

Autoencoder-Based Motion Artifact Reduction in Photoplethysmography (PPG) Signals Acquired from Wearable Sensors during Construction Tasks

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ABSTRACT

Construction workers often experience high levels of physical and mental stress due to the demanding nature of their work on construction sites. Real-time health monitoring can provide an effective means of detecting these stressors. Previous research in this field has demonstrated the potential of photoplethysmography (PPG), which represents cardiac activities, as a biomarker for assessing various stressors, including physical fatigue, mental stress, and heat stress. However, PPG acquisition during construction tasks is subject to several external noises, of which motion artifact is a major one. To address this, the study develops and examines an autoencoder network—a special type of artificial neural network—to remove PPG signals' motion artifacts during construction tasks, thereby enhancing the accuracy of health assessments. Artifact-free PPG signals are acquired through subjects in a stationary position, which is used as the reference for training the autoencoder network. The network's performance is examined with PPG signals acquired from the same subjects performing multiple construction tasks. The developed autoencoder network can increase the signal-to-noise ratio (SNR) by up to 33% for the corrupted signals acquired in a construction setting. This research contributes to the extensive and resilient use of PPG signals in health monitoring for construction workers.

INTRODUCTION

The construction industry is currently facing a multitude of challenges that affect the physical and mental well-being of its workers. According to the Bureau of Labor Statistics, 36% of all occupational heat-related deaths in the US occurred in the construction industry, which uses 6% of the country's total workforce, making it the sector with the highest rate of fatalities (Dong et al. 2019). Apart from frequent accidents, chronic fatigue and tiredness are significant concerns. In the United States, 40% of the construction workforce experiences severe fatigue at some point during the day (Pablo Ruiz Padillo et al. 2022). Added to the physical health complexities, construction workers are also among the most prone to mental problems. A recent study found that construction workers are more likely to engage in behaviors that contribute to a higher risk of health complications, such as substance abuse, lack of sleep, and poor safety practices (Boal et al. 2020). The ability to detect stressors or signs of problems can help alleviate these problems in the industry, which demands a robust health monitoring system for real-time health monitoring of construction workers.

Health monitoring has evolved to encompass a range of methods, with environmental-based, survey-based, and physiological methods being among the frequently employed approaches. Environmental-based methods access various environmental parameters like temperature,

humidity, etc., to assess the worker's health status. This process undermines individual physiological differences and differences in activities that can be performed under the same environmental conditions, and such massive generalizations may not be able to yield accurate estimations. On the other hand, survey methods are intrusive and, thus, cannot be used for continuous assessment and are prone to bias (Ojha et al. 2023a). The physiological method measures and monitors various available metrics like temperature, heart rate, cortisol level, electrodermal responses, etc., for accessing multiple stressors in the body and making corresponding assessments. The remarkable progress made in the microchip industry during the past few decades has led to the miniaturization of physiological devices into wearable forms, facilitating the implementation of wearable physiological health monitoring.

Wearable physiological devices can provide real-time health monitoring for construction workers in a non-invasive and continuous frequency. Real-time detection of various stressors relating to physical and mental fatigue/stress from multiple wearable sensors can help inform better decisions regarding health in real time, which can thus prevent severe fatalities and related health problems (Hwang and Lee 2017). The literature has explored several wearable devices for capturing electrocardiogram (ECG), photoplethysmography (PPG), and electromyography (EMG) signals for construction health monitoring (Ojha et al. 2023b; Shakerian et al. 2021). PPG devices, which detect blood volume changes in the microvascular bed of tissue, have the advantage of compact size, ease of use, and ability to offer vital insights into cardiopulmonary activities.

PPG represents information regarding cardiac activities such as blood pressure, oxygen saturation (SpO_2), and pulse rate, providing access to various stressors like physical fatigue, mental fatigue, and heat stress. Real-time access to this information can assist in determining the different physical and mental health statuses of the given construction worker, making it an attractive technology for real-time health monitoring. Despite the multiple advantages, wearable PPG signals are prone to several artifacts, and much research has been performed to tackle them. However, motion artifact (MA) remains one of the significant challenges for obtaining a reliable PPG signal. One of the reasons is the frequency overlap of MA, and PPG signals over a broader range, making it challenging to filter the MA from the PPG signals (Park et al. 2022). Moreover, the dynamic nature of construction activities requires frequent motion of construction workers, making motion artifacts a more dominant problem for PPG usage in the construction industry. Such artifacts can cause significant loss and modification of the information, which cannot create a reliable health monitoring assessment. Thus, there is a need for the development of a dedicated MA removal method for PPG signals based on the construction industry for robust wearable physiological health monitoring of construction workers.

To bridge the gap, the study develops an autoencoder network for motion artifact removal from the PPG signals acquired in a construction setting. An autoencoder is a type of artificial neural network that learns to encode the input data into a lower-dimensional representation and then decode it back to the original data. In this research, a deep autoencoder network is designed, trained, and tested for MA removal from PPG signals. The network utilizes MA-corrupted PPG signals as input to reconstruct MA-reduced signals. A case study is conducted to validate the developed network for construction workers. The results show that the developed network, when tested on data from the construction environment, provided up to a 33% increase in signal-to-noise ratio (SNR) over the MA-corrupted signals. This study contributes to the existing body of knowledge by proposing a dedicated method for reducing motion artifacts in PPG signals, specifically tailored for the construction industry.

PHOTOPLETHYSMOGRAPHY FOR HEALTH MONITORING OF CONSTRUCTION WORKERS

Photoplethysmography is a non-invasive technique based on hemoglobin's absorption of light that measures changes in blood volume in tissue represented as blood volume pulse (BVP) (Alian and Shelley 2014). PPG signals are frequently obtained from the fingertip, earlobe, or wrist. They have been employed for a variety of medical applications, including the assessment of blood oxygen saturation (SpO_2), heart rates, and other derivatives such as pulse rate, heart rate variability, and pulse pressure. Because of this vital access to various cardio-pulmonary metrics, it has been frequently used for cardiovascular monitoring.

The author's previous study has explored the usage of PPG for accessing construction workers' physical and mental status and verified its feasibility (Jebelli et al. 2018). There have been other studies in construction settings; for instance, Ojha et al. investigated the usage of PPG to analyze dehydration in construction workers (Ojha et al. 2020). Although the use of PPG for monitoring the health of construction workers has been validated using various methods, the wide-scale adaptation is still lagging.

PPG SIGNAL DENOISING AND ARTIFACT REMOVAL FOR ENHANCED HEALTH MONITORING IN CONSTRUCTION WORKERS

One of the challenges for the extensive use of PPG for health monitoring is separating the physiological information from noise and artifacts. Because of the overlapping of MA frequency and PPG signal frequency, MA removal remains one of the significant barriers (Couceiro et al. 2014), affecting the measurement's accuracy and reliability.

Wavelet transform-based techniques have been widely used for motion artifact removal in PPG signals. These techniques use the wavelet transform to decompose the PPG signal into different frequency bands and remove the artifact by selectively reconstructing the signal from the high-frequency sub-bands. Some popular wavelet-based methods for artifact removal in the PPG signals used in the literature include discrete wavelet transform (DWT) (Joseph et al. 2014), stationary wavelet transform (SWT) (Lee and Zhang 2003), and dual-tree complex wavelet transform (DT-CWT) (Raghuram et al. 2012). Wavelet transform-based methods may introduce phase distortion, which can cause a loss of information (Goh et al. 2020).

The other common approach is leveraging IMU or accelerometers to reference the motion and then reconstructing the PPG signals with the corresponding motion information (Asada et al. 2004; Lee et al. 2019; Wood and Asada 2006). This approach requires extra hardware, calibration, and synchronization between the two devices. Moreover, motion artifacts in the PPG signal and accelerometer data do not strongly correlate as well (Yousefi et al. 2012).

Deep learning has emerged as a powerful signal processing and denoising application tool. In recent years, various deep learning models have been proposed and applied in denoising signals, including audio (Purwins et al. 2019), and biomedical signals (Tobore et al. 2019). Autoencoder has been a popular deep-learning network for denoising images, and works have also been extended to signals (Saad and Chen 2020). There have also been some similar investigations on physiological signals as well. For instance, Leite et al. proposed a deep denoising autoencoder (DDAE) for removing noise from electroencephalography signals (Leite et al. 2019). Machine learning methods thus have been able to achieve better performance compared with traditional signal processing and hardware-based methods mentioned earlier.

While prior research has indeed demonstrated the effectiveness of machine learning (ML) models in reducing noise from various physiological signals, the potential of modern machine learning algorithms in denoising PPG signals remains relatively unexplored. This gap in the literature is even more pronounced when it comes to the context of the construction industry. Addressing these gaps, this study introduces a novel approach. It focuses on the design, development, and validation of an autoencoder network tailored to removing motion artifacts (MA) from PPG signals, particularly within the challenging construction environment. An autoencoder is a specialized neural network that learns to extract essential features from input data, effectively enabling the separation of valuable information from unwanted noise.

Through the development of this specialized autoencoder network, our study not only addresses the existing research gap but also unlocks opportunities for the extensive application of PPG signals in monitoring the real-time health of construction workers. By incorporating sophisticated machine learning methods like autoencoders, there is potential for substantial improvements in signal accuracy and dependability. Consequently, this advancement can make notable contributions to the overall well-being and safety of individuals employed in the construction industry.

METHODOLOGY

The study is carried out in two phases. In the first phase, data acquisition is performed for subjects in a controlled construction setting with prespecified construction tasks for a predetermined time frame. Through the experiment, motion artifact-free reference signals and motion artifact corrupted signals are acquired for the study. This phase is explained in more detail in the next section. In the second phase, reference PPG signals acquired during the stationary phase are used to train an autoencoder network that learns to reconstruct the MA-free PPG signal as the output of the network. For testing the performance of the trained network, unseen data acquired from multiple subjects performing various construction tasks is leveraged. The second phase is explained in more detail in the following subsection.

Network architecture and training. The autoencoder network comprises two parts, an encoder and a decoder connected by an embedding layer, as shown in Figure 1. The encoder and decoder networks are based on a Dense layer with opposite sequences and an embedding unit to transit between the encoder and decoder. The encoder uses blood volume pulse (BVP) signals acquired through photoplethysmography as input to transit to the embedding vectors. The encoder layer encodes the BVP input vector to a double unit embedding vector using the W_j matrix, passing through two sets of hidden dense layers, both activated by the sigmoid functions. Based on the information in the embedding vector, the decoder layers decode the embeddings to the output vector representing the regenerated BVP signals. In the decoder, the W_k matrix transforms the embeddings to the final size, combining two hidden dense layers activated by the sigmoid function. Equations 1, 2, and 3 present the computation in encoding, decoding, and sigmoid functions, respectively.

$$y_j = \sigma(W_j * X + b) \quad (1)$$

$$X^* = \sigma(W_k * Y + b_1) \quad (2)$$

$$\sigma(x) = \frac{e^x}{1+e^x} \quad (3)$$

Here, $X, W_j, W_k, Y, X^*, \sigma$, and b represent input signals, encoding weights, decoding weights, embeddings, autoencoder output (regenerated signal), sigmoid function, and bias vector respectively. The input(X^*) and output(X^*) data for the network consist of time series data points representing BVP data obtained from photoplethysmography with a window size of two seconds. Window size defines the length of a segment, encompassing a specific number of sequential time steps, used as input for processing in the autoencoder network. For the training process, the mean absolute error is used as the loss function $\mathcal{L}(\theta)$ (Equation 4). During each iteration of the training process, the weights $\{\theta \in W, b\}$ are updated to minimize the given loss function $\mathcal{L}(\theta)$ as given by Equation 5 based on Adam optimizer with a learning rate of 0.0001. The autoencoder network is designed and developed using Keras API with TensorFlow backend.

$$\mathcal{L}(\theta) = \frac{1}{n} * \sum_{i=1}^N |X_i^* - X_i| \quad (4)$$

$$\theta^* = \operatorname{argmin}_{\theta} \mathcal{L}(\theta) \quad (5)$$

The reference signals acquired during the stationary phase are leveraged for training the autoencoder network. The reference signal is used as both input (X) and output (X^*), enabling the network to learn the general structure of the uncorrupted signals. Additionally, the reference signals are corrupted with the Gaussian noise and then used as an input (X) with the reference signals as output (X^*). This second set trains the network to reconstruct the BVP signals in the presence of artifacts. A sample result of denoised signals from the developed autoencoder network is presented in Figure 2.

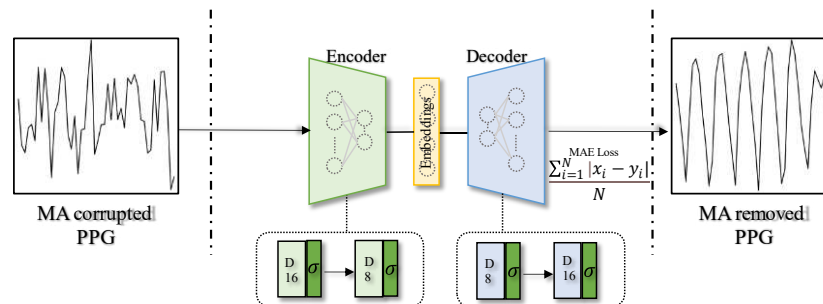


Figure 1. Architecture of the developed autoencoder network for artifact reduction.

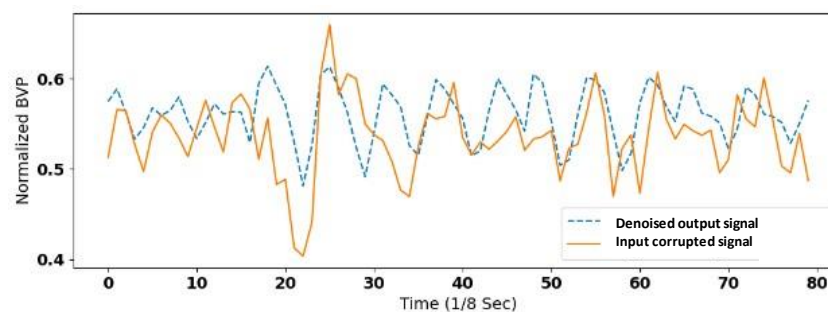


Figure 2. A sample of MA removed output signal reconstructed by the autoencoder network compared with the corrupted signal acquired during the rebar tying task.

For testing purposes, data collected from various construction tasks, namely rebar tying, low-intensity material handling, and high-intensity material handling (explained in more detail in the next section), are used to assess the autoencoder networks' performance and compare it with other competing methods. All the comparisons are evaluated against signal-to-noise ratios (SNR) presented in the analysis and results section.

EXPERIMENT AND DATASET DESCRIPTION

This section explains the experiments performed for validating the study. An off-the-shelf wristband biosensor was used to obtain PPG signals from the less dominant wrist of the subject ("E4 wristband"). In total, 7 subjects were employed for the study, where data acquired during the stationary phase is used as training data and data acquired during the specific construction task is used for testing. The construction tasks performed for the experiment are illustrated in Figure 3.

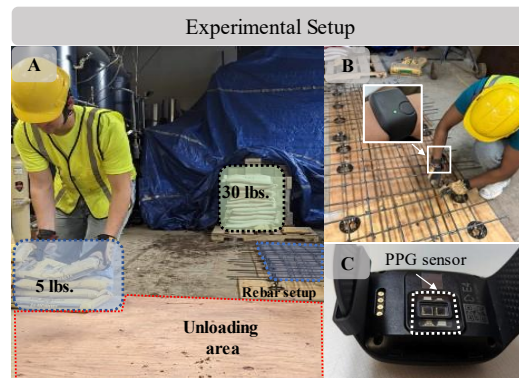


Figure 3. Experimental setup for material handling and rebar tying; 3A: Material handling-task with an overview of the experimental location; 3B: Subject performing rebar tying task with wristband bounded in a white box; 3C: PPG sensor with light emitting diode (LED) and photodetectors (PD) bounded in the white dashed box.

For the first task, the subjects tie up rebars set up in an area of 1.21m by 0.6m for a total of 480 seconds with 120 seconds break after the first 180 seconds. 30 rebars of 0.5 inches in diameter with a length of 4 feet are put in a cross position, and the subjects tie up the rebar with tie wire using a manual wire twister. The average number of knots during the study was 5 knots per 60 seconds. The second task is to perform a loading-unloading of a 2.3 Kg (5 lbs.) bag to 6 meters. This task is performed for a total of 480 seconds with 120 seconds break after the first 180 seconds. During the tasks, the subjects transport an average of 1 bag per 15 seconds. For the third task, the same structure as that of task 2 is used but with a bag weight of 13.6 Kg (30 lbs.). During this task, the subject transported the bags at an average rate of 1 bag per 22 seconds. The activities are summarized in Table 1.

RESULTS AND DISCUSSION

To assess the effectiveness of the proposed approach in mitigating motion artifacts, the authors employed the signal-to-noise ratio (SNR) metric, as established in (Gonzalez-Moreno et

al. 2014). SNR quantifies the relationship between the signal power and motion artifact power. A higher SNR value indicates superior performance in removing artifacts. The autoencoder network was evaluated independently for distinct construction tasks, and outcomes are summarized in Table 2.

Table 1. Summary of the construction task performed for the data acquisition.

S.no.	Activity	Number of Subjects	Duration (S)
1	Rebar tying	7	480
2	Low-intensity material handling	7	480
3	High-intensity material handling	7	480

Table 2. Task-wise SNR value comparison for the autoencoder network

Tasks	Initial SNR	Final SNR	% Change
Rebar tying	16.2	23.33	44%
Low-intensity material handling	31.08	32.77	5%
High-intensity material handling	15.15	23.00	52%
Overall	16.12	21.43	33%

Table 2 presents the computation of initial and final SNR values for unprocessed and denoised PPG signals acquired during the construction task. Notably, a substantial increase in SNR values was observed for the high-intensity material handling and rebar tying tasks, both of which had initially lower SNR values. Conversely, the low-intensity material handling task, with a comparatively higher initial SNR value, exhibited only marginal enhancement after denoising. Particularly, the SNR improvement was remarkable for the high-intensity material handling task, showing a gain of over 52%, whereas the low-intensity material handling task demonstrated a modest 5% enhancement.

In order to comprehensively evaluate the proposed method's efficacy, a comparative analysis was conducted against alternative techniques, including the wavelet decomposition method and interval-dependent denoising method (Chen et al. 2015; Joseph et al. 2014). Each method was independently applied to the PPG dataset, and SNR served as the metric for comparison. The obtained results are detailed in Table 3.

Table 3. Comparison of the proposed autoencoder with other denoising methods

Name	SNR	% change
Unprocessed Signal	16.12	-
Wavelet Decomposition Method	17.70	10%
Interval Dependent Denoising	18.94	17%
Proposed Network	21.43	33%

The autoencoder model exhibits superior performance compared to the competing methods, achieving a remarkable up to 33% enhancement in the SNR value of motion artifact-corrupted signals. The wavelet decomposition method yields a 10% improvement, while interval-dependent denoising algorithms yield a 17% improvement. Impressively, the proposed

autoencoder network surpasses even the best-performing alternative, Interval Dependent Denoising, with a 13% higher SNR value. In essence, the comparative analysis underscores the potential of the proposed method to significantly enhance the quality of physiological signals by proficiently eliminating motion artifacts.

CONCLUSION

The study introduces an autoencoder-based approach to tackle motion artifacts in PPG signals, particularly designed for construction environments. It focuses on reconstructing motion-affected PPG signals, yielding clearer output. The method's effectiveness was evaluated through diverse experiments involving individuals in construction tasks. The findings have valuable implications for bolstering the reliability of PPG signals in monitoring construction workers' health. The developed model could be integrated into existing health monitoring systems utilizing PPG signals for further validation and framework advancement. While the study employs a simple autoencoder model with a compact size, future research could delve into more advanced architectures and hyperparameter tuning, especially when working with larger training datasets. Another limitation emerges in real-time deployment due to recorded data usage. To address this, future work could extend the approach to real-time operation and optimize model size and inference time for portable devices like mobiles and microcontrollers. In essence, the proposed network holds the potential to revolutionize health monitoring at construction sites, ensuring dependable and precise utilization of PPG signals.

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