Towards an Efficient Physiological-Based Worker Health Monitoring System in Construction: An Adaptive Filtering Method for Removing Motion Artifacts in Physiological Signals of Workers

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ABSTRACT

Construction workers are vulnerable to physical and mental health challenges, causing illnesses, injuries, and fatalities. This fact stresses the need to closely assess and monitor the health and safety conditions of construction workers. Recently, researchers have used biosensor technology to develop several health monitoring frameworks that can monitor workers' safety and health status through the acquisition and analysis of workers' physiological signals. Despite the potential of these frameworks in monitoring subjects' health status in a controlled lab environment, there is a concern regarding the performance of these frameworks in the field environment. One of the main limiting factors affecting the field performance of these frameworks is motion artifacts in the captured physiological signals. The frequent movements of workers while performing construction tasks can cause motion artifacts during signal acquisition, which will significantly reduce the quality of the captured physiological signals and thus degrade the performance of health monitoring frameworks. To address this gap, this study developed a motion artifacts removal method based on least mean squares adaptive filtering algorithms. To examine the performance, 12 subjects were asked to perform a material delivery construction task while their physiological signals were captured via a wristband-type biosensor, and the proposed method was applied to the signal acquisition process. Results reported that the proposed method removed 61.9% of motion artifacts from the captured EDA, PPG, and ST signals and improved the corresponding signal-to-noise ratio by 51.6%. This study contributes to the establishment of efficient physiological-based health-monitoring frameworks for construction workers.

INTRODUCTION

Construction workers are more vulnerable to work-related mental and physical health challenges than workers in other industries, resulting in illnesses, injuries, and fatalities (U.S. Bureau of Labour Statistics 2018). Studies have shown that nearly 40% of the U.S. construction workforce experiences severe physical and mental fatigue, which can negatively impact worker safety and well-being (Jiang and Messner 2020; Ricci et al. 2007). Statistics also indicate that over 80% of construction workers have experienced mental stress at work, which leads to a high suicide rate within the construction industry (Office for National Statistics 2017). Moreover, the shift from traditional construction processes to industrialized construction processes in the construction industry is likely to worsen the mental and physical health challenges faced by workers. The use of construction machines (construction robots) may impose excessive physical fatigue and cognitive load on workers (Liu et al. 2021a; b, 2022), leading to new mental and physical safety challenges. Given these facts, it is critical to monitor the mental and physical health conditions of construction workers in order to detect and prevent work-related injuries and illnesses.

Recent advances in biosensors and artificial intelligence (AI) techniques have led to the development of several physiological data-driven health monitoring frameworks (Jebelli et al. 2018; Liu et al. 2021b; Maman et al. 2017). These frameworks aim to objectively assess the mental and physical health conditions of workers, enabling the early detection and prevention of health and safety challenges faced by workers. The existing frameworks involve three steps: (1) using biosensors to capture physiological signals from workers, such as electrodermal activity (EDA), photoplethysmogram (PPG), and skin temperature (ST) signals; (2) decoding the captured signals into informative features; and (3) utilizing AI algorithms to analyze the decoded features and predict workers' mental and physical states, including physical fatigue, mental stress, and cognitive overload (Jebelli et al. 2018; Liu et al. 2021b; Maman et al. 2017). For instance, researchers developed a physiological data-driven health monitoring framework that could process EDA, PPG, and ST signals of workers and leverage machine learning techniques like Support Vector Machines to assess the level of physical fatigue experienced by workers (Jebelli et al. 2019).

Currently, the performance of health monitoring frameworks has been demonstrated to be efficient in a controlled lab environment. However, when these frameworks are implemented in naturalistic construction environments, their performance may be significantly affected. One of the main factors that affect their performance is the presence of motion artifacts in the captured physiological signals. Specifically, workers performing construction tasks in the field environment often engage in a lot of movement, which can result in the introduction of significant motion artifacts during the capture of their physiological signals. According to the investigation (Han et al. 2007), motion artifacts will distort the patterns (amplitude or shape) of the captured signals. This reduction in signal quality will further degrade the performance of health monitoring frameworks (Han et al. 2007), leading to inaccurate monitoring of workers' mental and physical health conditions. Therefore, it is necessary to develop a method to reduce motion artifacts in the collected physiological signals to improve the quality of the captured signals, thereby enhancing the performance of health monitoring frameworks in field environments.

This study, therefore, set out to enhance the performance of health monitoring frameworks by removing motion artifacts from the physiological signals. To this end, the authors developed a motion artifact removal method based on the least mean squares (LMS) adaptive filtering algorithms (Dixit and Nagaria 2017). The method recursively optimized the coefficients of the adaptive filter to minimize the error between physiological signals contaminated by motion artifacts and reference signals free from motion artifacts, enabling the filter to eliminate motion artifacts from the physiological signals. The authors evaluated the performance of the method using physiological signals collected from twelve subjects while they performed material delivery construction tasks. The results demonstrated the capability of the developed filter to detect and remove motion artifacts from physiological signals, including EDA, PPG, and ST signals. With the development of this method, the quality of the physiological data can be improved, which can further enhance the performance of the health-monitoring frameworks in accurately assessing workers' health status. This study contributes to developing robust and efficient physiological-based health-monitoring frameworks for construction workers.

METHODOLOGY

The authors proposed an artifact removal method based on the least mean squares (LMS)-based adaptive filtering technique to remove motion artifacts from captured physiological (EDA, PPG, and ST) signals. As shown in Figure 1-a, the method first preprocessed the captured physiological signals using frequency-based methods, including a 0.5-5Hz bandpass filter for EDA and ST signals and a 22Hz lowpass filter for PPG signals, to eliminate high-frequency noise, including electromagnetic noise and power frequency interference (Jebelli et al. 2019; Shayesteh et al. 2023). Next, an adaptive filter was developed for each captured physiological signal to remove motion artifacts. The developed filter leveraged its coefficients, $\mathbf{h}(n)$, to recursively match the input signal, $\mathbf{I}(n)$, to the desired signal, $\mathbf{d}(n)$, that was free from motion artifacts. In each round of the matching process, the developed method calculated an error signal, $e(n)$, between the desired signal and the physiological signal filtered by the prior round (with the initial signal being $\mathbf{I}(n)$). Based on the $e(n)$, the proposed method adjusted the filter coefficients to reduce the error. Correspondingly, the adjusted coefficients were used for the next round of matching. Once the error was minimized, the method generated the final output, which was the physiological signal with minimal motion artifacts. Figure 1-b outlines the pseudo-code and the corresponding equations for the developed adaptive filtering method.

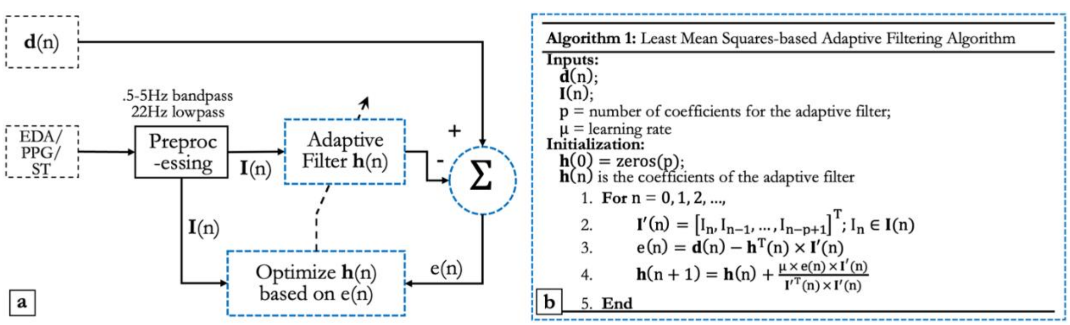

Figure 1. Details for the developed LMS-based adaptive filtering algorithm.

As outlined in Figure 1-b, the inputs of the developed adaptive filtering method are $\mathbf{d}(n)$, $\mathbf{I}(n)$, the filter order p, and the learning rate μ. p determines the number of coefficients in the developed adaptive filter ($\mathbf{h}(n) = \text{zeros}(p)$), while μ controls the rate at which the filter optimizes its coefficients to produce an optimal filter. At each iteration ($n = 0,1,2, \dots$), the method first determined the appropriate window size based on the value of p and used it to select a segment of the input signal ($\mathbf{I}'(n) = [I_n, I_{n-1}, \dots, I_{n-p+1}]$) to remove the motion artifacts in it. Next, the error signal, $e(n)$, between the desired signal and $\mathbf{I}'(n)$ was calculated using the equation shown in Line 3. The filter coefficients, $\mathbf{h}(n)$, were then updated based on $e(n)$ and the learning rate μ (Line 4). Notably, to optimize the filter coefficients, the previous LMS-based adaptive filtering method used the equation: $\mathbf{h}(n+1) = \mathbf{h}(n) + \mu \times e(n) \times \mathbf{I}'(n)$. Investigations showed that this equation was sensitive to the amplitude of its input $\mathbf{I}(n)$, making it difficult to determine the optimal learning rate μ (Rahman et al. 2011). To address this issue, the authors used a new equation shown in Line 4 to update the filter coefficients at each iteration. Compared to the previous methods, this new equation normalized the update rule in the adaptive filtering method, which could lead to a more efficient determination of the learning rate and a faster convergence rate (Ojha et al. 2023; Rahman et al. 2011). By following the steps outlined in Figure 1-b, the developed adaptive filtering method is expected to detect and remove the motion artifacts from the physiological signals. In the next section, the authors will describe the dataset to evaluate the performance of the developed method.

CASE STUDY

To assess the effectiveness of the proposed motion artifact removal method, the authors conducted a case study. During the case study, subjects were asked to perform a construction task, while the authors collected their physiological signals, including PPG, EDA, and ST signals. Then, the proposed filter was applied to the collected signals. The filtered signals were used to evaluate the proportion of motion artifacts eliminated by the filter from the collected signals.

Twelve subjects, consisting of nine male and three female subjects, were recruited for the case study. The mean age, weight, and height of the subjects were 24.3 years, 159 pounds, and 5' 9", respectively. Prior to the data collection, all subjects were screened to ensure that they were in good physical and mental condition, and none of them had been working night shifts (Liu et al. 2021b). During the data collection, each subject was asked to perform 15 rounds of a common construction task, the material delivery task. In each round, the subject picked up a 10-pound bag of cement from the material unloading area, delivered it to the material staging area, and then returned to the unloading area for the next round. The entire task lasted for around 10 minutes for each subject. Figure 2-a depicts several images of the task as mentioned above.

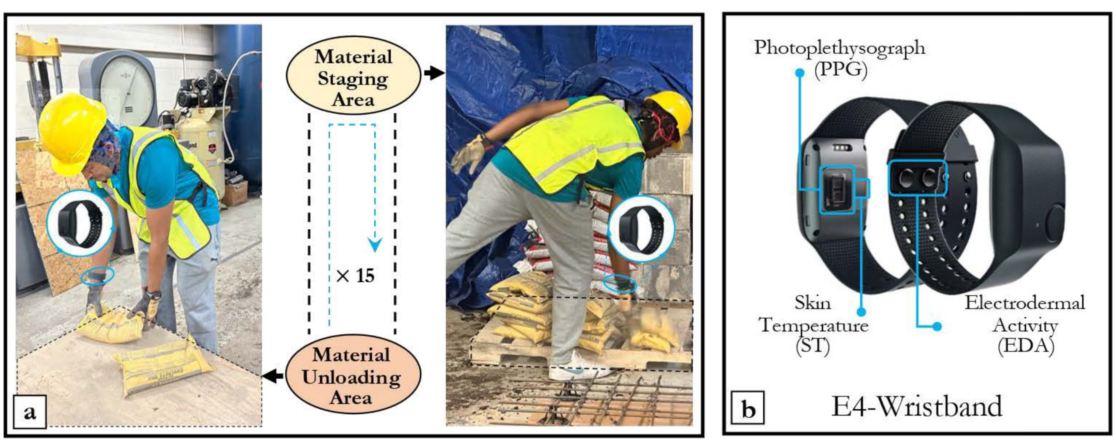

Figure 2. The material delivery task for capturing physiological signals from subjects.

To capture the physiological signals of the subjects during the task, the authors employed the E4 wristband, a wristband-type biosensor (Figure 2-b) (Jebelli and Choi 2018). Throughout the

15-round material delivery task, the subjects were required to wear the E4 wristband. The E4 wristband collected EDA, PPG, and ST physiological signals from subjects, with a sampling rate of 4Hz, 64Hz, and 4Hz, respectively. As mentioned, the data collection process for each subject lasted around 10 minutes. In addition, before starting the first round of the task, each subject was asked to stand in a stationary condition for 10 minutes. This stationary condition was used to collect the artifact-free reference signals from subjects, which were subsequently used as desired signals to enable the proposed adaptive filter to remove the motion artifacts from captured physiological signals (Gao et al. 2010).

Once the physiological signals were collected from all twelve subjects during the 15-round material delivery task, the authors generated three separate datasets based on the type of physiological signals: $\mathrm{Dateset_{EDA}}$, $\mathrm{Dateset_{PPG}}$, and $\mathrm{Dateset_{ST}}$. The details of each dataset are shown in Table 1. The reference signals captured from 12 subjects before the task were used to generate $\mathrm{R_{EDA}}$, $\mathrm{R_{PPG}}$, and $\mathrm{R_{ST}}$ desired signals for each dataset, respectively. Relying on $\mathrm{R_{EDA}}$, $\mathrm{R_{PPG}}$, and $\mathrm{R_{ST}}$, in this study, the authors applied the proposed adaptive filtering method to each dataset to eliminate the motion artifacts (see METHODOLOGY section). The corresponding filtered datasets were regarded as $\mathrm{Filtered_{EDA}}$, $\mathrm{Filtered_{PPG}}$, and $\mathrm{Filtered_{ST}}$. By comparing the proportion of the motion artifacts in the collected and filtered dataset, the performance of the proposed method in motion artifact removal was evaluated. The results of this evaluation will be reported in the next section.

Table 1. Specifications of the collected datasets.

	No. of subjects	Sampling rate	Collected data points
$\mathrm{Dateset_{EDA}}$	12	4Hz	29,818
$\mathrm{Dateset_{PPG}}$	12	64Hz	466,808
$\mathrm{Dateset_{ST}}$	12	4Hz	29,818

RESULTS AND DISCUSSION

To evaluate the performance of the proposed method in reducing motion artifacts, the authors applied two widely accepted metrics, mean square error (MSE) and signal-to-noise ratio (SNR). The MSE metric measures the amount of noise present in the signal; the SNR gauges the ratio of the power of the signal to the power of the motion artifacts. Lower MSE values indicate better artifact removal performance, while higher SNR values mean better artifact removal performance. Details on calculating MSE and SNR can be found in (Liu et al. 2020). Table 2 summarizes the results of the proposed adaptive filtering method in removing motion artifacts. Specifically, the denoised PPG signal ($\mathrm{Filtered_{PPG}}$) had an MSE that was 59.3% lower than the collected PPG signal ($\mathrm{Dateset_{PPG}}$), while the SNR value of the denoised PPG signal increased by 85.2% compared to the collected signal. The denoised EDA signals ($\mathrm{Filtered_{EDA}}$) showed similar improvements, with a 69.4% reduction in MSE value and a 47.6% increase in SNR value compared to the collected EDA signals ($\mathrm{Dataset_{EDA}}$). For the ST signals, the proposed method enhanced the MSE value of the denoised signal ($\mathrm{Filtered_{ST}}$) by 57.1% and the corresponding SNR value by 22.0% when compared to the collected signal ($\mathrm{Dateset_{ST}}$). All these improvements demonstrated that the proposed method could efficiently detect and remove motion artifacts from physiological signals. In addition, Figure 3 visualizes the performances of the proposed method in removing motion artifacts from EDA, PPG, and ST signals. The red line represents the collected physiological signal with motion artifacts; the blue line indicates the reference signal free from motion artifacts, and the green line shows the physiological signal filtered using the proposed method. This figure provides clear evidence of the effectiveness of the proposed method in removing motion artifacts from physiological signals.

Table 2. MSE and SNR values of the collected ($\mathrm{Dataset}_i$) and denoised signals ($\mathrm{Filtered}_i$).

	MSE ($unit^2$) of			*SNR (dB) of*		
	i = EDA	i = PPG	i = ST	i = EDA	i = PPG	i = ST
$\mathrm{Dataset}_i$	8.47	213.28	1.89	5.35	3.05	10.13
$\mathrm{Filtered}_i$	2.59	86.71	0.81	7.9	5.65	12.36

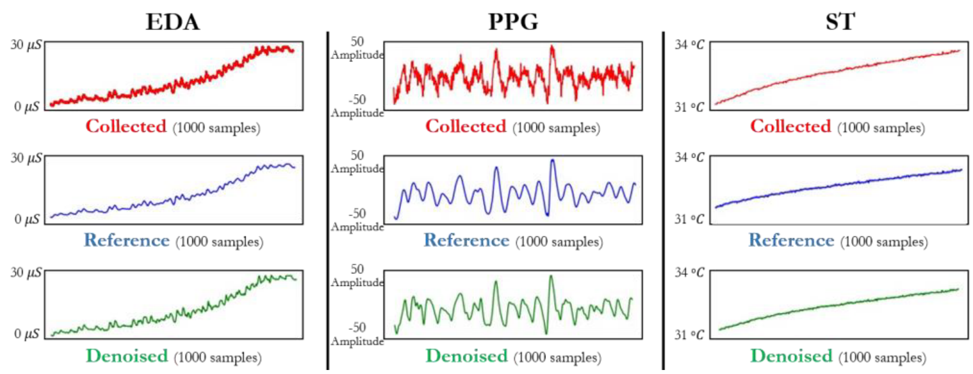

Figure 3. Performance of the proposed method in removing motion artifacts.

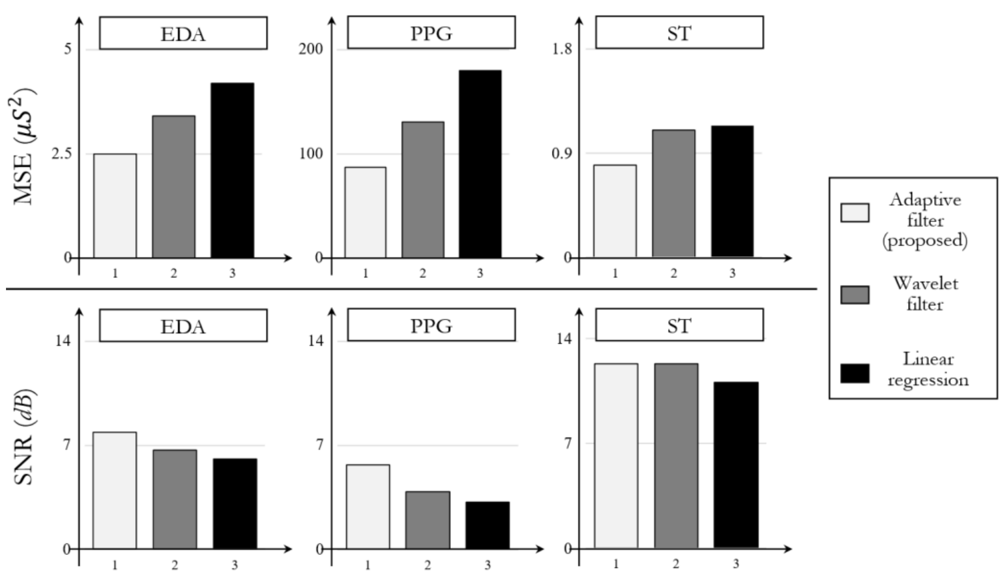

Figure 4. Performance comparison of the proposed and competing methods in eliminating motion artifacts from EDA, PPG, and ST physiological signals.

To further assess the effectiveness of the proposed method, the authors compared its performance with several competing methods, including linear regression (Patel et al. 2014) and wavelet filtering methods (Chen et al. 2015). All selected methods have demonstrated the capability of removing motion artifacts from physiological signals (Chen et al. 2015). The authors applied each of these methods to the $\mathrm{Dateset}_{\mathrm{EDA}}$, $\mathrm{Dateset}_{\mathrm{PPG}}$, and $\mathrm{Dateset}_{\mathrm{ST}}$ for motion artifact removal. Similarly, the metrics used to evaluate the performance of artifact removal were SNR and MSE. Figure 4 shows the comparison results between the proposed and competing methods. According to the MSE measurement, the proposed adaptive filtering method outperformed all competing methods in removing motion artifacts from the three types of physiological signals. Particularly for the PPG signal, the MSE value demonstrated the greatest improvement (33.7%) when comparing the proposed method with the second-best method (wavelet filter). Based on the SNR measurement, the proposed method also presented a competitive performance with other methods. For instance, for the EDA signal, the SNR value of the proposed method was 29.5% higher than that of the linear regression method, and 17.9% higher than that of the wavelet filter. Overall, the comparison with competing methods demonstrated that the proposed method has the potential to improve the quality of physiological signals by effectively removing motion artifacts.

CONCLUSION

The objective of this study was to improve the quality of physiological signals captured from workers to enhance the performance of monitoring workers' health conditions, including physical fatigue and mental stress. To accomplish this goal, the authors developed a motion artifact removal method based on LMS-based adaptive filtering algorithms. This method is capable of iteratively and continuously detecting and removing motion artifacts from physiological signals, including EDA, PPG, and ST signals. The authors further designed a material delivery task to collect physiological signals from twelve subjects performing tasks and accordingly examine the feasibility of the proposed method. The results confirmed that the proposed method could effectively remove the motion artifacts from the EDA, PPG, and ST physiological signals. Furthermore, the proposed method proved to be more effective in detecting and reducing motion artifacts when compared to other competing methods, such as wavelet filtering and linear regression methods. In sum, this study can contribute to improving the quality of data collection for the physiological signals in the construction field. In the future, the authors suggest investigating the application of this method to remove other artifacts in physiological signals, including muscle movement and respiratory artifacts. Future research can also integrate the proposed method with physiological data-driven health monitoring frameworks to continuously capture workers' high-quality physiological signals and monitor workers' health conditions during construction tasks. This integration has the potential to enable enhanced assessment of workers' health status and facilitate early detection of abnormalities, enabling prompt interventions to prevent potential work-related injuries and illnesses.

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