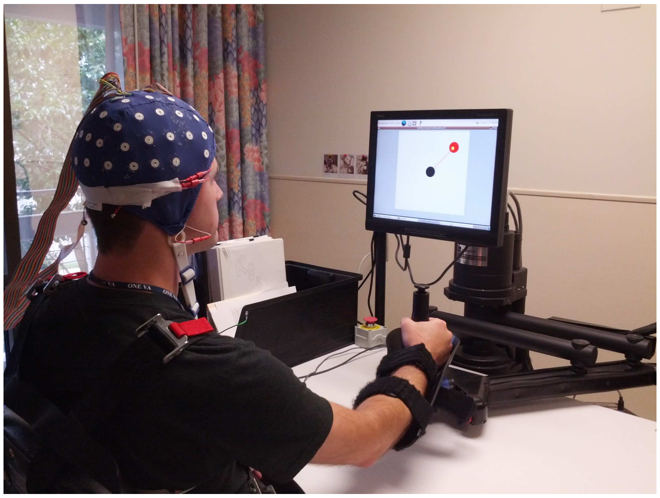

Fig. 2. Subject performing center-out reaching task with ARM system, as prompted by visual display.

B. Task 1: Active Movement

The initial task was intended to record EEG signals during volitional movements of engaged subjects. At the beginning of each trial ($t = 0s$), a target was presented on screen in one of eight directions (North, Northeast, East, Southeast, South, Southwest, West, and Northwest). While the target was displayed, the subject moved his or her hand slowly and continually in the direction of the target. After five seconds ($t = 5s$), the target was removed from the screen. At this time, the subject moved his or her hand back to the center point and rested there, waiting for the next target to be presented after five seconds ($t = 10s$). The timeline of a single trial is shown in Fig. 3. Movement of the hand was represented on screen as a yellow cursor, providing visual feedback to the subject.

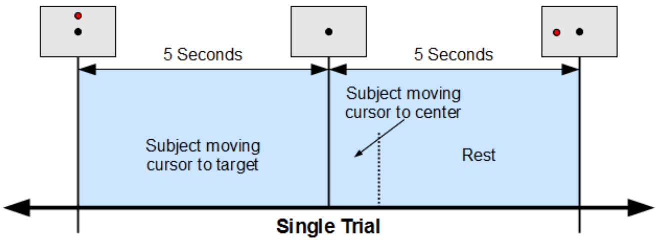

Fig. 3. Timeline of a single trial, with target display at top. The subject moves slowly toward the target for five seconds, then returns quickly to center and rests until the beginning of the next trial, five seconds later.

Four healthy subjects participated in this study: three male, and one female. All were at least 50 years old, and all used the right (dominant) hand. Three of the subjects performed 224 total trials each, and the fourth performed 160. An equal number of trials were performed in each of the eight directions, and were presented in a pseudorandom order.

An additional set of 32 trials was performed by one subject while the electrode cap was secured beneath the chin (as opposed to the chest strap), in order to explore the effects of the chest strap on signal quality during movement. The same subject also performed the passive movement task described below.

C. Task 2: Passive Movement

In order to investigate the causes of motion artifacts, a second task was designed to record EEG signals during passive movement. This task was organized similarly to the first, utilizing the same timeline. However, the visual display was not presented on screen to the subject, and the subject did not engage in (or imagine) active movement. Instead, the subject relaxed, gazing straight forward, and passively allowed his hand to be pulled in each direction by the ARM system. In this manner, it was possible to record motion artifacts comparable to those found in the active movement condition, but devoid of neural signals representing motor planning or intent, and free of extraneous electrooculogram (EOG) artifacts.

One subject performed 32 trials of this task, evenly divided among eight directions, presented in a pseudorandom order.

IV. RESULTS AND DISCUSSION

The proposed adaptive algorithm successfully extracts the previously noted low frequency trends, enabling specific experimentation to determine their source. Selection of the LMS step size presents a compromise between completely extracting trends that may be artifactual, and retaining useful neural information. Fig. 4 shows the raw EEG signal, detrended EEG, and the extracted trend over the course of several continuous trials. Particular attention is paid to electrode C3, which is located over the area of primary motor cortex that corresponds to movements of the right arm/hand.

When averaged over trials and compared by direction, patterns become obvious. While there is some variance among subjects, most exhibit a decrease in amplitude near

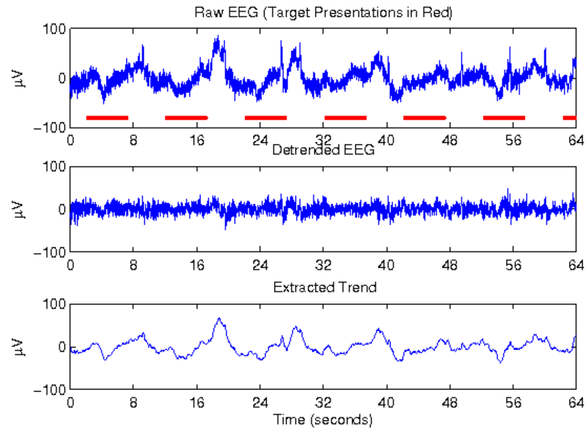

Fig. 4. Results of LMS detrending filter on channel C3, subject C03: (1) Raw EEG signal (with timing of target presentation to the subject in red), (2) Detrended EEG signal, (3) Extracted trend.

the onset of movement, followed by a gradual increase as movement continues. For subject C04, shown in Fig. 5, these patterns appear insubstantial for the Northeast and East directions (predominantly humeral external rotation, which can be executed for this task with little humeral motion in the sagittal or coronal planes). But for the remaining directions, C04 shows distinct patterns, which are potentially associated with humeral motion in the sagittal or coronal planes. This same general pattern was observed for the group. These observations led to the development and study of separate active and passive movement tasks.

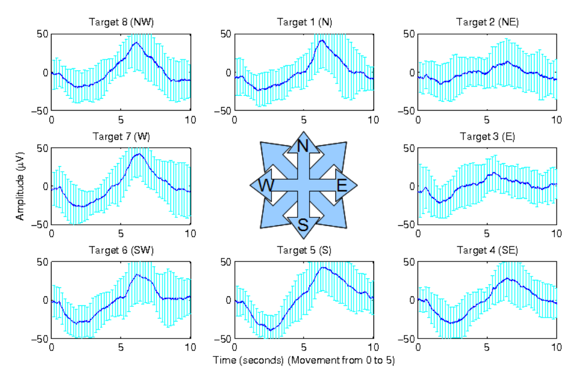

Fig. 5. Low frequency trend of channel C3 for each of eight directions, averaged over trials. Subject C04 moves toward the target from time $t = 0s$ to $t = 5s$, then returns to center and rests.

Active and passive movement tasks, along with the active movement task that forewent the use of the chest strap, are juxtaposed in Fig. 6. Comparison of the active and passive tasks seems to support the theory that these trends are, in fact, artifactual. During the passive movement task, the subject was not engaged in movement, but conspicuously similar low frequency trends were recorded. Clearly they do not signify neural signals of motor planning or intent.

Comparison of the two active movement tasks reinforces the hypothesis that the chest strap, which is designed to secure the electrode cap in place, causes movement artifacts when used during experiments that require subject movement. Removal of the chest strap reduces the appearance of these artifacts significantly (though not entirely).

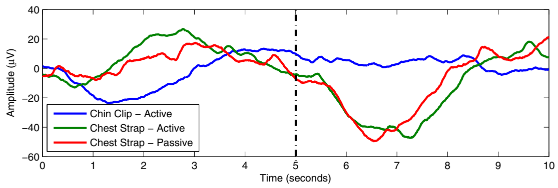

Fig. 6. Low frequency trend of channel C3 for West direction, averaged over trials. Active movement with and without chest strap and passive movement are shown. Subject moves toward the target from time $t = 0s$ to $t = 5s$, then returns to center and rests.

This topic is complicated by evidence that neural information relevant to the direction of arm movement may be encoded in this frequency band, or in adjacent frequencies [6], [7], [8], [9]. For example, [7] present features that are notably reminiscent of the low frequency trends discussed herein. One must take particular care in such studies of EEG-based neural feedback applications, as motion artifacts that are correlated with direction of movement could precipitate erroneously positive discrimination results.

Various methods that have been applied to remove ocular and electromyographic (EMG) artifacts could conceivably be adapted to this task. However, autoregressive and adaptive filter based methods tend to require one or more artifact reference channels, which are not available in this case [13], [14]. In contrast to approaches based on independent component analysis (ICA) or other source separation methods, the proposed method does not rely on spatial models or assumptions of independence or uncorrelation, and does not require a minimum set of EEG channels. It is also simpler and less computationally expensive than methods based on template matching or wavelet decomposition, utilizing only one previous sample at a given time step, which makes it ideal for online implementation [15].

An adaptive method similar to the one proposed in [16] might also prove effective in such applications by taking advantage of the kinematic information recorded by the ARM system. However, this data is not currently available online during task execution.

V. CONCLUSION

The presented adaptive filter method proves an effective tool for the extraction and examination of low frequency movement artifacts in EEG signals. These trends display distinct patterns that are correlated with direction of movement, but are shown to be largely artifactual in nature. In addition, they demonstrate that the securing of an electrode cap with a chest strap during center-out reaching tasks is inadvisable.

This method may be employed as an online preprocessing step for various EEG feature extraction and classification methods. Adopting a correntropy-based cost function (as opposed to squared error) might serve to further reduce sensitivity to impulsive noise.

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