ICCEPM 2024 https://dx.doi.org/10.6106/ICCEPM.2024.0902
The 10th International Conference on Construction Engineering and Project Management
Jul. 29-Aug.1, 2024, Sapporo

Challenges and Improvement Methods for Monitoring Workload of Construction Workers through EEG

Yuting Zhang[1]*, Jiayu Chen[2]

[1]*School of Civil Engineering, Tsinghua University, China, Email address: yuting-z22@mails.tsinghua.edu.cn*
[2] *School of Civil Engineering, Tsinghua University, China, Email address: jiayuchen@tsinghua.edu.cn*

Abstract: A large number of construction accidents are caused by workers' unsafe behavior under excessive workload. Despite the demonstrated effectiveness and advantages of current portable electroencephalogram (EEG) devices in workload monitoring, accurate data acquisition remains challenging due to motion artifacts in dynamic environments. Consequently, most current research is limited to static conditions, thus restricting its application to construction tasks that inherently involve bodily movements. In this study, an innovative signal filtering framework is introduced that employs the principles of adaptive filtering to integrate acceleration signals containing motion information for the correction of motion artifacts in EEG signals. The experimental results demonstrate that this approach effectively eliminates motion-induced artifacts in EEG signals, thereby improving the preprocessing of hybrid kinematic-EEG signals acquired during bodily and muscular movements. By enhancing signal quality and reliability, this preprocessing framework aims to broaden the application of portable EEG devices for real-time workload monitoring among construction workers. This advancement is expected to enhance the practicality of EEG in construction safety management and ultimately contribute to safer construction practices.

Key words: safety performance, workload, EEG, motion artifacts

1. INTRODUCTION

A large number of construction safety accidents are induced by workers' unsafe behaviors [1]. Numerous studies suggest a significant correlation between physical or mental workloads and safety performance [2-4]. It is crucial to establish a real-time monitoring mechanism that enables the early detection of excessive workload in construction workers. Neuroscientists have demonstrated that EEG signals exhibit characteristics indicative of both physical and mental workload [5]. Contemporary portable EEG devices facilitate the real-time, non-invasive collection of these signals through wearable technology. Consequently, numerous studies have been conducted to establish quantitative workload models based on EEG analysis [6].

However, the technical limitations of portable EEG devices pose a significant challenge in collecting accurate EEG data in dynamic scenarios involving physical exertion, as motion artifacts seriously interfere with the signal quality [7]. Hence, the majority of EEG experiments conducted in research settings are inherently static, emphasizing the crucial need for participants to minimize bodily movements, particularly those involving the head, throughout the experimental procedures. However, due to the complexity of construction tasks, workers are required to perform sustained high-intensity construction operations in a dynamically changing environment, necessitating inevitable large-scale bodily movements. Under such conditions, the utilize of EEG for real-time monitoring of workers' workload levels must take into account the crucial issue of motion artifacts contaminating the signals acquired by portable EEG devices. Therefore, it is imperative to adopt a new signal processing framework that incorporates motion artifact correction and feature extraction.

The primary objective of this study is to explore effective correction methods for the aforementioned motion artifacts, thereby expanding the application scenarios of portable EEG devices to allow for real-time collection of EEG signals from construction workers. At this point, , it aims to provide a preliminary signal preprocessing framework for future workload feature extraction and model establishment, further enhancing the practicality of EEG in serving the safety management of the construction industry.

2. LITERATURE REVIEW

2.1. Workload and safety performance

Although there is currently no unified definition, in most cases, workload is defined as the portion of an individual's limited capacity that is actually required by task demands [8]. Workload level can vary depending on the nature of the job, the complexity of the tasks involved, and the individual's capabilities and training. Theories such as the multiple resource theory and the workload capacity model have attempted to capture these complexities, emphasizing the interaction between task demands and the individual's ability to meet those demands [9]. Early research in this domain has demonstrated that excessive workload, either physical or mental, can lead to a range of adverse outcomes. For instance, excessive workload has been demonstrated to trigger fatigue, which can significantly impact an individual's ability to perform tasks efficiently and safely [10]. Fatigue not only affects physical performance but also decreases situational awareness, the ability to perceive and interpret environmental cues accurately. Furthermore, excessive workload can compromise vigilance, the sustained attention required to detect and respond to hazards in a timely manner [11]. The cumulative effect of these factors can significantly undermine an individual's safety performance, leading to errors, accidents, and other unsafe outcomes.

A crucial aspect of workload research is its quantification. Researchers emphasize that by quantifying workload, precise measurements can be obtained, facilitating detailed analyses and subsequent interventions. The objective assessment of workload levels can be quantified to identify overloaded workers. This information can then be used to redesign tasks, improve work processes, and provide appropriate training to mitigate workload-related risks.

In conclusion, workload quantification is a critical tool in enhancing safety performance. By understanding and managing workload effectively, organizations can create safer work environments, reduce accidents, and improve overall performance. Future research in this area should focus on developing more accurate and practical methods for workload quantification, as well as exploring the role of workload in different industries and contexts.

2.2. EEG and workload assessment

Prior to the physiological monitoring tools, self-assessment questionnaires are widely employed for workload assessment. However, these questionnaires are often limited by subjects' self-knowledge, resulting in inaccurate assessments for tasks that exceeded their actual energy expenditure. Furthermore, this method exists a time lag evitably. Despite researchers' diligent efforts to minimize the temporal gap between task completion and self-assessment, biases introduced by subjects' short-term memory decay persists [12]. Commonly used physiological monitoring methods for workload assessment include electrocardiogram (ECG), heart rate, eye movement, functional near - infrared spectroscopy (FNIRS), and EEG, etc. Among them, EEG has been widely used as a workload measurement due to the gradual development of its device portability [13]. However, the signal acquisition procedure of portable EEG equipment is easily affected by artifacts related to the movement of the subject [14]. This motion-induced artifact can significantly impact the accuracy and reliability of recorded EEG signals. To mitigate this challenge, existing experimental protocols typically instruct subjects to minimize their body movements during EEG recordings. For example, in commonly used stationary experiments, construction industry researchers often select the experimental material in advance and ask subjects to sit in front of a monitor and provide feedback on their decision-making via keyboard or mouse clicks. However, such constraints may lead to simplified or inadequate simulations of real-world working conditions. Consequently, the findings from these controlled experiments often have limited translational value in practical engineering settings. To bridge this research gap, it is imperative to develop and adopt effective motion artifact correction methods, thereby expanding the range of applicable scenarios for portable EEG equipment.

2.3. Artifact removal techniques in EEG signal processing

EEG artifacts, originating from diverse sources and broadly categorized as external or internal, are widely distributed across time and frequency domains [15]. Some common artifact elimination methods are shown in Table 1. Band-pass filters allow specific frequency bands to pass through while blocking other frequency bands. They are widely used in signal processing applications to isolate and extract desired frequency components from complex signal mixtures. Common physiological artifacts in EEG, including cardiac-related potentials, skin potential drift, and eye movement artifacts, primarily reside in the low-frequency range [16]. To mitigate these artifacts, high-pass filtering is commonly employed to eliminate low-frequency components, and bandpass filters with different parameters can also be used to effectively remove DC offsets and suppress powerline interference signals. However, bandpass filters are ineffective in eliminating signal artifacts that induce complex effects across multiple time and frequency domains. Consequently, numerous artifact removal techniques, often incorporating psychological research insights and signal processing principles, have been developed. Frameworks base on empirical mode decomposition (EMD), independent component analysis (ICA), principal component analysis (PCA), and combinations of these approaches, are commonly used. While satisfactory results are often achieved in static experiments, particularly with the widespread integration of ICA into EEG signal processing toolkits, these methods often encounter challenges in dynamic experiments due to the evolving nature of the signals [17].

Table 1. Common artifact elimination methods and applications

Method	Application	Principle
Independent Component Analysis (ICA)	Eye movement artifacts, muscle activity artifacts, heartbeat artifacts, and other physiological artifacts.	ICA decomposes the EEG signal into independent components. Artifactual components can then be identified and removed based on their characteristic features, such as high amplitude or frequency content.
Notch Filtering	Electrical noise, especially power line interference.	Notch filters remove specific frequencies from the EEG signal, typically the frequency of the power line (e.g., 50 Hz or 60 Hz) to reduce interference.
Artifact Subtraction	Eye movement artifacts (EOG), heartbeat artifacts (ECG).	Artifactual signals, such as EOG or ECG, are recorded simultaneously with the EEG. These signals are then subtracted from the EEG to reduce the corresponding artifacts.
High-Pass Filtering	Muscle activity artifacts, slow drifts, and other low-frequency noise.	High-pass filters attenuate low-frequency components of the EEG signal, reducing artifacts caused by slow drifts or muscle activity.
Reference Electrode Standardization Technique (REST)	Reducing artifacts caused by poor electrode contact or uneven distribution of electrodes.	REST re-references the EEG data to a virtual reference electrode created by combining all other electrodes, reducing the impact of local artifacts.
Regression-Based Artifact Correction	Poor electrode contact, movement artifacts, or other sources of interference.	Regression analysis is used to model the relationship between the artifact and the EEG signal. The artifact is then predicted and subtracted from the EEG to correct for its influence.

3. RESEARCH METHODOLOGY

This study introduces a novel method for the mitigation of motion artifacts in EEG signals. The approach utilizes adaptive filtering techniques and incorporates information from an inertial measurement unit to accurately estimate and cancel out motion-induced noise. In contrast to traditional bandpass filtering, adaptive filtering does not rely on fixed parameters or statistical characteristics of the signal. Instead, it dynamically adjusts its transmission function based on the characteristics of the input signal and optimizes the output signal by minimizing the error between the desired signal and the actual output signal, thus provides superior adaptability to changing motion artifacts. The widely used least mean squares algorithm is employed to optimize filter coefficients, minimizing the mean squared error between the reference and output signals, thereby enhancing artifact removal. The filter is designed to establish a precise mapping between motion sensor data and the EEG signal space, enabling the subtraction of motion-related artifacts from the raw EEG data. This enhanced method aims to improve the quality and reliability of EEG recordings, particularly in dynamic environments. The basic structure of the adaptive filter is shown in Figure 1.

In this study, a portable EEG device and the EPOC+ manufactured by Emotiv is used to acquire the real-time EEG signals from 30 subjects in both sitting and walking states. The device is configured to record 14-channel EEG signals, following the international 10-20 system, including AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4. The movement information of the portable EEG device is recorded by the three-axis acceleration sensor, synchronized with the real-time EEG signals, and used for further adaptive motion artifact correction. Subsequently, the pre-processed signal underwent Wavelet Packet Decomposition (WPD), and the inherent power was computed using wavelet packet coefficients for further analysis.

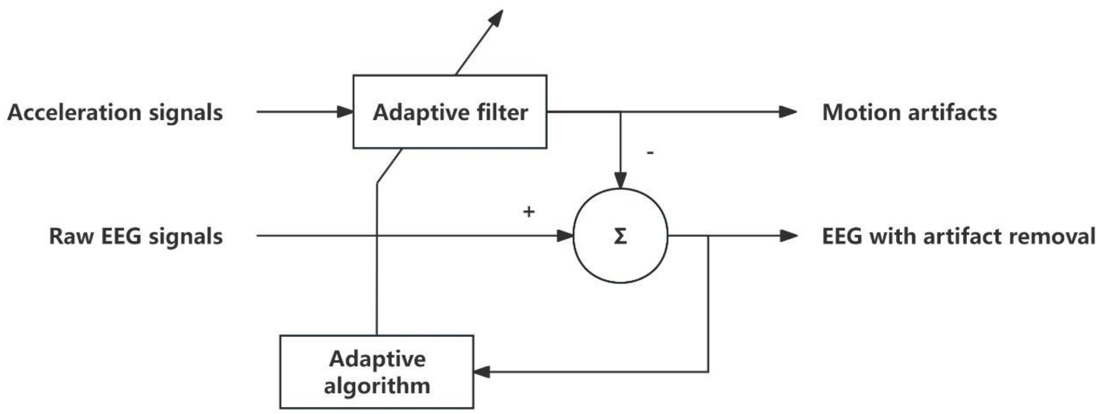

Figure 1. The basic structure of adaptive motion artifact elimination filter

4. RESULT AND DISCUSSION

To establish a baseline comparison with the walking state, EEG signals are collected from each subject while they are seated, serving as a control condition. During this sitting state, the overall amplitude of the EEG signals remain low. The signal value of the subject 1 in the given state is presented in Figure 2.

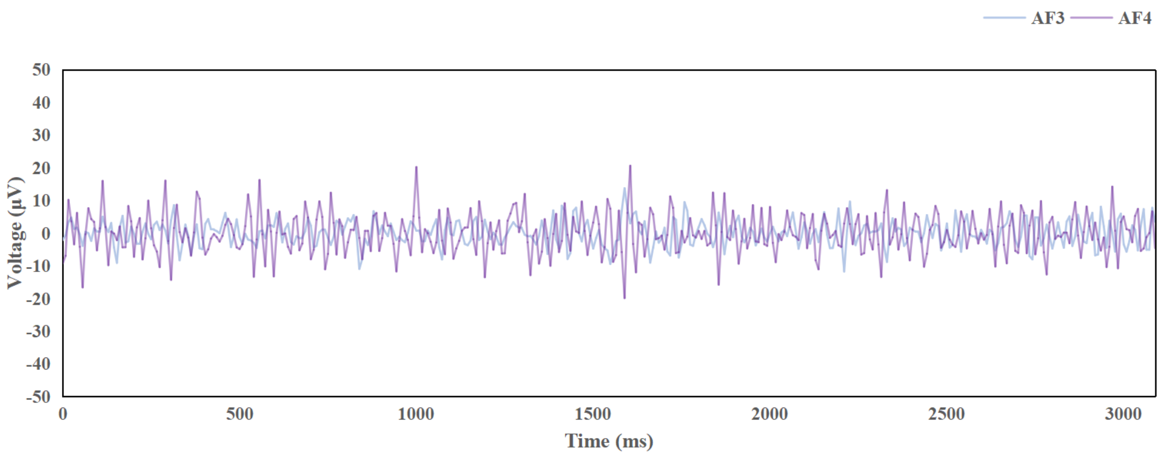

Figure 2. Signal value after artifact correction in sitting state from subject 1

After motion artifact correction, the amplitude of the signal is relatively low. However, the peak value of the EEG signal in the time domain is significantly higher for walking subjects compared to those in a sitting state. Our time-frequency analysis further reveals a relationship between gait patterns and the time-frequency characteristics of the EEG, despite the absence of a direct significant correlation between the signal amplitude and the accelerometer signal during walking. This observed similarity underpins the principle of adaptive filtering. Figure 3 shows the signal value of the identical subject during the walking state.

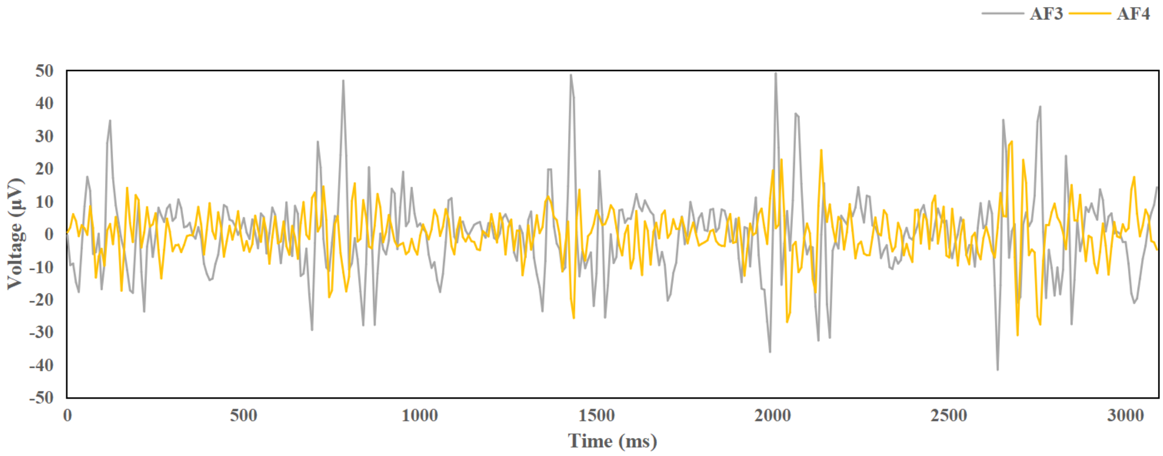

Figure 3. Signal value after artifact correction in sitting state from subject 1

A comparison with the acceleration signal reveals that the peak value of the EEG signal and the peak value of the acceleration signal emerged nearly concurrently, coinciding with the gait cycle of the subject. This observation suggests that, despite achieving some degree of effectiveness, the motion artifact correction method employed may not be sufficient in eliminating all motion-related artifacts.

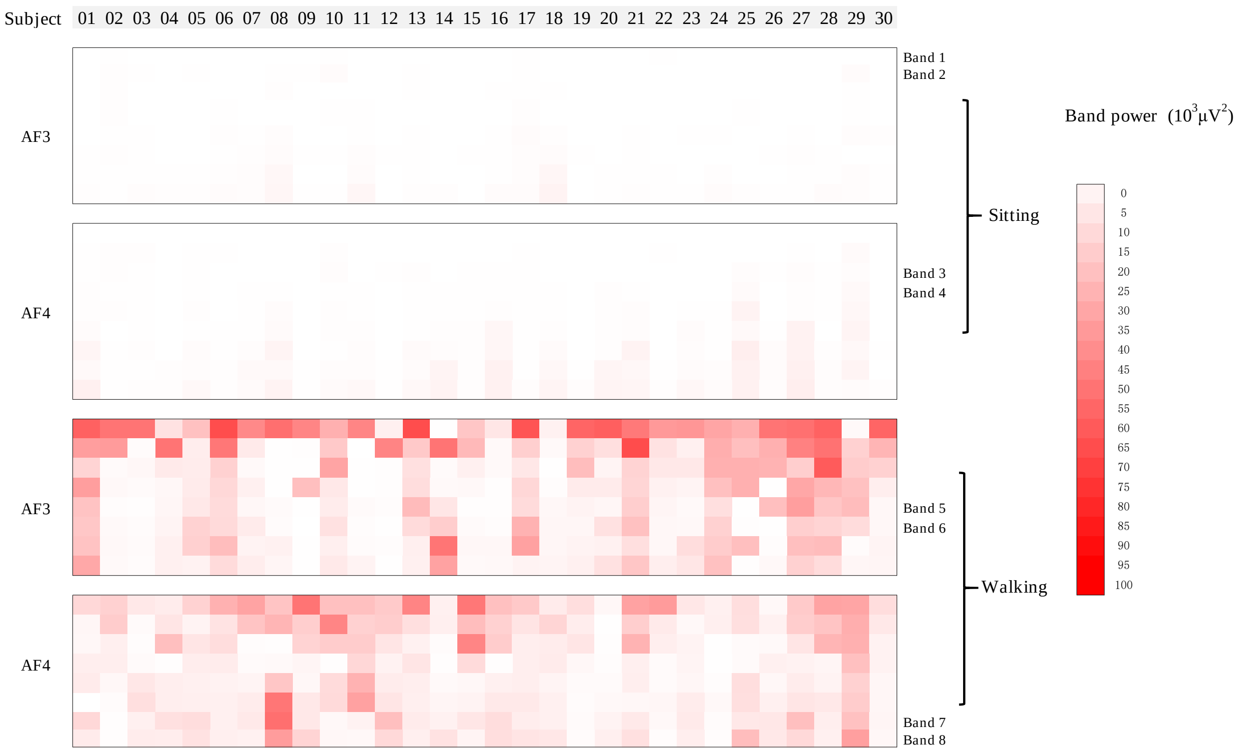

Figure 4. Comparison of band power between sitting and walking state

Based on this, the pre-processed signal undergoes WPD, resulting in a division encompassing bands 1 to 8, ranging from low to high frequencies. Figure 4 shows the power values of each subband of 30 experimental subjects in the sitting and walking states respectively. Subsequently, the sub-band power is computed. Upon preliminary analysis of the results, it becomes evident that, in comparison to the sitting state, the energy within multiple frequency bands is elevated during walking. Notably, the degree of activation among different subjects within specific frequency bands exhibits variance, yet the enhancement of energy is particularly pronounced in the low-frequency region.

4. CONCLUSION AND RECOMMENDATIONS

EEG data recorded during movement is likely to contain substantial motion artifacts exhibiting variations based on speed, subject, and channel, which are not sensitive to traditional signal processing methods. This study introduces a new signal filtering framework to efficiently target and eliminate motion-induced artifacts. The aim is to refine the preprocessing methodological framework for hybrid kinematic-EEG signals, acquired using a portable EEG device during tasks involving bodily and muscular movements executed by the subject. This enhanced preprocessing step aims to enhance signal quality and improve the reliability of subsequent data analysis.

Despite achieving some results, the current method remains incapable of completely eliminating motion artifacts from the signal. Consequently, to harness the full potential of EEG technology in construction production environments, it is imperative to further refine its artifact correction techniques. Additionally, the exploration of more efficient methods for extracting such EEG features is crucial. This will facilitate the establishment of an effective workload model that can be extrapolated to real-world construction settings, thereby optimizing the utilization of EEG technology in this domain.

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