Anwer et al., (2024) Evaluation of data processing and artifact removal approaches used for physiological signals captured using wearable sensing devices during construction tasks: A State-of-the-Art Review. Journal of Construction Engineering and Management. (**Accepted**)

Title

Evaluation of data processing and artifact removal approaches used for physiological signals captured using wearable sensing devices during construction tasks: A State-of-the-Art Review

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Abstract

Wearable sensing devices (WSDs) have enormous promise for monitoring construction worker safety. They can track workers and send safety-related information in real-time, allowing for more effective and preventative decision-making. WSDs are particularly useful on construction sites since they can track workers' health, safety, and activity levels, among other metrics that could help optimize their daily tasks. WSDs may also assist workers in recognizing health-related safety risks (such as physical fatigue) and taking appropriate action to mitigate them. The data produced by these WSDs, however, is highly noisy and contaminated with artifacts that could have been introduced by the surroundings, the experimental apparatus, or the subject's physiological state. These artifacts are very strong and frequently found during field experiments. So, when there is a lot of artifacts, the signal quality drops. Recently, artifacts removal has been greatly enhanced by developments in signal processing, which has vastly enhanced the performance. Thus, the proposed review aimed to provide an in-depth analysis of the approaches currently used to analyze data and remove artifacts from physiological signals obtained via WSDs during construction-related tasks. First, this study provides an overview of the physiological signals that are likely to be recorded from construction workers to monitor their health and safety. Second, this review identifies the most prevalent artifacts that have the most detrimental effect on the utility of the signals. Third, a comprehensive review of existing artifact-removal approaches were presented. Fourth, each identified artifact detection and removal appraoches was analyzed for its strengths and weaknesses. Finally, in conclusion, this review provides a few suggestions for future research for improving the quality of captured physiological signals for monitoring the health and safety of construction workers using artifact removal approaches.

Keywords: Artifact Eradication; Construction Health; Construction Safety; Digital Construction; Noise Removal; Physiological Signals; Sensing Devices

1. INTRODUCTION

Wearable sensing devices (WSDs) provide a great deal of potential for improving the safety of construction workers. They can monitor workers and transmit information concerning safety concerns in real time, which enables decision-making that is both more effective and more preemptive (Awolusi et al., 2018). WSDs are especially helpful on construction sites since they can monitor workers' health and safety as well as their activity levels, in addition to tracking a variety of other variables that could assist workers in optimizing their daily activities (Nath et al., 2018). WSDs may also aid workers in recognizing health-related safety hazards (such as physical fatigue) and implementing proper measures to mitigate those risks when required (Nnaji et al., 2021). However, the data that is produced by these WSDs is extremely noisy and cluttered with artifacts. These artifacts could have been introduced into the data by the subject's physiological state, the experimental apparatus, or the surroundings (Mayeli et al., 2021). These artifacts have a high degree of durability and are commonly discovered during field research. The quality of the signal will suffer whenever there are a significant number of artifacts.

Monitoring health and safety using wearables is now within reach (Antwi-Afari et al., 2021, 2022, 2023; Anwer et al., 2021a, 2021b, 2022; Ahn et al., 2019; Lee et al., 2017), but before this can be effectively implemented, continuous data collection from construction workers at construction sites and data analysis in real-time face several challenges (Ahn et al., 2019; Anwer et al., 2021b). Specifically, there is a lack of well-established technologies that can be used to identify how to evaluate the data quality of wearable signals as a basis for data selection at this stage. In construction studies that make use of wearables, one factor that is usually underreported, particularly in quantitative terms, is the quality of the raw data that is gathered by the wearable devices (Ahn et al., 2019; Anwer et al., 2021b). In addition, the quality of the data can be portrayed in a variety of different ways, and the measurements of data quality may vary depending on the objectives of the associated research and project (Bangaru et al., 2020; Pal et al., 2019; Kleckner et al., 2017; Villeneuve et al., 2016). In addition, the quality of the data is a crucial factor in determining the integrity and validity of the information (Bent et al., 2020; Goldsack et al., 2020; Munos et al., 2016). Monitoring physiological signals, in comparison to monitoring many other signals, calls for a high temporal resolution. This is because physiological signals, such as heart rate, might be as brief as a few seconds (Ghosh et al., 2015; Masood & Alghamdi, 2019; Niu et al., 2019). For this purpose, having knowledge of the artifacts and techniques used to evaluate data quality and generate data reliability ratings is essential for subsequent analysis and, consequently, for the reliability of the results (Böttcher et al., 2022; Bangaru et al., 2020). It is possible for artifacts to be unique to a single modality or to occur simultaneously across several different modalities (Nathan & Jafari, 2017; Chen et al., 2021). Because of this, it is important to take each modality into consideration, both singly and in combination, when evaluating the quality of the data.

The performance of artifact removal has recently been considerably improved due to recent advancements in signal processing, which have also greatly improved overall performance (Islam et al., 2016; Urigüen & Garcia-Zapirain, 2015; Sweeney et al., 2012). Therefore, the purpose of the proposed state-of-the-art review was to give an in-depth evaluation of the approaches that are currently utilized to evaluate data and remove artifacts from physiological measurements obtained by WSDs while performing tasks associated with construction. To begin, this paper offers a summary of the physiological signals that are likely to be recorded from construction workers in order to keep an eye on their well-being and ensure their safety. Second, this study indicates the types of artifacts that are the most common and that have the most deleterious effects on the quality of the signals. Third, a detailed analysis of the various artifact removal approaches currently in use was provided for consideration. Fourth, each artifact identification and removal approach that had been identified was evaluated in light of the construction industry to determine its pros and cons. In conclusion, this review presents a few suggestions for future research to improve the quality of collected physiological signals utilizing artifact removal approaches for the purpose of monitoring the health and safety of construction workers.

2. RESEARCH METHODOLOGY

The study approach can be divided into three primary stages, as outlined in **Figure 1**. The first step is to conduct a literature survey of previous published studies in the four electronic databases (e.g., Web of Science, IEEE Explorer, ASCE Library, and Scopus). These electronic databases were searched using a combination of keywords and their derivatives as follow: "Physiological signals" OR electrocardiogram OR "Heart rate" OR "Heart rate variability" OR Electrophysiology OR "data processing" AND artifacts OR Artefacts OR Noise OR "Motion artifact" OR "motion corrections" OR filtering OR cancellation OR filter OR "Artifact removal"

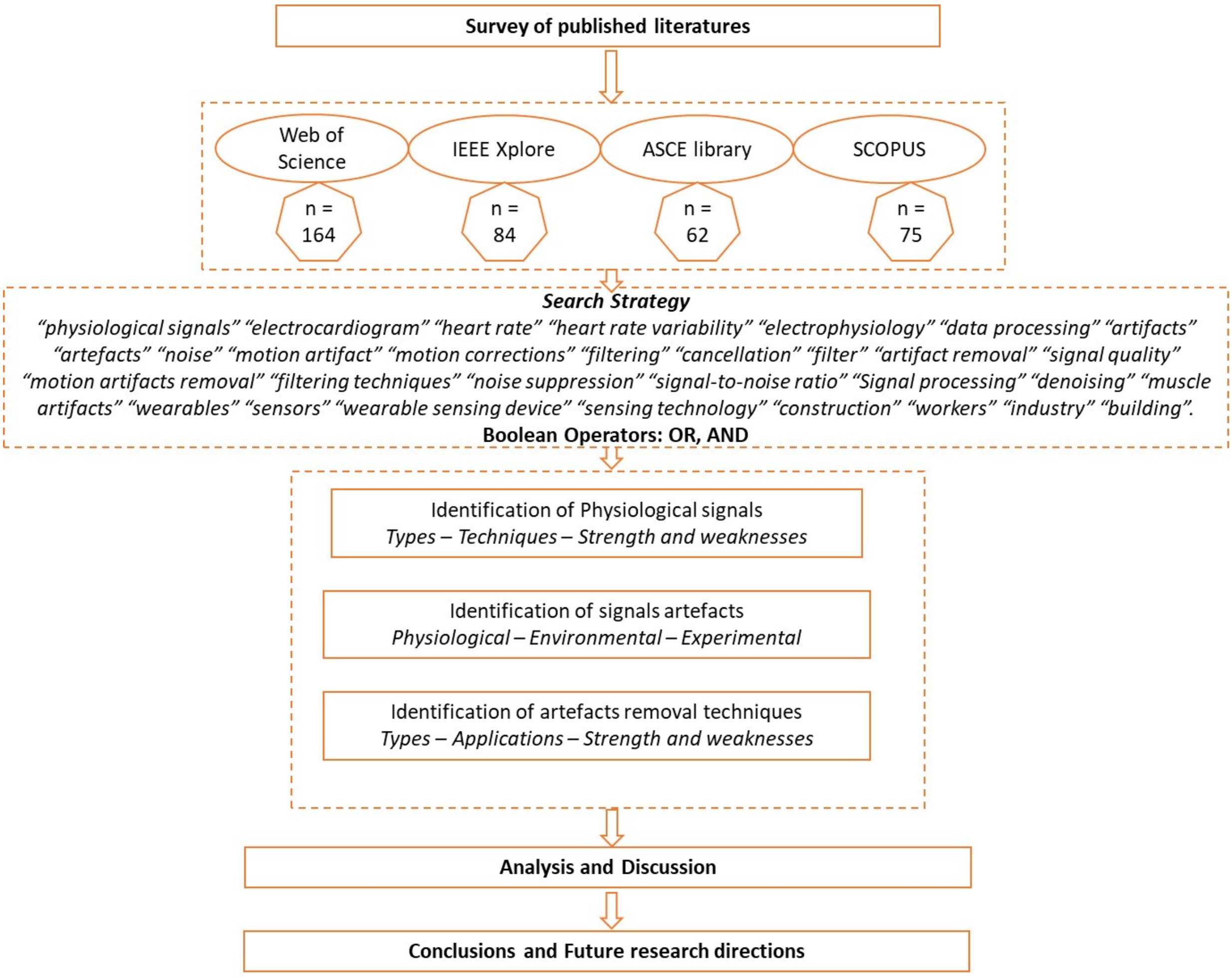

Fig. 1. Flow of adopted research methodology.

OR "signal quality" OR motion artifacts removal OR filtering techniques OR noise suppression OR signal-to-noise ratio OR Signal processing OR Denoising OR muscle artifacts AND Wearables OR sensors OR wearable sensing device OR sensing technology AND Construction OR workers OR Industry OR Building. With the results from the first search in hand, a second search was done, this time focusing on articles about health and safety in the construction industry and physiological monitoring. The authors evaluated the abstracts of each publication to ensure that their inclusion matched within the scope of this review. Only papers published in English have been included in this review. For the purpose of monitoring construction workers' health and safety, previous research has been searched through to discover a number of physiological signals that can be collected by employing WSDs. In addition, a literature review was conducted to determine the various artifacts that were obtained from physiological signals and the methods that were utilized to eliminate those artifacts. Challenges for the applications of artifacts removal approaches for real-time physiological monitoring in the construction industry were analyzed and discussed. There are a lot of high-impact research publications that have been examined, such as Automation in Construction, the Journal of Construction Engineering and Management, and the Journal of Civil Engineering and Management. In order to derive the suggestions and findings of the studies, a total of over **300** research papers—which were published between the years 2000 and 2023—were studied and examined. The second step of a research approach involves a discussion and analysis of the articles under consideration, and the third step consists of overall findings and recommendations for future study. Thus, the following methodology can be used as a template for analyzing studies that are comparable to the one being reviewed. One method used in research is content analysis, which involves examining the content of predetermined texts (Bengtsson, 2016; Assarroudi et al., 2018). However, content analysis has several drawbacks, including the fact that it can take a long time to complete, that information may be lost due to improper categorization, and that it may be biased (Grimmer & Stewart, 2013; Assarroudi et al., 2018). In situations where text mining techniques are computationally necessary, content analysis might be challenging to automate or computerize. As a result, content analysis has a higher margin of error. Content analysis' performance in text interpretation and analysis may suffer when dealing with complex texts. Therefore, to get a comprehensive qualitative perspective on the evaluation of data processing and artifact removal approaches for physiological signals acquired by WSDs, this study employed a narrative review strategy (Gregory & Denniss, 2018).

3. OVERVIEW OF PHYSIOLOGICAL SIGNALS

The human body emits a wide range of physiological signals that can be monitored to determine a person's health, including perspiration (Jia et al., 2013), core or skin temperature (Nyein et al., 2016), and electrical activity in the brain, heart, and muscles using techniques like electroencephalography (EEG), electrocardiography (ECG), and electromyography (EMG). An illustration of physiological signals and wearable sensing devices commonly used in the construction industry is given in **Figure 2**. EEG and ECG signals are regarded as fundamental physiological signals due to their capacity to predict wellbeing level in real time. The electrical activity of the heart produces an ECG, which is thought of as a nonstationary, non-linear time series signal (Han et al., 2017). The ECG is the most common signal used to check the health of the heart electrically. Capturing the electrical signal and rhythm of an ECG allows for the extraction of heart rate-like properties. ECG signals can be recorded either invasively or non-invasively by attaching a series of potentials to the human body. Monitoring and analysis of ECGs have several uses in many fields, including construction (Li, 2018).

Wearable devices can track ECG signals to calculate heart rate (HR) and stress levels by analyzing the cardiac waveform. In the construction industry, HR is the most popular physiological indicator of physical exertion (Abdelhamid and Everett 2002; Anwer et al. 2020; Chan et al. 2012; Gatti et al. 2014; Ueno et al. 2018; Wong et al. 2014). A greater HR was seen

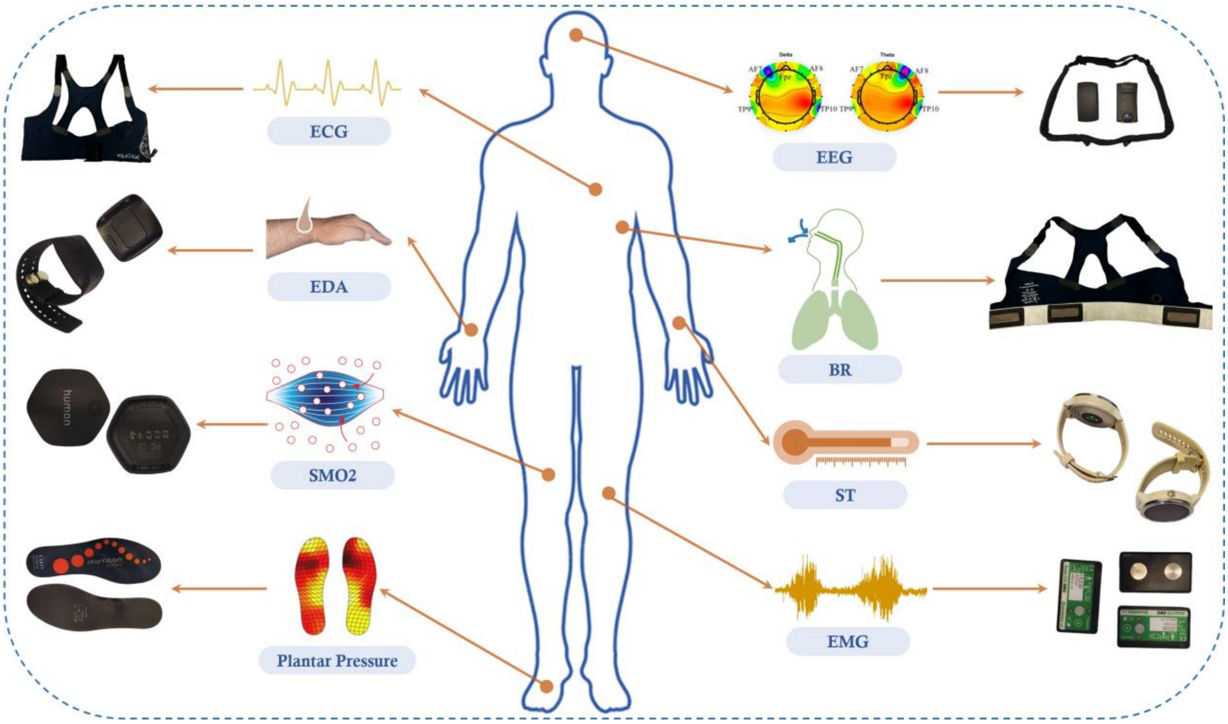

Fig. 2. Illustration of physiological signals and wearable sensors commonly used for construction health and safety. ECG = electrocardiogram; EEG = electroencephalogram; EMG = electromyogram; BR = breathing rate; EDA = electrodermal activity; ST = skin temperature; and SMO2 = muscle oxygenation.

when lifting and lowering from floor to floor compared to other lifting and lowering heights (Li et al. 2009). Similarly, Li et al. (2009) found that a lifting task performed twice per minute was associated with a higher HR than the same task performed once per minute. Furthermore, Anwer et al. (2020) found that HR significantly increased following a simulated fatigued task when compared to the HR scores at the beginning of the study. Recent studies have shown that incorporating multiple physiological signals in addition to HR can enhance fatigue prediction. Umer et al. (2020) used HR, thermoregulatory, and respiratory signals to predict 95% of physical fatigue levels in college students performing a simulated construction task. In a similar vein, Aryal et al. (2017) reported that a combination of HR and skin temperature data was more accurate in predicting physical fatigue than each individual statistic alone (59% vs. 72%). This research demonstrates the value of integrating multiple physiological signals for fatigue prediction.

Likewise, photoplethysmography (PPG) is an easy and inexpensive method of tracking vital signs like heart rate and breath rate. It is commonly used to take a reading from the skin's surface in a painless manner (Allen, 2007). PPG is an indirect technique of monitoring heart activity in contrast to ECG, and as a result, there is a time delay when using PPG to depict cardiac activity (Lu et al. 2009). PPG, on the other hand, only requires the use of a single optical sensor (an infrared emitter and detector), and the site at which the sensor is placed is more convenient (for example, the earlobe, the fingertip, or the wrist), both of which are advantages in comparison to ECG. Research and development in PPG have increased exponentially over the past few years due to advances in sensor technologies, methods for measuring physiological signals, cardiology, and numerous clinical applications.

EMG signals are frequently investigated for rehabilitation therapy due to their ability to electrically simulate the characteristics of muscle activity (McManus et al., 2020; Fang et al., 2020). Incorporating EMG sensors into devices for use in a variety of fields is now possible because of technological advancements in wearable devices. EMG sensors have been introduced for a wider range of applications due to the increase in wearable applications with highly customized aspects (Pourmohammadi & Maleki, 2020). One such application is physiological stress prediction through measuring trapezius muscle activation. The analysis of muscle movement is aided by feature extraction from EMG signals. In addition, previous studies have demonstrated that detecting the surface EMG activity of the target muscle while performing a variety of tasks is an effective way for continuously monitoring muscle fatigue (Cifrek et al. 2009). In the past, researchers have evaluated muscle fatigue in symptom-free college students and construction workers (such as masons) performing repetitive tasks by using surface EMG metrics (such as median frequency and root-mean square amplitude), such as median frequency and root-mean square amplitude (Anton et al. 2005; Calvin et al. 2016; McDonald et al. 2016; Yin et al. 2019).

Due to the emergence of developing technologies in various industries, wearable technologies have attracted a lot of attention in recent years as a way to improve workers' health and safety and their overall quality of life. EEG is one of the rapidly developing technologies in this group for assessing workers' mental and cognitive states in a variety of work settings (Zhang et al. 2019). Cortical neuronal electrical activity can be recorded using an EEG (Sanei & Chambers, 2013). As computing platforms and sensory technologies advance so too do EEG systems, which have become increasingly portable, lightweight, ultra-low power (Awolusi et al., 2018), wireless (Zhang et al., 2012), and affordable (Debener et al., 2012). Thus, there has been a rise in the use of portable and mobile EEG in a variety of settings (Ahn et al., 2019). Studies in the field of construction using EEG and mobile EEG to improve the built environment are known as neuro-architecture and neuro-urbanism (Banaei et al., 2015, 2017; Bower et al., 2019; Hekmatmanesh et al., 2019; Djebbara et al., 2020). Because of its low cost, great time precision, and portability, the EEG has proven to be an invaluable instrument in the field of construction research. EEG has the advantage that it may be used for both in-lab and on-site research in the construction sector (Banaei et al., 2015, 2017; Bower et al., 2019; Hekmatmanesh et al., 2019; Djebbara et al., 2020). Recently, a portable EEG headset became commercially available, allowing for the noninvasive recording of EEG data with a maximum of 20 electrodes and a sampling rate of 256 hertz. As a result of this adaptability, it may be possible to record people's brain activity as they are working in their natural environments. Consequently, a number of studies have recently attempted to enhance workers' comfort by tracking their feelings (Hwang et al. 2018, Jebelli et al. 2017), cognitive load (Chen et al. 2016, 2017), and psychological stress (Jebelli et al. 2018).

For in-vivo monitoring of tissue oxygenation, functional near-infrared spectroscopy (fNIRS) has recently been developed as an alternative brain imaging approach to EEG. With the help of infrared light of varying wavelengths and an estimate of the difference in optical absorption (Bunce et al., 2006), fNIRS can determine the concentration of hemoglobin (Hb) within the human brain (Sangani et al., 2015). Noninvasive brain function measurement (Huppert et al., 2009; Holper et al., 2010), identification of cognitive tasks (Izzetoglu et al., 2004; Cui et al., 2011), and brain-computer interface (Matthews et al., 2007; Khan & Hong, 2015) are the main areas of focus for fNIRS studies. The application of fNIRS in the identification of brain regions involved in the recognition of hazards suggests a neuropsychological foundation for judgment (Zhou et al., 2021). Their findings suggest that NIRS-based brain-computer interfaces could be of assistance in identifying and evaluating hazards in the building and construction sector (Zhou et al., 2021). Improvements in non-invasive fNIRS have allowed for the measurement of cortical surface oxygenation and blood flow from secondary circulation. Because of its higher mobility and temporal resolution, fNIRS is the best technique for measuring stress and anxiety in ecologically valid settings (also known as fieldwork) (Quaresima and Ferrari, 2019). Other key physiological signals, such as electrodermal activity (EDA) and skin temperature (ST), can also be monitored through the measurement of skin response (e.g., thermoregulatory measures). Previous research has shown that there are robust associations between thermoregulatory parameters and fatigue onset following heavy workloads, such as construction tasks (Aryal et al., 2017; Anwer et al., 2020). It is a standard procedure to employ infrared temperature sensors to track changes in skin temperature and other thermoregulatory functions as fatigue sets in. Skin temperatures in particular regions of the body (such as the face, ear, forehead, and temple) are affected by the underlying muscular activity, sweating patterns, and cutaneous blood flow in those regions (Formenti et al. 2017). Similarly, EDA is utilized for stress evaluation in the construction industry. EDA refers to the autonomic changes in the electrical characteristics of the skin caused by sweat secretion (Benedek and Kaernbach, 2010). Since perspiration is triggered solely by the sympathetic nervous system, EDA provides a valuable indicator of this system's activities (Kappeler-Setz et al. 2013, Poh et al. 2010). This means that EDA is not affected by parasympathetic nerve processes, unlike other autonomic physiological variables (Braithwaite et al., 2013; Picard et al., 2016). EDA has been used to better comprehend a person's mental and physical health under different conditions, such as in the workplace, during human-computer interactions, or when dealing with traffic or automation (Boucsein 2012). Perceived risk is correlated with increased sympathetic nervous system activity (Herrero-Fernández 2016;

Schmidt-Daffy 2013), making EDA a useful tool in the field of safety research. Several ambulatory investigations have continually evaluated EDA to better comprehend affective events (Kappeler-Setz et al. 2013; Picard et al. 2016). There have been a few attempts to use EDA signals to better comprehend construction workers' emotional states (Guo et al., 2017; Jebelli et al., 2018b; Anwer et al., 2022).

Muscle oxygenation (SMO2) and breathing rate (BR) are two other potential sources of information useful for ensuring worker safety on construction sites. The physiological demands of construction tasks have been quantified using these measures (Abdelhamid and Everett, 2002; Wong et al., 2014). An increase in SMO2 and energy expenditure, both of which can contribute to physical exhaustion, was found by Abdelhamid et al. (2002) in the construction industry. Construction tasks, such as bar fixing and bar bending, have been shown to increase SMO2 and energy expenditure, as reported by Wong et al. (2014). In particular, the frequency with which a person breathes can improve workload monitoring and modeling for construction tasks. Newer research has shown that BR is a more reliable indicator of physical exertion than heart rate and SMO2 measurements for a wide variety of exercises (continuous or intermittent), as well as under a range of experimental conditions that could affect physical exertion, such as hypoxia, muscle fatigue, heat exposure, and glycogen depletion (Nicol et al., 2014, 2016a, 2017a; Hayashi et al., 2006). Given the significance of brain function, we can explain the robust connection between exertion and BR. The magnitude of central command controls the amount of physical effort, which can be thought of as the level of motor effort (Nicol et al., 2016b). A similar relationship exists between physical exertion and BR since both are controlled by the brain during exercise (Nicol et al., 2017b).

4. OVERVIEW OF SIGNAL ARTIFACT

Notwithstanding the physiological signals that have been mentioned above and that are utilized in the construction industry, their full potential has not yet been explored. In construction studies, the quality of the raw collected data using wearables is often underreported, especially in quantitative terms. Data quality measures may also vary based on the objectives of the associated analysis and project, and data quality can be expressed in a variety of ways (Bangaru et al., 2020; Pal et al., 2019; Kleckner et al., 2017; Villeneuve et al., 2016). As an added note, the quality of the data is crucial to its consistency and accuracy (Bent et al., 2020; Goldsack et al., 2020; Munos et al., 2016). In this scenario, the accountability of subsequent analysis and, by extension, outcomes depend on familiarity with artifacts and methods for evaluating data quality and generating data reliability ratings. It is possible that the evaluation of data quality might benefit from taking into account both the individual and combined effects of the various modalities, as artifacts can affect only one or all of them. Despite the great potential of physiological signals for evaluating workers without interfering with their ongoing tasks, their application in the field is complicated by the signal artifacts manifested in the data, in particular those related to signal noise from the construction sites or from the frequency of workers' movements (Jebelli et al. 2018; Ahn et al. 2019). In this context, "signal artifacts" refer to any unwanted signals or signal distributions that interfere with the actual signal of interest (De Luca et al. 2010). There are two classification systems used to classify signal artifacts: category A and category B. Category A classifies artifacts into intrinsic and extrinsic artifacts. Category B classifies artifacts into physiological and environmental artifacts. Artifacts in data that come from outside the data are called extrinsic artifacts, and those that are part of the data itself are called intrinsic artifacts.

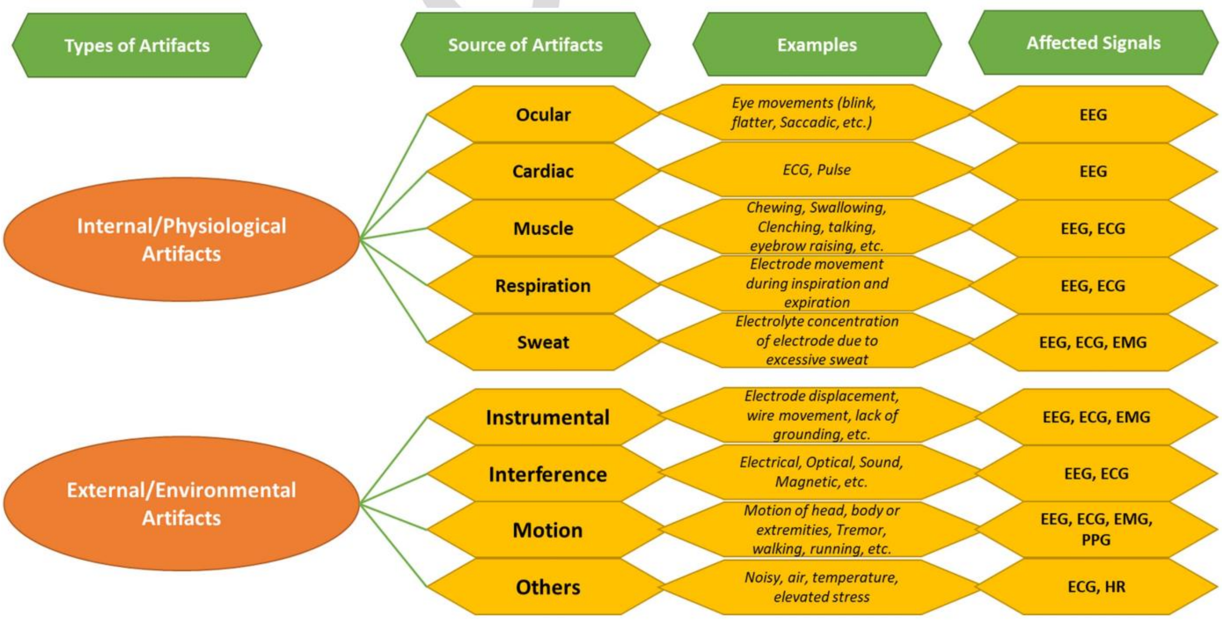

Fig. 3. Overview of types and sources of signal artifact found in physiological signals. ECG = electrocardiogram; EEG = electroencephalogram; EMG = electromyogram; HR = heart rate; and PPG = photoplethysmography.

The possible sources of various signal artifacts are presented in Figure 3. The majority of the time, extrinsic signal artifacts are produced by external sources such as environmental noise and the motions of employees, motion artifacts, device powerline interference, electrode movement artifacts, and sensor deployment and positioning (Ahn et al. 2019). Intrinsic signal artifacts are those that come from within the body itself. Some examples of intrinsic signal artifacts are artifacts caused by respiration, pulse, skin, movements, muscles, and the eyes (Jebelli et al. 2018b). Likewise, physiological artifacts are introduced because secondary physiological processes in the human body interfere with the basic physiological signal. Most unwanted components of EMG signals are introduced by cardiac signals and eye movement-associated abnormalities. However, an EEG signal is a weak signal that can be easily distorted by even a single blink of the eyelid. Capturing high-quality EEG signals in the field, for example, is more difficult than other physiological signals due to many intrinsic artifacts (e.g., eye blinking and face muscle movement). Furthermore, measuring physiological signals with a wristband-type biosensor at real-world construction sites remains difficult due to the large number of extrinsic signal artifacts and distortions caused by worker movements, sensor displacement, environmental noises, and lower sensor electrode quality compared to wired biosensors (Jebelli et al., 2019b). According to the findings of another investigation (Chae and Kang, 2021), extrinsic artifacts can be caused by either the presence of an electric device next to the EEG equipment or the presence of an electric node popping noise. The EEG devices can pick up on the electrical signal that is produced by the contractions of the heart. Additionally, because the EEG device is placed on the subject's head, any movement of the eyeball can cause a disturbance in the signal. Heartbeats can also interfere with EEG and EMG. It is possible to distinguish these aberrations from EEG and EMG readings because of the high signal strength of an electrocardiogram (Miljkovi et al., 2017). Extrinsic and intrinsic artifacts in EDA data, as in other types of physiological data, serve to mask the signal of importance. Noise from the subject's excessive movement and drifts in the EDA caused by environmental factors like humidity and temperature are examples of extrinsic artifacts. Muscle activation noise, irregular breathing, heavy breaths, and coughing are examples of intrinsic artifacts in EDA (Chae et al., 2021). Similarly, the principal cause of environmental artifacts is the laying of connecting wires and mains power leads. These artifacts can also be introduced by electromagnetic interference (EMI) from certain electronic or electrical devices during the recording or data storage phase. Interference from radio frequency sources can cause inductive coupling between measurement cables, which in turn causes noise in the recording setup. These abnormalities, which are caused by the circuit components themselves, can be seen in the 1/f noise, shot noise, and thermal noise that are produced by recording devices (Prakash et al., 2021). Additionally, although a PPG sensor is intended to record numerous physiological signals, it also captures a considerable amount of undesired and unrecognized signals (e.g., noise from body and sensor motions, power line noise, and environmental noise) that interfere with the signal of interests (Jebelli et al., 2019a). Several studies indicated many challenges of data collection of physiological signals on construction sites, such as the frequent movement of workers and the dynamic nature of the construction environment. In particular, standard signal preprocessing methods like digital filtering or amplitude thresholding have issues with distinguishing between artifacts and intended physiological signals due to the wide range of artifacts and their overlap with signal of interest in the spectrum and temporal domains. Therefore, conventional filters have a poor track record of success in eliminating signal distortion and other artifacts. With the help of modern improvements in signal processing techniques/algorithms, several researchers have tried to create effective ways for artifact detection and removal. As a result, there is a need for further advancement of wearable sensing technologies on construction sites to enhance data collection of physiological signals for monitoring the health and safety of construction workers. In the following section, several of the filtering methods and algorithms that can be utilized to eliminate artifacts will be discussed.

5. ARTIFACT REMOVAL APPROACH

Removing or reducing signal artifacts is suggested prior to signal processing as they might obscure otherwise detectable signals (Ahn et al., 2019). There have been many different filtering algorithms created to decrease the impact of signal artifacts like these (Iriarte et al., 2003; Manoilov, 2006; Ram et al., 2011; Daly et al., 2013). Previous research utilized a variety of methods, such as wavelength shrinkage, to cut down on the amount of random noise that was picked up by the wearable sensor (Kang et al. 2017). Gibbs and Asada (2005) came up with an active noise-cancellation strategy to mitigate signal distortions brought on by movement of the body that occurred during the process of data collection utilizing wearable PPG sensing equipment. However, due to the substantially bigger signal artifacts that are observed in the actual world, these approaches might not be adequate for usage in construction sites. Therefore, the objective of this study is to provide an overview of several different methods for removing artifacts from physiological signals. This review will attempt to collate and discuss the most significant methods that have been utilized in previous research to eliminate artifacts throughout the process of acquiring physiological data. Researchers in several fields have used methods for eliminating artifacts in physiological data.

Table 1 presents a comparison of several artifact removal approaches to improve the signal quality of sensors. A total of 12 studies developed and examined a few novel artifact removal approaches to eliminate intrinsic and extrinsic artifacts and noises from EEG (Sweeney et al., 2013; Hossain et al., 2022; Phadikar et al., 2022; Porr et al., 2022; Roy et al., 2017), fNIRS (Sweeney et al., 2013; Zhang et al., 2012; Hossain et al., 2022; Robertson et al., 2010; Izzetoglu et al., 2005, 2010; Nguyen et al., 2018; Chiarelli et al., 2015), and electrophysiological (Zhan et al., 2009) signals. Most of the included studies tested motion artifacts, while others examined different kinds of artifacts, including physiological artifacts and background noise. Sweeney et al. (2013) found Ensemble Empirical Mode Decomposition (EEMD) along with Canonical Correlation Analysis (CCA) techniques outperformed other methods for artifact removal from both fNIRS and EEG signals. Similarly, Hossain et al. (2022) proposed two innovative motion artifact removal approaches, including wavelet packet decomposition (WPD) and WPD combined with canonical correlation analysis (WPD-CCA) for fNIRS and EEG signals. Zhang et al. (2012) reported that adaptive filtering using the least-squares recursion method was found to provide faster convergence and a lower mean square error (MSE) than the least mean squares (LMS) adaptive filter. However, the findings of Robertson et al. (2010) reveal that independent component analysis (ICA) generated the best motion artifact removal results across all datasets. Moreover, Izzetoglu et al. (2005, 2010) compared Wiener, Kalman, and adaptive filter methods for fNIRS signals. While both the Wiener and Kalman filters were effective in eliminating motion artifacts from fNIRS signals, the Kalman filter had the added advantage of real-time application capacity. Furthermore, Phadikar et al. (2022) investigated a new automatic hybrid approach for denoising muscular artifacts from EEG signals using WPD and a modified non-local means (NLM). Likewise, Porr et al. (2022) used a deep neural filter based on deep learning models to do simultaneous learning and noise reduction in real time from an EEG signal. Moreover, Roy et al. (2017) introduced a novel algorithm for EEG signals using Gaussian Elimination Canonical Correlation Analysis (GECCA) that is 18% faster than traditional CCA.

Table 2 presents an overview of several artifacts' removal approaches used in construction studies. A total of 13 studies are included in this review, which give detailed information about artifact removal approaches used for several physiological signals tested in construction-related studies. Most of the included studies tested PPG, EDA, skin temperature, HR, HRV, and EEG signals. All included studies have used bandpass filters, except one study that used a moving average filter (Newton, 2022) for removing artifacts from PPG signals. Likewise, while all included studies have used a low-pass filter, two studies used a high-pass filter (Lee et al., 2021; Shayesteh et al., 2023) for cleaning EDA data. A few studies have used the Hampel, high-pass, low-pass, and notch filters for cleaning the skin temperature signal (Jebelli et al., 2019a, 2019b; Lee et al., 2021). Three studies have used band pass filters (Chae et al., 2021; Shayesteh et al., 2023; Xu et al., 2017), and two studies have used independent component analysis (ICA) (Chae et al., 2021; Shayesteh et al., 2023) for EEG data.

6. DISCUSSION

6.1. Discussion of several artifact removal approaches

This review presents an overview of various physiological signal, artifacts, and artifact removal approaches used in both construction and non-construction scenarios. Physiological signal processing is an important area of study that needs more investigation into how to enhance the quality of output signals and better interpret data. WSDs are a common tool for recording physiological signals in order to keep an eye on the health and safety of construction workers. Capture signals are perpetually muddied by artifacts emanating from both within and without the system. Asking the subject to constrain their movement, removing potential sources of power line interference, and increasing the density of the electrode placement are all precautions that can be implemented. This approach, however, may not always be effective, particularly for long signal acquisition experiments and experiments involving movement and physical tasks such as construction. It is best to use a computational method to handle the artifacts. The artifact filtration phase is especially important because it affects feature extraction and ultimately how the data is interpreted. For instance, this review uncovered various artifact removal approaches that may be implemented in the processing of several physiological signals.

Removing artifacts from a physiological signal can be done either before or after the signal is recorded. Most studies rely on traditional filtering methods, either implemented in hardware or as simple filtering algorithms, during the data acquisition process, i.e., in real time. Meanwhile, the highly developed algorithm is used to clean up the archived data from artifacts. When processing signals, conventional filtering is typically applied during the pre-processing stage. Filtering relies heavily on the correlation coefficients. To estimate the filter's coefficient, a researcher must know the desired order, filter type (FIR, IIR, etc.), and frequency response (band-pass, low-pass, high-pass, etc.). For instance, the Kalman filter used in the pre-processing phase is an example of a static filtering approach because its filtering coefficients do not vary, while a filter whose coefficients do change based on optimization criteria is an example of an adaptive filter. There are many methods for static filtering, but the Wiener filter of the FIR variety stands out as the most common. With linear time-invariant signals, it is particularly effective at minimizing the MSE between the desired signal and the estimated signal. Additionally, the adaptive filter estimates coefficients using a variety of algorithms like least mean square (LMS) and recursive least square error (RLS) based on the condition of optimization being applied. However, researchers need to know the nature of the artifacts to use these filters effectively on linear time-variant signals like EEG and fNIRS (Guerrero-Mosquera & Navia-Vázquez, 2012). Artifacts have been corrected from fNIRS, respiratory, and ECG signals using Kalman filters, a linear approximation of probabilistic Bayesian filters (Rheinberger et al., 2007; Hesar & Mohebbi, 2016; Sameni et al., 2007).

Because most of the study that was conducted on construction only used conventional methods for eliminating signal artifacts, we discussed a few advanced artifacts removal methods that were utilized in situations that did not include construction domain. In addition, studies that were published in the construction area only provide a limited amount of information regarding the artifacts removal approaches that were applied, and they do not provide any performance metrics to assess the efficiency of the approach that was applied. In contrast, studies that did not involve construction domain not only investigated the efficacy of the various artifact removal approaches that they implemented, but they also evaluated and contrasted a variety of cutting-edge strategies for minimizing signal artifacts. We believe that these approaches can be useful for reducing the signal artifacts that are associated with environments involving construction. When analyzing physiological data from a human subject, it is common practice to combine the clean signal with artifacts produced by other physiological sources. In this case, the reference channels are the artifacts themselves, which can be acquired independently by various devices. Examples of such reference signals or artifacts when processing EEG include EOG, EMG, and ECG. The goal of linear regression methods is to quantify the amount of noise in an otherwise well-characterized primary physiological signal. It has been possible to clean up EEG signals by subtracting out ECG and EMG noise using linear regression. However, only a small number of studies have adapted machine learning strategies, such as those that employ adaptive neural fuzzy inference systems and neural networks to eliminate artifacts (Jeyhani et al., 2015; Al-Jebrni et al., 2020; Chiang, 2015). Denoising ECG and EEG signals with deep recurrent neural networks and comparing the results to those of more traditional denoising methods has been studied (Antczak, 2018). Sweeney et al., (2013) found the effectiveness of EEMD algorithms on the EEG and fNIRS data. However, the newly developed EEMD-CCA technique was found to be most effective in reducing signal artifacts during processing of fNIRS data. Additionally, Zhang et al. (2012) used a recursive least-squares (RLS) technique for adaptive filtering for removing signal artifacts associated with the physiological interference found in the fNIRS signal. The RLS method has shown faster convergence and reduced MSE, which makes this approach more effective at reducing the impact of physiological interference. Furthermore, Phadikar et al. (2022) combines wavelet packet decomposition (WPD) with a modified nonlocal means (NLM) algorithm to improve processing of EEG signals, which was found to be superior as compared to recently published denoising techniques. More recently, a new real-time deep learning algorithm was presented by Porr et al. (2022), which adaptively generates a signal counter to the noise, causing adverse interference. There are many different biological, industrial, and consumer applications that could benefit from this approach, from industrial sensing to noise-cancelling headphones.

In this review, we found that most studies in the construction industry studied PPG, EDA, skin temperature, HR, HRV, and EEG signals. Unfortunately, no studies have used new and improved approaches to the elimination of artifacts and noises in physiological signals during construction tasks. While some research did detail the artifact removal approaches, they employed, no comparative studies were found, nor were any artifact removal approaches formally designed. To clean up their physiological data, most studies solely utilized widely used and accessible tools, including band pass filters, moving average filters, low-pass filters, high-pass filters, Hampel filters, and notch filters. Independent component analysis (ICA) for EEG data has been employed in only a handful of research studies (Chae et al., 2021; Shayesteh et al., 2023). Intrinsic artifacts, as opposed to external sources, share frequency ranges with the EEG signals. Accordingly, such noise cannot be eliminated by employing bandpass filtering. As such, authors used ICA to filter out the noise and eliminate the intrinsic artifacts (Chae et al., 2021; Shayesteh et al., 2023). There has been extensive use of ICA (Jebelli et al., 2018c; Makeig et al., 1995) to clean EEG signals by identifying and eliminating sources of intrinsic artifacts. This approach presupposes that the recorded EEG signal may be broken down into its constituent parts and examined as the sum of separate components (Jebelli et al., 2018c). By first deconstructing the EEG signal into its constituent parts, artifacts like blinking eyes and muscle activity may be filtered out individually.

6.2 Advantages and limitations of various artifacts removal approaches

While this review discussed several artifacts removal approaches used in construction and non-construction related research, they all have some strengths and weaknesses, which need to be discussed for better understanding and application.

6.2.1 *Empirical Mode Decomposition - Canonical Correlation Analysis (EEMD-CCA) approach*: Certain scenarios demand for physiological signals to be processed in real time or online. Thus, an artifact removal approach would be selected for this application in such a way that it has the necessary minimal computational complexity to be suitable for real-time/online processing. In that circumstance, the performance of the artifact removal approach must be compromised against its computational complexity. However, there are programs that rely on offline processing. When this is the case, optimizing for performance over computational time becomes the primary concern. Sweeney et al. (2013) studied the computational cost of the EEMD-CCA algorithm to see if the better artifact elimination achieved by the CCA extension to EEMD came with any extra computational costs. It was discovered that CCA takes far less time to calculate than EEMD does, hence it does not significantly increase the computational complexity of the system. Furthermore, certain artifacts reduction approaches are only applicable to multi-channel recordings of physiological signals, whereas others can be used with single-channel recordings as well. However, for a single recording, wavelet or EMD-based algorithms can be used, selecting artifacts removal methods with the number of channels being considered is therefore crucial (Islam et al., 2016). For instance, Both the ICA and CCA algorithms are multi-channel signal processing methods, which means they require input from several channels. As a result, separate implementations of the ICA and CCA algorithms cannot be used to process single-channel data (Sweeney et al. 2013). Moreover, the CCA algorithm is computationally efficient in comparison to the ICA algorithm because it uses second-order statistics rather than higher-order statistics (Sweeney et al., 2012c).

6.2.2 *Adaptive filtering with least-squares recursion approach*: Similarly, adaptive filtering with least-squares recursion is a popular method for de-noising physiological signals (Zhang et al., 2012). While there are certainly benefits to using this method, there are also drawbacks that must be acknowledged. Removing physiological interference from physiological signals is best accomplished by adaptive filtering utilizing least square recursion (Lu et al., 2009b). For instance, it can be used to filter out background noise resulting from factors like the heartbeat, breathing, and muscular action. The online processing of physiological signals is another potential use of this method, which can be executed in real-time. In addition, it can handle the non-stationary signals that are typical in the construction industry. Furthermore, the method utilized in this strategy is easy and simple to apply. The adaptive filter can improve results, but only if sufficient training data is provided. The effectiveness of a filter depends on its ability to accurately represent the signal it is designed to process in training data. Moreover, matrix operations, like those used in the least square recursion approach, can be computationally expensive for massive data sets. Furthermore, it can only be used to linear systems (Yang et al., 2016). The effectiveness of the filter may be diminished if the input signal is very non-linear. Overfitting to noise in the training data is another potential pitfall of the adaptive filter that might lead to inferior results in the test data. Regularization methods and careful selection of training data can help with this.

6.2.3 *Wavelet packet decomposition and the canonical correlation analysis (WPD-CCA) approach*: Wavelet packet decomposition and the canonical correlation analysis (WPD-CCA) technique were also explored in this review as a means of feature extraction and classification of signals (Hossain et al., 2022). There are advantages and disadvantages to this method, as well. By breaking a signal down into subbands with distinct frequency components, Wavelet packet decomposition combined with CCA can efficiently extract useful characteristics. The combined use of wavelet packet decomposition and CCA has been found to increase classification accuracy over individual methods, allowing the obtained features to be employed for signal classification (Hossain et al., 2022). The combination of WPD-CCA is noise-tolerant because it can pick out useful characteristics even when there is background noise. The features obtained using this method can be interpreted, leading to a deeper comprehension of the signal's properties. However, for big datasets, the computationally intensive operations involved in the wavelet packet decomposition in conjunction with CCA might be time-consuming (Hossain et al., 2022). In addition, the method's efficacy is reliant on the accuracy and completeness of the training data. It could be possible that the accuracy of the classification will be low if the training data is not indicative of the signal being classified. Like CCA alone, this method can only be used to linear systems. The performance may be unsatisfactory if the signal to be classified is substantially non-linear. In addition, the success of the WPD is linked to the choice of wavelet basis (Li et al., 2017). Decomposition may fail to successfully extract useful features if the incorrect basis is used. In addition, if the number of features extracted is immense in comparison to the size of the training dataset, there is a risk of overfitting, just as there is with adaptive filter.

6.2.4 *Independent component analysis (ICA) approach*: Another effective method for artifact elimination during physiological signal processing is independent component analysis (ICA), which is frequently used for electroencephalography (EEG) and magnetoencephalography (MEG) (Çınar and Acır, 2017). ICA is a blind source separation approach that can decompose a muddle of signals into their constituent parts, which can be useful for isolating the signal of interest from noise (Mijović et al., 2010). When dealing with complicated artifacts that are challenging to remove using other methods, ICA can be used to separate many sources of artifacts simultaneously. Numerous researchers and professionals have used ICA due to its simplicity of implementation and computational efficiency (Akhtar et al., 2012; Quiñones-Grueiro et al., 2019). ICA is a data-driven method that may be used in various contexts without any prior information about the origins of artifacts. However, it does have certain limitations. Artifacts' origins are assumed to be statistically independent in ICA, which might not be the case. The effectiveness of ICA may be hindered if the sources are not truly independent. Further, the extraction of a significant number of independent components is necessary for isolating the signal from the noise (Tripathi et al., 2021). The effectiveness of ICA may once again be constrained if there are insufficient components. Further, ICA can be vulnerable to noise and may not function well in loud situations, limiting its use in specific settings, such as the construction sector. Finally, ICA can be challenging to interpret since its output may not correspond exactly to the original artifact sources. This necessitates expertise and potentially some trial and error in interpreting the findings.

6.2.5 *Weiner filtering approach*: The Wiener filter is a type of linear filter employed in signal and image processing. It is a computationally efficient technique that is simple to implement in practical, real-time settings. Since it is an adaptive filter, it may be modified to fit a variety of signal scenarios and put to excellent use in many environments (Chandra et al., 2021). It can filter out extraneous noise from signals without significantly altering the original signal. Because of its flexibility, it finds widespread application in the field of signal processing, where it may be applied in both the time domain and the frequency domain (Khiter et al., 2020). However, in actuality, the assumptions made by the Wiener filter—that noise and signal are uncorrelated, and that noise is Gaussian distributed—may not remain true (Appathurai et al., 2019). Furthermore, it necessitates information about the power spectral densities of the signal and noise, which may not be readily available or may be difficult to estimate (Cai et al., 2018). Moreover, it is sensitive to the values of the filter parameters, and finding the best values for these might be difficult. Also, if the filter's assumptions fail to be fulfilled, it could cause artifacts or distortions in the signal. The Wiener filter is an effective tool for signal processing in general, and it benefits in situations when additive noise is present. However, it is sensitive to the details of the signal and the noise and requires thorough parameter tuning and validation to achieve its full potential.

6.2.6 *Deep Neural Filter (DNF) approach*: The deep neural filter is a cutting-edge method for processing signals and performing filters. Signals having nonlinear dynamics can be modeled and filtered with the help of deep neural networks due to their ability to learn complex nonlinear correlations between input and output data. It is a potent tool for signal processing in a variety of contexts since it can be trained from start to finish without requiring any constructed features or preconceptions about the data being processed (Lee, M. B., et al., 2021). They may be trained on massive datasets, which increases their precision and generalization ability. It has several applications in signal processing, such as noise removal, blur removal, deconvolution, and prediction. To get effective results, though, a lot of training data is needed, which might be challenging to collect for some uses. Since deep neural networks are computationally intensive and necessitate strong technology for training and execution (Li et al., 2020), their applicability may be constrained in particular scenarios such as physiological signals obtained during construction tasks. It can be challenging to interpret the results of deep neural networks, which can reduce their utility in many applications. Overfitting is another issue that could arise with deep neural networks, especially if the dataset used for training is too short or the model is too complicated (Baraldi et al., 2013). As a whole, deep neural networks show promise as a useful tool for signal processing, especially for problems with intricate nonlinear connections between input and output. However, they are only as efficient as the training data they are given, and the characteristics of the signal being processed. The high computing cost and lack of interpretability may also reduce their utility in some applications.

Finally, adaptability is a key consideration when choosing an artifact removal approach because different types of artifacts affect and/or alter distinct physiological signals across various recording techniques and scenarios. To assess the potential of any artifact removal approach to detect and remove artifacts from a specific physiological signal, it is necessary to demonstrate its stability across various setups for experiments (or distinct applications or scenarios) and various participants.

6.3 Challenges and future directions of artifact removal approaches

Artifact removal from physiological signals is an important task for analyzing physiological data captured during construction task due to nature of construction job. While there have been many advances in artifact removal approaches, there are still several challenges and future directions to consider.

6.3.1 *Lack of standardized evaluation metrics*: There is a growing need for standardized evaluation metrics so that various artifact removal approaches can be compared with one another about their level of efficacy (An and Stylios, 2020). Metrics such as signal-to-noise ratio, distortion metrics, and physiological performance metrics are examples of these types of measurements.

6.3.2 *Integration of multiple techniques*: Because of the complicated configuration of physiological signals and the wide variety of artifacts that may be present, it is highly likely that a number of methods will be required in order to successfully remove artifacts from the data (Sweeney et al., 2012b). To be able to attain the highest level of artifact removal performance possible, future research should concentrate on combining several approaches.

6.3.3 *Real-time implementation*: Real-time implementation is essential for many applications of artifact removal, including construction work, for example. In the future, research should be focused on the development of real-time artifact removal programs that may be used in these types of situations.

6.3.4 *Interpretation of post-filtering results*: It is essential to ensure that the findings of artifact removal approaches are correctly interpreted in order to avoid incorrectly interpreting the underlying signal (Wirawan et al., 2022). The development of methodologies that can evaluate the effect that artifact removal has on applications that are developed later in the research process ought to be the top priority of future study.

6.3.5 *Generalizability across different physiological signals and populations*: There are a lot of approaches for artifact removal that are developed and tested on particular physiological signals or individuals (Delorme et al., 2007). The development of methods that are applicable to a diverse set of physiological signals and population types need to be the primary emphasis of research that will be conducted in the future.

6.3.6 *Ethical considerations*: Carelessly removing artifacts from a signal could result in the loss of essential information. Future study should take into consideration the ethical concerns of using artifact removal techniques for the purpose of construction-related research.

Overall, the challenges and potential developments in artifact removal approaches emphasize the need for more study and innovation in this field. By resolving these issues, we may enhance signal processing for data obtained during construction tasks and enhance the accuracy and reliability of physiological signal analysis.

8. CONCLUSION

The findings of this review show that there is currently no gold-standard approach that is both effective and reliable across a wide range of scenarios. In light of this, it is conceivable that situationally-specific algorithms may emerge in the near future. Additionally, this review failed to identify any unique artifact removal approaches that can be used for cleaning physiological data captured from construction fields. However, this review presents an overview of many novel artifact removal algorithms to improve the quality of physiological signals obtained from non-construction domain. Therefore, it is recommended to examine and adopt such approaches in the construction field to improve the quality of physiological signals captured during construction tasks for further analysis and interpretation. For example, artifacts and noise in construction-related physiological data can be removed using various filters and deep learning methods, including the Wiener filter, Kalman filter, adaptive filter, wavelet packet decomposition, and others.

Data Availability Statement

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

Acknowledgment

The authors acknowledged the following two funding grants: 1. General Research Fund (GRF) Grant (15201621) titled "Monitoring and managing fatigue of construction plant and equipment operators exposed to prolonged sitting"; and 2. General Research Fund (GRF) Grant (15210720) titled "The development and validation of a noninvasive tool to monitor mental and physical stress in construction workers".

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Table 1. Comparison between different artifacts removal techniques.

Citations	Types of filtering techniques	Type of signals tested	Types of artifacts	Performance Metrics			Conclusions
				Reduction of artifacts (%)	ΔSNR (db)	Others	
Sweeney et al., 2013	Wavelet Denoising	fNIRS EEG	Motion artifacts	fNIRS: 38.2 EEG: 51.2	fNIRS: 2.88 EEG: 7.81	-	Due to the inclusion of the EEMD algorithm, a unique artifact removal technique, EEMD-CCA, was presented, which is capable of functioning on single-channel measurements. However, when EEMD is used in conjunction with CCA, the outcomes are typically better.
	Empirical Mode Decomposition (EMD)			fNIRS: 13.2 EEG: 38.7	fNIRS: 1.84 EEG: 7.01	-	
	Ensemble Empirical Mode Decomposition (EEMD)			fNIRS: 42.2 EEG: 48.5	fNIRS: 3.21 EEG: 7.88	-	
	EMD – Independent Component Analysis (ICA)			fNIRS: 14.9 EEG: 40.0	fNIRS: 2.12 EEG: 7.22	-	
	EMD - Canonical Correlation Analysis (CCA)			fNIRS: 17.3 EEG: 39.6	fNIRS: 1.98 EEG: 6.98	-	
	EEMD-ICA			fNIRS: 39.7	fNIRS: 3.42	-	

				EEG: 48.3	EEG: 8.02		
	EEMD-CCA			fNIRS: 46.4 EEG: 48.5	fNIRS: 3.44 EEG: 8.04	-	
Zhang et al., 2012	Recursive least-squares (RLS) adaptive filter	fNIRS	Physiological artifacts			MSE = small Convergence = fast	Adaptive filtering using least-squares recursion was applied to eliminate physiological disturbance. For reducing physiological interference, the RLS method provides a faster convergence and a lower MSE than the LMS algorithm.
	least mean squares (LMS) adaptive filter					MSE = large Convergence = slow	
Hossain et al., 2022	Wavelet packet decomposition (WPD)	EEG fNIRS	Motion artifacts	EEG: 52.58 fNIRS: 26.4	EEG: 29.21 fNIRS: 16.11	-	For EEG and fNIRS modalities, two innovative motion artifact removal approaches have been proposed: wavelet packet decomposition (WPD) and WPD combined with canonical correlation analysis (WPD-CCA). In terms of % reduction in
	WPD in combination with canonical correlation analysis (WPD-CCA)			EEG: 55.88 fNIRS: 41.4	EEG: 28.86 fNIRS: 12.41	-	

							motion artifacts, the unique WPD $_{(db1)}$-CCA and WPD $_{(fk8)}$-CCA techniques performed best, while the WPD$_{(db1)}$-CCA technique produced the highest average SNR for both EEG and fNIRS.
Phadikar et al., 2022	Wavelet packet decomposition (WPD) and a modified non-local means (NLM)	EEG	Muscle (EMG) Artifacts	-	-	Average CC: 0.8675 SSIM: 0.6809	For the first time, a new automatic hybrid approach for denoising muscular artifacts from EEG is presented, in which WPD is paired with an optimized NLM algorithm. The suggested system removes muscular artifacts from the EEG signal regardless of how many artifacts are present; it can remove artifacts from multi-channel EEG data.

Robertson et al., 2010	two-input recursive least squares (RLS) adaptive filter	fNIRS	Motion artifacts	λ_{760mm}: 0.13 λ_{830mm}: 0.33		SNR improves moderately when the signal is regressed or adaptively filtered. Although the wavelet-based filtering method improves SNR, the SNR improvement for the dataset without known motion was not significantly better than regression or adaptive filtering. The approaches that take into consideration signal changes on all 30 co-located channels, notably ICA and regression, generated the best motion artifact removal results across all datasets.
	wavelet-based filter			λ_{760mm}: 0.89 λ_{830mm}: 0.58		
	independent component analysis (ICA)			λ_{760mm}: 3.20 λ_{830mm}: 3.67		
	two-channel regression			λ_{760mm}: 0.35 λ_{830mm}: 0.44		
	multiple-channel regression			λ_{760mm}: 3.01 λ_{830mm}: 2.54		
Izzetoglu et al., 2005	Wiener filter	fNIRS	Motion artifacts (Head Motion)	ΔSNR_{Slow}: 5.2526 ΔSNR_{Medium}: 9.0539	ΔCC_{Slow}: 0.2929 ΔCC_{Medium}: 0.2977 ΔCC_{Fast}: 0.4407	Wiener filtering was used to propose a novel strategy for motion artifact removal in NIR spectroscopy. The

					ΔSNR$_{Fast}$: 5.7574		suggested technique requires no additional hardware or sensors and still performs best in terms of mean squares. Offline functionality is a disadvantage of the suggested algorithm.
	Adaptive filter				*ΔSNR*$_{Slow}$: 3.3560 *ΔSNR*$_{Medium}$: 4.1722 *ΔSNR*$_{Fast}$: 2.7906	ΔCC$_{Slow}$: 0.1519 ΔCC$_{Medium}$: 0.0024 ΔCC$_{Fast}$: 0.1431	
Porr et al., 2022	Deep Neural Filter (DNF)	EEG	Muscle (EMG) Artifacts		ΔSNR$_{DNF}$ = 4.1±2.8 dB	SNR was statistically better in DNF as compared to LMS (p = 0.000026).	To extract EMG from EEG, a novel electrode was designed that, in conjunction with the real-time deep learning system, implements a constantly adapting spatial Laplace filter. In this study, deep neural networks were used to do simultaneous learning and noise reduction in real time.
	The least mean squares (LMS)				ΔSNR$_{LMS}$ = 1.8±1.3 dB		
Roy et al., 2017	Ensemble Empirical Mode Decomposition-	EEG	Motion artifacts	λ$_{DWT}$: 66.8838	ΔSNR$_{DWT}$: 17.7248	-	GECCA, a novel algorithm, is introduced in conjunction with EEMD and stationary

	canonical correlation analysis (EEMD-CCA)			λ_{SWT}: 66.2544	ΔSNR_{SWT}: 17.2621		wavelet transform (SWT) for the quick and efficient suppression of motion artifacts in a single-channel EEG data. To solve the linear equations, the suggested GECCA method employs a backslash operation. This enhances the approaches' computational efficiency. The proposed GECCA-based technique is 18% faster than traditional CCA.
	Gaussian Elimination Canonical Correlation Analysis (GECCA)			λ_{DWT}: 86.0016 λ_{SWT}: 87.2759	ΔSNR_{DWT}: 29.0387 ΔSNR_{SWT}: 30.2080	-	
Nguyen et al., 2018	Adaptive-filtering with a recursive least-squares estimation method	fNIRS	Physiological artifacts			The obtained hemodynamic responses were analyzed using a one-way analysis of variance. The obtained hemodynamic responses for the Kalman filter showed statistically significant differences in the means ($p = 1.04\times10^{-7}$). Mean hemodynamic responses were significantly different in the	A unique adaptive-filtering-based technique was presented to decrease physiological and surface noises. Noise was reduced on average by 77% for oxy-hemoglobin (HbO) and 98% for deoxy-hemoglobin (HbR).
	Kalman filter						
	Low-pass filter (LPF)						

						LPF ($p = 3.1\times10^{-6}$). Adaptive filtering using recursive least-squares estimation, on the other hand, yielded no statistically significant results ($p = 0.03$). This demonstrates that the extracted hemodynamic response is more reliably provided by the adaptive-filtering approach than by the LPF and Kalman filter techniques.	
Izzetoglu et al., 2010	Kalman filter	fNIRS	Motion artifacts	-	ΔSNR_{Slow}: 8.5055 $\Delta SNR_{\text{Medium}}$: 7.8306 ΔSNR_{Fast}: 6.6282	-	A unique method for removing motion artifacts from NIRS measurements using Kalman filtering was proposed. It addresses artifacts by merging the benefits of existing adaptive and Wiener filtering methods into a single algorithm. The suggested approach has SNR comparable to Wiener filtering, but without the
	Wiener filter			-	ΔSNR_{Slow}: 5.2526 $\Delta SNR_{\text{Medium}}$: 9.0539	-	

					ΔSNR_{Fast}: 5.7574			stationarity constraints and with efficient real-time application capacity.
	Adaptive filter			-	ΔSNR_{Slow}: 3.3560 $\Delta SNR_{\text{Medium}}$: 4.1722 ΔSNR_{Fast}: 2.7906		-	
Chiarelli et al., 2015	kurtosis-based wavelet algorithm	fNIRS	Motion artifacts		SNR: 96%	MSE: 5%		To remove motion artifacts from fNIRS data, a novel algorithm, kbWF, was presented. It results in larger MSE reductions and SNR enhancements than any other processes examined over a wide range of signal and noise levels.
	Wavelet filter (WF)				SNR: 70%	MSE: 29%		
	Principal component analysis (90%)				SNR: 36%	MSE: 71%		
	Principal component analysis (97%)				SNR: 14%	MSE: 88%		
	Targeted principal component analysis				SNR: 76%	MSE: 26%		
	Spline interpolation				SNR: 73%	MSE: 34%		
	Kalman filter					$SIFT_{\text{Coh}}$:		

Zhan et al., 2009		Electrophysiological data	Background noise		5Hz: 0.85 25Hz: 0.94 45Hz: 0.88 Wavelet_{Coh}: 5Hz: 0.88 25Hz: 0.94 45Hz: 0.88	In order to reduce noise in the interpretation of multi-trial electrophysiological data, two major optimum filtering approaches were investigated. Wiener filtering with adaptive Wiener and decreased update Kalman filtering is used in a novel way to shape data into a two-dimensional image format. These methods were able to outperform the noise, leading to more accurate estimates of coherence.
	Adaptive Wiener filter				SIFT_{Coh}: 5Hz: 0.82 25Hz: 0.91 45Hz: 0.91 Wavelet_{Coh}: 5Hz: 0.88 25Hz: 0.91 45Hz: 0.86	

Note: fNIRS, functional near-infrared spectroscopy; EEG, electroencephalography; SNR, Signal to noise ratio; MSE, Mean square error; EMG, Electromyography

Table 2. An overview of several artifacts' removal techniques used in construction studies.

Citations	Type of signals	Types of artifacts	Filtering methods	Desired signal frequency range	Approaches used
Jebelli et al., 2019a	PPG	The existence of different sources and forms of noises (e.g., electrodes noise, excessive movement, adjustment of sensors, noise from power line, etc.) recorded in the signal.	Band pass	0.5–5 Hz	In order to get rid of this unwanted signal, a bandpass filter was created with a cutoff frequency range of 0.5 Hz to 5 Hz. In the range of 0.05–0.05 Hz (EDL) and 0.05-0.15 Hz (EDA), EDA can be found (EDR). The scientists employed a low-pass filter with a cutoff frequency of 1.5 Hz to remove all background noise from the EDA signal. A notch filter focused on the power-line frequency was also applied to further eliminate power-line interference in the recorded data. Additionally, a Hampel filter was implemented to smooth out the physiological data and remove any out-of-the-ordinary spikes.
			Hampel		
			Notch		
	EDA		Low pass	0–0.1.5 Hz	
			Hampel		
			Notch		
	ST		High pass	>0.05 Hz	
			Hampel		
			Notch		
Jebelli et al., 2019b	PPG	The most common artifacts (e.g., environmental artifacts, sensor motion artifacts,	Band pass filter	0.5–5 Hz	Bandpass filter with low cutoff frequency of 0.5 Hz and high cutoff frequency of 5 Hz was designed to eliminate noise in the signal. Between 0 and 0.05 Hz (EDL) and 0.05 and 1.5 Hz, low-frequency EDA occurs (EDR). The authors utilized a low-pass filter with a cutoff frequency
			Hampel filter		
			Rolling filter		
			Notch filter		

	EDA	muscle movement artifacts, etc.) recorded in the signals.	Low pass filter	0–0.1.5 Hz	of 1.5 Hz to remove any non-EDA-related noise. In addition, a notch filter focused on the power-line frequency was applied to the recorded signals to cut down on power-line interference. Additionally, the physiological signals were filtered with a Hampel filter to remove any spikes by using the median value of the neighboring signals.
			Rolling filter		
			Notch filter		
			Hampel filter		
	ST		Hampel filter	>0.05 Hz	
			Low pass filter		
			Notch filter		
Kim et al., 2020	IMU	Signal artifacts and noise (e.g., electrode contact noise, movement artifacts)	Butterworth low-pass filter	4 Hz	The IMU data was filtered using a Butterworth low-pass filter with a 4 Hz cutoff frequency to get rid of the high-frequency noise. To smooth out the EDA signals and remove the effects of the outliers, the authors applied a Bateman lowpass filter with a length of 12.
	HR		Not reported	Not reported	
	EDA		Bateman low pass filter	Not reported	
Chae et al., 2021	EDA	Extrinsic artifacts in EDA, include humidity and temperature around	low-pass filter	3Hz	This research utilized a low-pass filter of 3 Hz to the raw EDA signal to remove most of the extrinsic sounds recorded in the signal, which had a much smaller influence due to the considerably lower impact of intrinsic artifacts.

	EEG	the subject and noise from the subject's excessive movement. Intrinsic artifacts in EDA, include noise from high activation of muscles, irregular respiration, deep breathing, and coughing. Extrinsic artifacts in EEG include electrode popping or mechanical noise. Intrinsic artifacts in EEG, include eye blinking, eye	Bandpass filter Independent component analysis (ICA)	The high- and low-frequency cutoffs were determined to be 36 Hz and 0.5 Hz, respectively	The raw data from the EDA sensor was processed using Ladalab, free software for analyzing skin conductance data in MATLAB. Before further investigation, this software can help users filter and decompose skin conductance data. The EEG signals were also analyzed with EEGLab. Free software, EEGLab, has been developed for the analysis of EEG data by the Swartz Center for Computational Neuroscience (SCCN) at the University of California, San Diego. The tool is tailored to the needs of analyzing EEG data in MATLAB. EEGLab has been used in numerous research projects that analyzed electrophysiological data.

		movement, and facial muscle movement.			
Umer et al., 2022	HRV	Not reported	median filtering	Not reported	To eliminate the artifacts, a threshold-based artifact correction method was used to each individual segment. Each data segment's average interbeat interval was calculated using median filtering. The data was then subjected to a threshold value, which enabled the identification of artifacts whenever an interbeat interval deviated noticeably from the mean.
Shayesteh et al., 2023	EEG	Extrinsic artifacts (generated due to environmental noises) and intrinsic artifacts (generated due to human body functions, such as ocular artifacts or muscle artifacts).	Fixed-gain filtering	0.5–45 Hz	Artifacts in the EEG data were diminished by use of independent component analysis (ICA) and a fixed-gain filtering approach. In order to reduce the effect of background noise, the authors specifically employed a band-pass filter with a cutoff frequency range of 0.5-45 Hz. Artifacts and genuine EEG signals were both extracted from 2D scalp map projections using image processing methods. They used a high-pass filter with a cutoff frequency of 0.05 Hz on the EDA signals in order to get rid of the low-frequency disturbances from the surrounding environment. In addition, a moving average filter was used to dampen the high-frequency disturbances in the EDA signals. Finally, a band-pass filter with a cutoff frequency range of 0.5-5 Hz was used
			ICA		
			band-pass filter		
	EDA		High pass filter	0.05 Hz	
			moving average filter		
	PPG		band-pass filter	0.5–5 Hz	

					to remove low- and high-frequency disturbances from the PPG signals.
Aryal et al., 2017	HR	Not reported	third order one-dimensional median filter	Not reported	EEG activity was recorded every second, heart rate (in beats per minute) was recorded every 15 seconds, and core body temperature (in degrees Celsius, with a resolution of 0.01 degrees) was monitored constantly and in real time. By applying a third order one-dimensional median filter and a Savitzky-Golay filter to all of the sensor data, we were able to eliminate the big spikes in the signals earlier in the processing pipeline. To make the sensor results easier to interpret, we then used a moving average filter. After the noise was removed from the signals, they were inspected visually to ensure that the main trends were not altered.
	ST		Savitzky-Golay filter		
	EEG		moving average filter		
Lee et al., 2017	HRV	Not reported	Not reported	Not reported	The HRVs of the workers were analyzed using the free and open-source academic application Kubios HRV 2.2 (Kubios, Finland). Authors used the powerful artifact repair feature offered in Kubios HRV during processing data to erase the effects of artifacts created by the program.
Lee et al., 2021	EDA	Environmental factors (e.g.,	Moving average High pass filter	0.05 Hz	Applying a high-pass filter with a cutoff frequency of 0.05 Hz to the raw EDA data eliminated low-frequency

	PPG	ambient light, thermal noise, motion, and electromagnetic sources) induce plenty high frequency noise into the signal of interest.	Band-pass filter	0.5–4.0 Hz	sounds brought on by variations in the impedance of the EDA sensor electrodes or ambient variables like temperature and humidity. High-frequency disturbances caused by user motions and electromagnetic interference were further suppressed by applying a moving-average filter with a six-data-point window. Using a band-pass filter between 0.5 and 4.0 Hz for PPG helped mitigate low- and high-frequency disturbances (including flicker noise, LED shot noise, and ambient light noises). Due to inadequate contact between the infrared thermopile temperature reader and human skin, the authors used a hamper filter to clean up the ST signals.
	ST		Hamper filter	Not reported	
Newton, 2022	PPG	Motion artifacts	Moving average	Not reported	By employing a PPG sensor, the Empatica E4 is able to track the volumetric change in blood flow to and from the hand throughout each cardiac cycle. Samples of blood volume pulse are taken at 64 Hz. The software in the device then selects peaks in the signals and logs the most likely time periods (more than 0.3 s and less than 2.0 s) as the beats' separations. By averaging HR from the inter-beat intervals over a sliding 10-s window, the raw PPG data has had most of its severe motion artifacts eliminated. The raw data from the EDA sensor is sampled every 4 milliseconds. Raw data from the Empatica E4 is processed by the Matlab program
	EDA		adaptive smoothing automatic artefact correction		

					LedaLab (leda.de/), which is available for download under the GNU General Public License. LedaLab will perform adaptive smoothing and automatic artifact correction on the raw data to get it ready for further analysis.
Xu et al., 2017	EMG	Motion of the participants and electrode displacement caused signal artifacts.	High pass filter	40Hz	As a first stage in signal processing, applying a frequency filter helps get rid of extraneous noise. A fifth-order Butterworth high-pass filter is employed to filter out the noise at a sampling rate of 500 hertz because the electromyography (EMG) data is a high-frequency signal. The maximum frequency allowed through the filter is 40 Hz. For this reason, the EDA signal is filtered using a Butterworth low-pass filter of fourth order with a cut-off frequency of 5 Hz and a sampling rate of 500 Hz. Using a sampling rate of 500 Hz, we apply two filters to get rid of the background noise in the EEG recordings: a high-pass Butterworth filter with a cut-off frequency of 4 Hz and a low-pass Butterworth filter with a cut-off frequency of 40 Hz, both with eight orders. The BVP noise is filtered out using a fourth-order Band pass filter with low and high cut-off frequencies of 1 Hz and 8 Hz, respectively.
	EEG		Band pass filter	4Hz – 40Hz	
	ECG		Band pass filter	3Hz – 45Hz	
	EDA		Low pass filter	5Hz	
	BVP		Band pass filter	1Hz – 8Hz	

Note: PPG, Photoplethysmography; EDA, Electrodermal activity; ST, Skin temperature; EMG, Electromyography; EEG, Electroencephalography; ECG, Electrocardiography; BVP, Blood volume pulse; IMU, Inertial measurement unit; HRV, Heart rate variability; HR, heart rate; BR, Breathing rate