Real-time Motion Artifact Detection and Removal for Ambulatory BCI

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Abstract— **Although human cognition often occurs while moving, most studies of the dynamics of the human brain examine subjects while static and seated in a highly controlled laboratory. EEG signals have been considered to be too noisy to record brain dynamics during human locomotion. Here, we present a real-time ambulatory brain computer interface which allows us to detect gait phases and remove motion-related artifacts from EEG signals during walking in real-world environments. We first construct stride-based artifact templates employing a gyroscope to measure the angular velocity of the human body. Then, we apply an adaptive Kalman filter to estimate the mapping between the stride-based artifact template and EEG space, subtracting the motion-related noise from the raw EEG signal. This study demonstrates the robustness of our system to remove gait-related movement artifacts during human locomotion. Experiments in real-world environments show the potential practicality of real-life applications of low-cost wearable and wireless BCI systems for users actively working in and interacting with their environments.**

Keywords-locomotion; brain computer interface; mobile BCI; adaptive Kalman filter; motion-related artifact removal; automatic gait phases detection

I. INTRODUCTION

Building mobile electroencephalogram (EEG)-based brain-computer interfaces (BCIs) to record human electrocortical brain dynamics in noninvasive ways while moving could have far-reaching benefits for various real-life applications. These applications include home entertainment as well as clinical monitoring, assessment and rehabilitation [1]. Thus, understanding the natural translation from human behaviors to EEG dynamics is considered to be the key point for researching and developing the practical applicability of mobile BCIs [2]. However, one of the challenging issues is that the mechanical artifacts in EEG signals, associated with head movements during locomotion, can have an amplitude that is an order of magnitude larger than the underlying brain-related EEG signals [3]. To measure brain dynamics during locomotion, additional information is required to combat the reduced level of measurement and therefore control. Recently, locomotion-based mobile BCI technologies have shown its efficacy during walking and running [4, 5, 6]. The main idea of these technologies is based on electrocortical activity that is coupled to the gait cycle phase [7]. However, most of these studies have been limited to highly-controlled laboratory environments such as walking on a treadmill [5, 6]. Unfortunately, applying these technologies in real-world environments cannot be carried out easily because the speed and length of a human's stride are vary in real-world environments. In this paper, we present a real-time ambulatory BCI system to enable recording of brain dynamics reliably during human locomotion in a real-world environment. The proposed system aims to remove motion-related artifacts adaptively under various circumstances so that the quality of the recovered EEG signal is comparable to the EEG signal recorded in a static, seated, or highly controlled situation. Our system is stride-based, where freely moving human strides are detected automatically so as to recognize how much EEG signals are contaminated during locomotion. To best of our knowledge, detecting human gait phases automatically under real-world scenarios has not been fully explored for ambulatory BCI applications. Therefore, the contribution of the proposed system, as an alternative to existing work, is a new, effective system that addresses the limitations of the previous systems in a single system:

1. Ambulatory BCI system - The quality of EEG signals during locomotion can be recovered enough to be comparable to EEG signals obtained in statically seated or prone conditions.
2. Automatic gait phase detection - Human strides are automatically detected when standing or walking in a real-world environment. Stride information such as length and speed provides critical clues to construct motion-related artifact templates.
3. Adaptive motion-related artifact removal - The proposed adaptive filtering method takes advantage of motion information to estimate the motion artifact noise. This filter is capable of removing motion artifacts, restoring EEG signals

The key technical challenge in designing the proposed system was the development of a motion-related artifacts removal algorithm that addresses the following requirements. First, the algorithm must have the ability to continuously detect the following gait phases: stance, heel-off, swing, and heel-strike in real time [8]. We employed a gyroscope to measure the 3-axis angular velocity of the body and associate the magnitude of the angular velocity with the gait phases. Using a

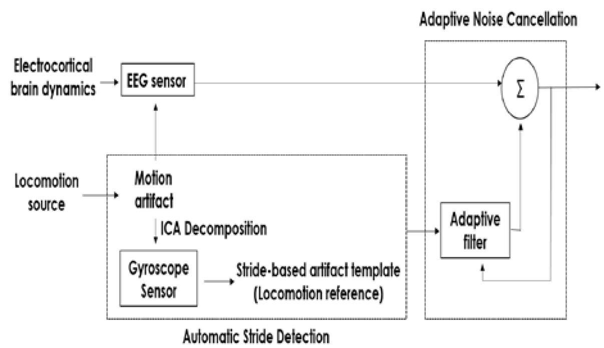

Figure 1. Overview of the proposed system

gyroscope is ideal because it can measure how much the human body has swayed until one gait phase is finished in real time. Second, due to possible subject motion and changes in electrode impedance, a time-varying mapping of the motion versus EEG is required. Our adaptive filtering algorithm is based on the Kalman filter algorithm [9]. The adaptive algorithm makes use of any correlation between the motion signal and the observed signal to remove the noise signal.

We experimented with two BCI protocols: steady-state visual-evoked potential (SSVEP) and event related potential (P300). To systematically evaluate the effectiveness of our system while walking for the two BCI protocols, this study instructed participants to stand, walk around, and go up and down stairs in a building at their natural pace for eliciting different degrees of head/body movements while subjects were performing visual tasks. We demonstrate how the proposed system can serve as a platform for mobile BCIs by evaluating the two filtered protocols through on- and offline analysis in terms of accuracy and SNR.

II. PROPOSED SYSTEM

Fig. 1 shows the overview of our entire system. The proposed system consists of mainly three parts; acquisition of EEG data, construction of stride-based movement artifact templates, and removal of motion-related noise in an adaptive way. Each part is described below.

A. Experiment setup and EEG data acquisition

Five healthy participants (5 males; 23-35 years of age; mean age: 29 years) with normal or corrected-to-normal vision participated in this experiment. Written informed consent was obtained from each participant. This study adopted a 16-channel mobile EEG system (Emotiv Epoc, US) featuring a low-cost wearable device and wireless data transmission to record signals with a sampling rate of 128 Hz [10]. All electrodes were used and placed over the frontal, parietal, and occipital areas in order to record SSVEP and P300 signals. From a 3-axis gyroscope built into the Emotiv Epoc, angular velocity values were also. Subjects were asked to stand, walk around, go up and down stairs in a building at their natural pace for 5 minutes while conducting visual tasks. The visual task of SSVEP was to gaze at a blank and white flickering stimulus of 12 Hz or 15 Hz [11]. The visual task of P300 was to conduct the typical oddball task [12]. All necessary programming was developed under the Android SDK and implemented on a Google Nexus 5.

B. Independent component analysis

ICA is a great technique to estimating statistically independent components (ICs) from signal mixtures. It has been widely applied to multichannel EEG signals to remove artifact signals and thus improve the signal-to-noise ratio (SNR) of EEG signals. In this study, we adopted the Fast ICA algorithm based an implementation in C++ [13] to decompose the 14-channel EEG signals into 10 components that distinctively modulate for the SSVEP and P300 BCI protocols. ICA finds an unmixing matrix, W, that linearly separates the time series data into an independent source matrix, U, by minimizing the mutual information among the output components, followed by the equation of $U=WX$. The rows of output data matrix, U, are the component activations. To remove artifact components, some ICs that have large punctuate activations or have a spectral peak above 20Hz are abandoned and considered to be related to eye movement.

C. The stride-based movement artifact template

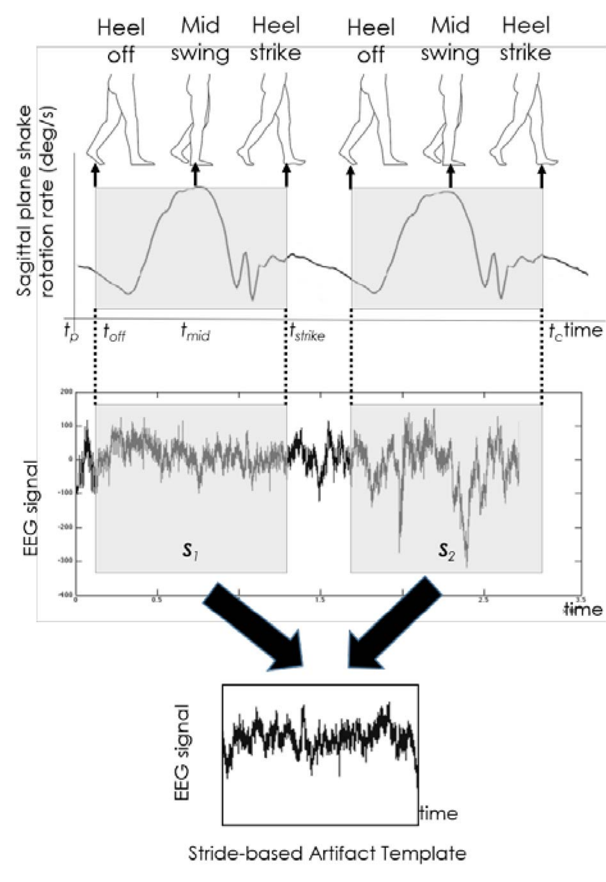

Figure 2. Overview of the stride-based movement artifact template

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Fig. 2 shows the overview to construct the stride-based movement artifact templates. Based on the [8], sagittal plane of rotational rate (deg/s) is minimized at the heel-off stage, maximized at the middle of the swing stage, and increased again until the heel-strike stage. Motivated by this, we employ a gyroscope to measure the 3-axis angular velocity of the body and associate the magnitude of the angular velocity with the gait phases. Given the current timestamp t_c, the magnitude of 3-axis gyroscope data points vector $\boldsymbol{G_m}$ during its past t_c - t_p are collected. From the $\boldsymbol{G_m}$, a pair of local minimum and maximum values is assigned as the sagittal plane of absolute rotational value at the heel-off and the mid-swing stage in a stride and their respective timestamps are assigned as the timestamp of the heel-off t_o and the timestamp of the mid-swing t_{mid}. Assuming the length between the heel-off and the mid-swing is same as the length between the mid-swing and the heel-strike stage, timestamps of the heel-strike stage is assigned as t_{strike} which is $2t_{mid}$ - t_{off}. Finding a pair of minimum and maximum value is conducted successively in time sequence and when the search is finished, we have a stride vector $\mathbf{S}_p^t = \{S_1,...,S_i,...,S_n\}$ where $S_i = \{ t_{off}, t_{mid}, t_{strike}\}$. Given S_i, EEG signals are collected from t_{off} to t_{strike}. At the last step, the collected EEG signals are averaged so called stride-based movement artifact template.

D. Adaptive Motion Noise Cancellation

We model the recorded EEG signal $y(t)$ as the sum of a "true" underlying EEG signal $s(t)$ and a signal $n(t)$ containing motion-related noise,

$$y(t)=s(t)+n(t)\,. \tag{1}$$

The relationship between the noise signal $n(t)$ and the stride-based template $m(t)$ is modeled linearly using a time-varying, finite impulse response (FIR) kernel $w_t(k)$ with the equation sentence,

$$n(t)=\sum_{k=0}^{N-1} w_t(k)m(t-k)\,, \tag{2}$$

where N is the order of the FIR kernel. An adaptive filtering algorithm is used to produce an estimate of the FIR kernel $w_t(k)$, which is in turn used to estimate the noise signal $n(t)$. The estimated noise signal is then subtracted from the recorded signal $y(t)$ to reveal the underlying EEG signal $s(t)$,

$$\hat{n}(t)=\sum_{k=0}^{N-1} w_t(k)m(t-k)\,, \tag{2}$$

$$\hat{s}(t)=y(t)-\hat{n}(t)\,. \tag{3}$$

The adaptive algorithm makes use of any correlation between the motion signal $m(t)$ and the observed signal $y(t)$ to estimate the FIR kernel $w_t(k)$ and remove the noise signal $n(t)$. Since

TABLE I. SSVEP ACCURACY (STANDARD DEVIATION)

Subject No.	Accuracy ($p < 0.05$)		
	Laboratory	Real-world	
	Without the proposed system	Without the proposed system	With the proposed system
1	79 (2.34)	62 (5.23)	**73 (2.89)**
2	83 (1.17)	69 (4.14)	**77 (1.57)**
3	76 (1.34)	63 (3.97)	**74 (2.18)**
4	74 (2.85)	58 (3.41)	**64 (2.73)**
5	79 (5.70)	67 (3.37)	**74 (2.94)**

TABLE II. P300 ACCURACY (STANDARD DEVIATION)

Subject No.	Accuracy ($p < 0.05$)		
	Laboratory	Real-world	
	Without the proposed system	Without the proposed system	With the proposed system
1	74 (1.12)	56(5.77)	**68(3.27)**
2	78 (1.26)	64(8.44)	**65(4.25)**
3	86 (0.86)	61(10.24)	**73(3.22)**
4	81 (1.55)	59(5.61)	**71(3.17)**
5	71 (2.45)	68(8.42)	**72(5.80)**

the true underlying EEG signal $s(t)$ is uncorrelated with the motion signal $m(t)$, the adaptive algorithm does not affect it, and on average the result of the noise cancellation process $\hat{s}(t)$ will be the true underlying EEG.

E. Support Vector Machine

Support vector machine (SVM) algorithm is known to a good solution for generalization and has been used for EEG-based classification [14]. Although SSVEP-based BCIs have largely adopted canonical correlation analysis (CCA) due to its ability to improve the SNR of SSVEPs, in this study the proposed system did not adopt CCA because we aim to develop an algorithm to work with several BCI protocols such as P300 and sensorimotor rhythms. The proposed system applies the linear kernel-based SVM. For robust classification during real-time execution, data points passed to SVM with 1*s* time window with 500*ms* increment.

III. EXPERMIMENTAL RESULTS

We evaluated the efficacy of our proposed system for removing motion-related noise in terms of accuracy and SNR. Table 1 and 2 show the averaged SSVEP and P300 detection accuracies in response to each visual flickering (12 Hz and 15 Hz) and visual evoking respectively. At first, significant drops in accuracy were happened between sitting in a laboratory and walking around a building (averaged 14.4% and 14.8%

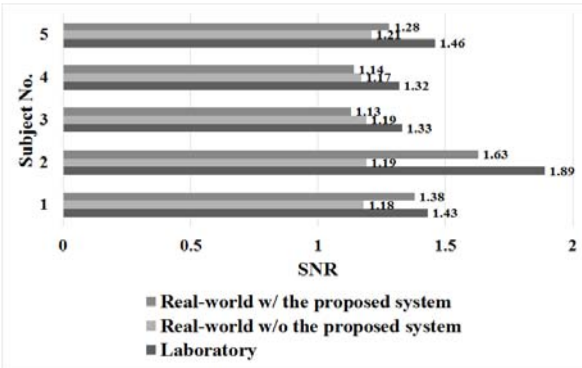

Figure 3. Average SSVEP SNR

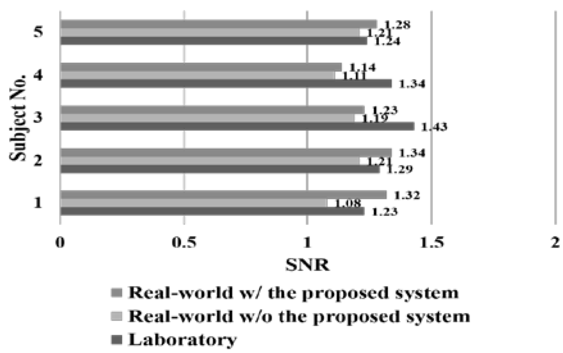

Figure 4. Average P300 SNR

increased for SSVEP and P300 respectively). This results have similar tendency with previous work [5, 6]. On the other hand, all results obtained from the proposed system achieved statistically significant improvements ($p < 0.05$). Furthermore, the results show the proposed system recovered its robustness with respect to accuracy comparable to the result obtained in seated condition. The proposed system restored contaminated EEG data up to 93%. Fig. 3 and 4 illustrate the averaged SSVEP and P300 SNR in response to each visual flickering (12 Hz and 15 Hz) and visual evoking. Similarly as the detection accuracies, our proposed system achieved statistically significant improvements ($p < 0.05$). The SNR was defined as the ratio of the amplitude of the SSVEP and P300 to the mean power at adjacent frequencies or times. For example, in the case of SSVEP,

$$\mathrm{SNR} = \frac{n \times \mathrm{PSD(12Hz)}}{\sum_{\mathrm{i}=12-\mathrm{n}/2}^{11} \mathrm{PSD}(i\ \mathrm{Hz}) + \sum_{\mathrm{i}=13}^{13+\mathrm{n}/2} \mathrm{PSD}(i\ \mathrm{Hz})},$$

where n is the number of adjacent frequencies. We used $n = 4$ for this experiment.

IV. Conclusion

This study focused on measuring human strides and using the information to remove motion-related artifact for improving BCI detectability in freely-moving humans in real-world environments. Through employing a gyroscope to measure the angular velocity of the human body and applying an adaptive Kalman filter to subtract the motion-related noise from the raw EEG signal, we demonstrated the practicality of real-life applications of mobile and wireless BCI systems for users actively working in and interacting with their environments.

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