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# PAIRED ELECTRODES- AND CONTRAINT INDEPENDENT COMPONENTS ANALYSIS-BASED DENOISING TO ALLEIVATE MOTION ARTIFACTS IN ELECTROENCEPHALOGRAM COLLECTED AT CONSTRUCTION SITES

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## Abstract

Despite the potential of mobile electroencephalogram (EEG) devices in managing construction workers' safety, health, and productivity, deploying mobile EEG at sites is hindered by significant motion artifacts introduced by worker movements. To address this issue, the authors propose a paired electrode- and constraint independent component analysis-based denoising that adaptively suppresses EEG motion artifacts via leveraging simultaneously collected motion artifact references. The proposed denoising was compared with an advanced benchmark on an EEG dataset collected under real human motions. Results show the proposed technique's denoising performance is statistically higher than the existing advanced benchmark. The finding of this study can improve the applicability of mobile EEG to construction sites, thereby significantly contributing to management of workers' safety, health, and productivity.

## Introduction

There have been comprehensive efforts to advance workers' safety, health, and productivity in the construction industry, which is one of the most dangerous and demanding fields (Harvey et al. 2018). One direction of such efforts is to continuously monitor construction workers' psychophysiological responses to work environments, such as emotion, stress, mental workload, and fatigue, thereby proactively identifying psychophysiological disruptions as a preceding sign of detrimental outcomes for worker safety, health, and productivity (Ahn et al. 2019). For example, workers' stress levels can be monitored to prevent depression or lack of task focus because prolonged high stress levels are likely to precede detrimental outcomes (Van Praag 2004). To this end, different wearable-type biosensors, such as wristbands, rings, and in-ears, have been applied to continuously collect construction workers' biosignals (e.g., electrodermal activity (EDA), photoplethsmogram (PPG) and skin temperature (ST)) in which changes in their psychophysiological responses manifest (Ahn et al. 2019).

Among these wearable-type biosensors applied in construction sites, mobile electroencephalogram (EEG) devices have a unique capability: capturing brain waves from central nervous system activities (i.e., brain activities). Although monitoring biosignals related to the peripheral nervous system (e.g., EDA, PPG, and ST) can provide information about workers' psychophysiological responses such as stress (Lee et al. 2020), risk perception (Lee et al. 2021) and physical demand (Hwang and Lee 2017), by monitoring brain activities, we could achieve richer and more detailed psychophysiological understanding. For example, workers' valence levels (i.e., from pleasure to displeasure), an emotional dimension important for understanding the quality of workers' field experiences (Hwang et al. 2018), can be understood by monitoring brain activities (Russell et al. 1989). Also, brain activity monitoring enables us to track workers' cognitive processes, such as perceiving sounds and visual cues, salient stimuli detection, information processing, and problem solving (Michel and Koenig 2018), thereby providing in-depth understanding of how workers cognitively interact with their environments. The emotional and cognitive status monitoring enables us to understand the underlying mental mechanism of construction workers' behavior that negatively affects their safety and productivity, such as unsafe behavior and absenteeism (Parasuraman 2011). Therefore, more effective interventions can be designed and conducted based on the mental understanding to improve their jobsite safety and productivity (Parasuraman and Rizzo 2006). Even though functional near-infrared spectroscopy (fNIRS) can be an alternative to EEG, EEG provides richer information that tracks activities across all brain regions including the limbic area near the center of the brain (Saha et al. 2015), which gives valuable information about physiological homeostasis (Pop et al. 2018). On the other hand, fNIRS sensing only provides information about activities that occur in the outer layer of the brain.

Despite such a unique capability, current mobile EEG sensing technology still suffers from motion-induced artifacts which make it challenging to analyze EEG signals collected from construction workers in the field, where workers' body movements are unpredictable and dynamic. The main source of motion artifacts in EEG is the gradient of the electromagnetic field (i.e., gradient artifacts) (Chowdhury et al. 2014). A gradient artifact is created by voltage induced at the scalp by surrounding magnetic field gradients. With head motions, electrodes move around within their surrounding electromagnetic field, introducing varying levels of electromagnetic interference (EMI) which cause fluctuations in EEG signal magnitudes. Given that EEG motion artifacts are typically much greater in amplitude than clean EEG signals, motion artifacts can lead to serious misinterpretations in EEG signal analysis (Barua and Begum 2014; Seok et al. 2021).

The most commonly applied denoising techniques to alleviate EEG artifacts are based on blind source separation such as independent component analysis (ICA) (Urigüen and Garcia-Zapirain 2015). Blind source separation-based denoising techniques first separate raw EEG signals into multiple independent components in a way that minimizes mutual information between different components. Then, these techniques filter out independent components whose signal characteristics (e.g., amplitude and frequency) are well matched with a pre-determined artifact source template, as artifact-related components (Castellanos and Makarov 2006). These denoising techniques perform well in alleviating artifacts whose signal characteristics can be predicted and pre-defined as a template, such as ocular (Nguyen et al. 2012) and muscular artifacts (Chen et al. 2017). However, as it is practically impossible to pre-define the signal characteristics of motion artifacts due to their inherent variability and the unpredictable nature of head movements, blind source separation-based denoising is not suited for EEG motion artifact removal (Chowdhury et al. 2014; Nordin et al. 2018).

To overcome the limitation of blind source separation-based denoising, attempts have been made to leverage motion artifact reference signals simultaneously collected with raw EEG signals, thereby alleviating motion artifacts without depending on a pre-determined noise source template. To collect reference signals, head motion data have been collected using optical motion-tracking sensors (LeVan et al. 2013) and accelerometers (Onikura and Iramina 2015). However, solely depending on these motion datasets might be insufficient for understanding motion artifacts in collected EEG signals because motion artifacts are determined by interactions between motions and their surrounding electromagnetic field (the Hall effect (Hall 1879)), which vary across contexts. In this regard, it has been recently suggested to pair reference electrodes with normal scalp electrodes as a means of collecting motion artifact references (Chowdhury et al. 2014; Luo et al. 2014; Nordin et al. 2018). In this approach, each normal electrode is paired with a reference electrode while keeping the electircal isolation between them, and thus the reference electrode records only the motion artifacts' references. Then, the motion artifact references are subtracted from raw EEG signals to acquire motion artifact-free EEG signals.

Although current paired electrode-based techniques have shown promising potential to suppress EEG motion artifacts (Nordin et al. 2018; Nordin et al. 2019), the applied reference subtraction algorithm in these current techniques might not be adaptive enough to alleviate motion artifacts resulting from unpredictable and irregular motions in real field applications. Specifically, the current method first identifies motion artifact-governing frequencies from the reference and cancels raw EEG signals under the identified frequencies via assuming that EEG signals under these frequencies are too governed by motion artifacts and thus do not contain any useful information about brain activity (Nordin et al. 2018). This frequency-based dichotomous approach might work when motion artifacts and clean EEG signals are clearly differentiated in frequency range. However, in applications to construction workers, motion artifacts and clean EEG signals often share a wide range of frequencies (1-10 Hz) due to the irregularity of the motion (Gwin et al. 2010; Islam et al. 2020; Shukla et al. 2020). Therefore, the current techniques might remove a significant portion of waves in EEG signals useful in understanding workers' brain activities, thereby compromising the reliability and validity of the following EEG analysis. To overcome this limitation, this study aims to develop a more adaptive reference subtraction that can seek out motion artifacts mixed with clean EEG signals over a wide range of frequencies and parallel the new reference subtraction with the paired electrode-based motion artifact reference recording, thereby enabling applications of mobile EEG at construction sites. To this end, this study first proposed an EEG motion artifact denoising technique that parallals a new adaptive reference subtraction with the paired electrodes. Then, to validate the proposed denoising technique, the denoising performance is compared with an advanced existing paired electrodes-based denoising technique on an EEG dataset collected in a lab setup where construction workers' dynamic motions are carefully reproduced.

## Proposed EEG motion artifact removal

### Acquisition of motion artifact reference

The authors adopted the paired electrode approach (Chowdhury et al. 2014; Luo et al. 2014; Nordin et al. 2018) to record motion artifact references. A commercially available EEG device (i.e., Mentalab Explore) was customized. This device provides up to eight EEG channels on a flexible cap and has a sampling rate ranging from 250 Hz to 1000 Hz. The authors customized this device to apply our own adaptive EEG motion artifact removal technique. The authors paired electrodes: The noise-reference electrodes were flipped and attached to their paired scalp electrodes using an insulating tape, and then a conductive fabric was layered over the noise-reference electrodes to short the noise-reference electrodes and ground them like the human scalp does for the normal scalp electrodes (Figure 1). In this setup, the noise-reference electrodes remain electrically isolated from the scalp but experience similar motion artifacts to what the normal scalp electrodes experience, allowing the noise-reference electrodes to record only motion artifacts.

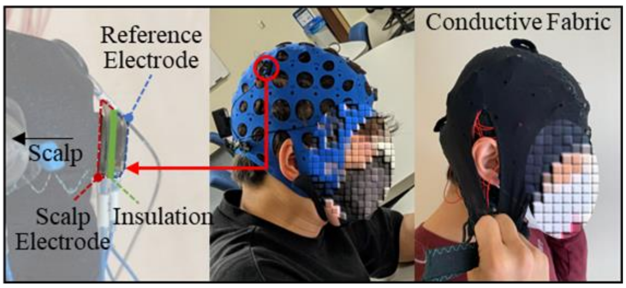


*Figure 1: Customized mobile EEG device and details of the paired electrodes*

**Subtraction of motion artifact from raw EEG by a constrained independent component analysis with motion artifact reference**

To adaptively alleviate motion artifacts using the references collected by the paired reference electrodes, a constraint independent component analysis (cICA; Figure 2) was applied. First, the raw EEG signals are synced with the motion artifact references collected by the noise-reference electrodes. Then, the cICA is applied to identify and filter out one IC whose signal shape is similar to the provided motion artifact reference, assuming that the IC results from the motion artifact. This method is based on an empirical finding; since paired normal and reference electrodes experience almost identical electromagnetic gradients from movements, motion artifacts implicit in EEG signals collected by a normal scalp electrode can have similar signal shapes in time domains with the motion artifact reference collected by the reference electrode paired with the normal electrode (Chowdhury et al. 2014), while the amplitude scale might be different due to different electric conductance of the circuits of the normal scalp electrode and the reference electrode. To this end, the authors designed the cICA to be sensitive to motion artifact references by having two conditions reflected as constraints in the process of identifying ICs: (i) minimized mutual information between ICs and (ii) one IC with similar signal shape to the provided motion artifact references in a scaleless manner. Specifically, the authors combined the ICA with a reference (ICA-R) (Lu and Rajapakse 2006) and the Fast ICA (Hyvärinen and Oja 2000) to realize the aforementioned cICA. Once the ICA-R extracts a weight vector corresponding to the IC similar with the provided motion artifact reference, a modified version of the Fast ICA is applied to calculate the other weight vectors corresponding to the other ICs that share minimal mutual information with the determined motion artifact-similar IC, thereby finalizing the demixing matrix. Then, by multiplying the demixing matrix and the raw EEG signals, ICs are acquired. Among the ICs, the IC identified as motion artifact-similar is linearly subtracted from the raw EEG signals, thereby denoising motion artifacts. Through this procedure, motion artifacts mixed with clean EEG signals across a wide range of frequencies are expected to be addressed.

## The proposed denoising technique validation

In validating biosignal denoising techniques, it is challenging to obtain a ground truth/noisy biosignal pair, which is essential to comparing the ground truth with denoised signals. As a means of acquiring the ground truth EEG signals together with ones contaminated by motion artifacts, the authors applied the phantom head approach (Oliveira et al. 2016). In this approach, an EEG sensor is put on a phantom head whose shape and electrical conductivity are similar to a real human head. Then, the phantom head is set to move so as to collect a pure EEG motion artifact. The collected EEG motion artifact is linearly combined with a prepared clean ground truth EEG to make a semi-simulated noise EEG. With the pair of the ground truth EEG and the semi-simulated noise EEG, denoising performance can be quantified by comparing between the ground truth EEG and a denoised version of EEG that is acquired by applying a denoising technique to test on the semi-simulated contaminated EEG. This study statistically compared the denoising performance of the proposed technique with the most advanced existing paired electrode-based denoising tehcnique (Nordin et al. 2019) on the dataset prepared by the phantom head approach.

**Phantom head generation**

A phantom head was first created to authentically imitate the shape and conductivity of a human head (Figure 3). Once the skull and its inner part were created with a mixture of dental plaster, water, and sodium propionate the authors duplicated human scalp skin with 1.2-1.5-mm thick conductive geletin. The conductivity of the plaster mixture and conductive gelatin skin were set to 0.0004 S/m and 0.3 S/m, respectively replicating the conductivity of a real human head. Also, unlike previous phantom-bead EEG denoising validation studies where an artificial regular and consistent motion was applied (Nordin et al. 2018; Oliveira et al. 2016), we intended to test real human motions. To do so, a steel plate was embedded in the bottom of the head through which real human motions could be delivered to the head.

**Motion artifact collection and generation of semi-simulated EEG contaminated by motion artifact**

The customized mobile EEG sensor with paired electrodes was put on the phantom head and EEG signals were collected in a nosy setup with motions to collect EEG motion artifacts with the motion artifact reference. In the data collection, two electrode pairs were installed on two nodes on prefrontal cortex area (i.e., F3 and F4; b

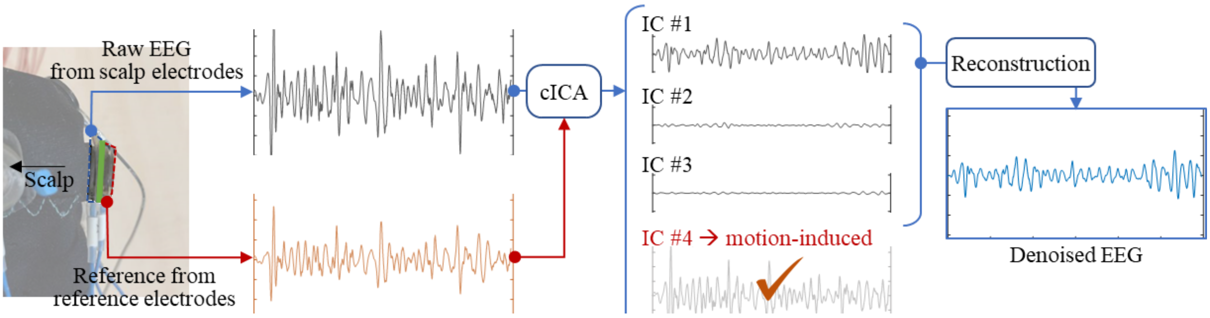


*Figure 2. Overview of the proposed cICA-based reference subtraction*

in Figure 3), where brain activities related to workers' stress and emotions (Hwang et al. 2018) can be monitored. The sampling rate was set by 250 Hz. Here, motions like those occurring in a construction worker's daily work at sites were provided. Specifically, a hands-free-camera-gimbal-style steel rack was connected to the steel plate embedded in the bottom of the phantom head, so that a person could comfortably wear the phantom head (d in Figure 3). A research staff member conducted a sandbag carrying task, a typical construction task, to elicit natural motions while wearing the phantom head on their back. Specifically, the staff member conducted four sessions of sandbag carrying, each of which took six minutes, so that a total of 24-minute-long EEG motion artifact signals were collected. A 24-minute timespan was determined sufficient for acquiring enough samples via statistical analysis (i.e., paired t-test), which is elaborated on in the following paragraph. In each sandbag carrying session, the research staff member carried moderately weighted sandbags (10 kg) between two spots 10 m apart. Their pace was controlled to 30, 25, 20, and 15 seconds per carry over the four sessions to introduce variability in motion intensity.

Once the motion artifacts were collected, they were linearly combined with a clean ground truth EEG signal to make a semi-simulated motion artifact-contaminated EEG signal. Since the motion artifacts originate from human motions which are totally independent from other legitimate brain activities, this linear superposition assumption can be valid (Islam et al. 2015; Islam et al. 2020; Shahbakhti et al. 2021). A publicly available EEG signal dataset, collected from 50 subjects under a well-controlled shielded noise-free lab condition, (Klados and Bamidis 2016) was used as a ground truth EEG signal. This EEG signal dataset has been widely used as a ground truth EEG among multiple denoising validation studies (Issa and Juhasz 2019; Mohammadpour and Rahmani 2017; Saini and Satija 2019). First, the collected motion artifact was downsampled from 250 Hz to 200 Hz to sync with the used ground truth EEG whose sampling rate is 200 Hz. Then, a bandpass filter (0.5-40 Hz) and a north filter (50 Hz) were applied on the motion artifacts just as they were applied on the ground truth EEG. Then, the beginning and ending segments of the 24-minute-long motion artifact signals were removed to minimize the impact of the bandpass-filter-induced distortion and the middle 1250-second-long motion artifact signal data was divided into 50 25-second-long segments. These 50 segments were paired and linearly combined with 50 different subjects' ground truth EEG signals acquired from the ground truth dataset. Through these procedures, the authors had a total of 100 25-second-long semi-simulated motion artifact contaminated EEG signal samples (50 segments and 2 channels per each segment).

### Statistical comparison with the existing technique

As a validation, this study statistically compared the performance of the proposed denoising technique with the most advanced paired electrode-based adaptive denoising (Nordin et al. 2019) as a benchmark. To this end, the proposed denoising technique and the benchmark were applied to the 100 noisy EEG signal samples. From each signal sample, three denoising performance metrics (i.e., signal-to-noise ratio ($SNR_{dB}$), root mean square error (RMSE) and cross correlation (CC)) were calculated by comparing denoised signals with ground truth EEG signals. Then, the three denoising performance metrics were statistically compared between the proposed technique and the benchmark by conducting paired t-tests. According to statistical power analysis (desired power: 0.95, alpha: 0.05, effect size: 0.35), the number of samples (100) was confirmed sufficient to conduct the planned paired t-tests. The higher denoising performance is represented by higher $SNR_{dB}$ and CC, and lower RMSE.

*Figure 3. phantom head used in this study; (a) created phantom head; (b) Normal scalp EEG equipped on the phantom head; (c) Paired reference EEG setup; (d) Phantom head worn by a staff*

## Results and findings

Figure 4 displays the different denoising results between the proposed technique and the benchmark on a sample of EEG. This visualization shows that the signal desnoised by the proposed technique is more similar to the ground truth EEG than the one denoised by the benchmark. This observation coincides with the results of the three paired t-tests; the proposed denoising technique showed statistically higher $SNR_{dB}$, CC, and lower RMSE than the benchmarks (p-values: almost zeros). Figure 5 shows box plots of the denoising performance metrics and the summary of the results of the three paired t-tests. These results indicate that the proposed denoising technique better denoises EEG motion artifact induced by real human motions occuring during a construction task (i.e., material handling task).

In particular, CC shows denoising perfomance difference between the two denoising techniques more clearly than $SNR_{dB}$ and RMSE. Given that CC measures how correlated the ground truth EEG and the denoised EEG are in the time domain, while $SNR_{dB}$ and RMSE quantify how close data points of the ground turh EEG and the denoised EEG are, this result means that while the EEG signal denoised by the proposed technique well reflects the ground truth EEG signals' 'up and down patterns,' the benchmark just reduces the amplitude of the noisy EEG to fit the scale of the ground truth EEG but fails to restore the signal patterns of the ground truth.

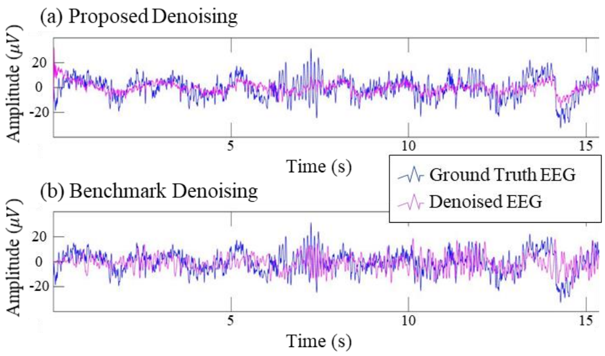


*Figure 4. Denoising results of the proposed technique and the benchmark*

To understand the underlying reason why the proposed technique shows better denosing performance than the benchmarks, the authors ploted a segment of the collected motion artifact reference in the frequency domain (Figure 6). As shown in this figure, the frequency ranges deteremined as motion artifact-governing and thus to be removed are widely distributed ranging from 0 to 20 Hz (red marked area). These ranges are overlapped with frequency ranges useful in understanding human psychophysioloigcal responses, such as delta (1-4 Hz), theta (4-7 Hz), alpha (8-12 Hz), and part of beta (12-30 Hz) (Holder et al. 2010). Since the benchmark denoising technique cancels the signals on the frequency ranges determined as motion artifact-governing, the informative waves in EEG signals will be eliminated, thereby compromising the following EEG analysis results.

Also, the authors exmined how similar the motion artifacts are to the motion artifact references by visualizing the signals collected by a normal electrode and its paired reference electrode. Aross most of the segments of collected EEG signals, the motion artifact and its reference showed a similar signal shape, but their amplitude scales differed (Figure 7). Through this visual investigation, the authors confirmed that the aformentioned conditions in the proposed cICA (i.e., similar signal shape in time domain with different amplitude scales) can be assumed.

These results demonstrate that the proposed denoising technique is more effective in alleviating EEG motion artifacts induced by real human motions than the existing paired electrode-based technique. The motion artifact is one of the most significant hurdles hindering deployment of mobile EEG at construction sites. The finding of this study can therefore significantly improve mobile EEG's field applicability, and thus contribute to monitoring construction workers' brain activities during their field work, which can help with the management of worker safety, health, and productivity.

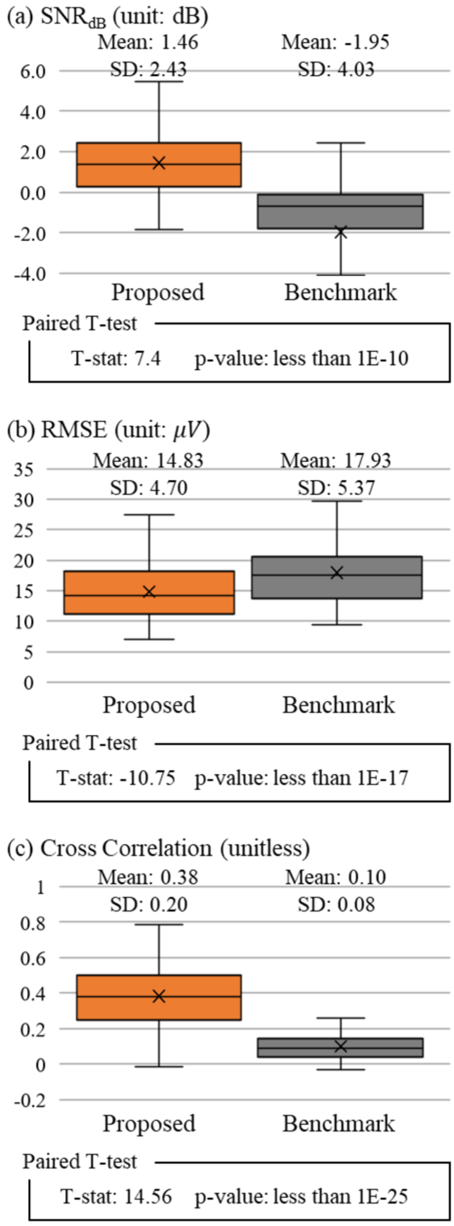


*Figure 5. Comparison of three denoising performance metrics and the results of paired t-tests*

Despite such significance, there are limitations in this study that should be addressed in future studies. First, even though the authors found that the proposed technique shows statistically higher denoising performance than the existing techniques, it needs to be additionally examined how significantly the improved denoising affects performance in tasks using EEG signals (e.g., EEG-based stress level classification and EEG-based cognitive load measurement). Also, this study tested two-electrodes-array only, but the required number of electrodes varies according to the type of EEG field applications. Therefore, whether the proposed technique's denoising performance is independent from the number of electrodes should also be investigated in a future study.

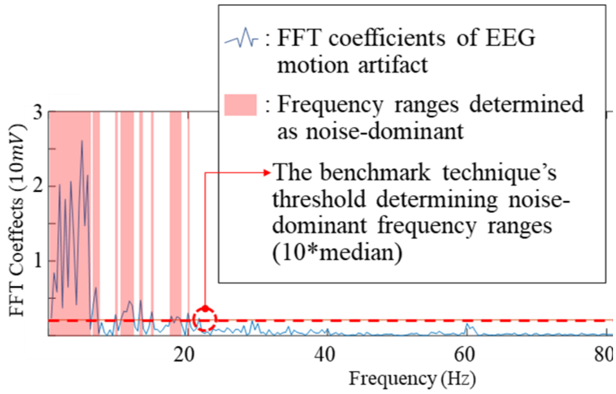


*Figure 6. Frequency domain plot of the collected motion artifact reference*

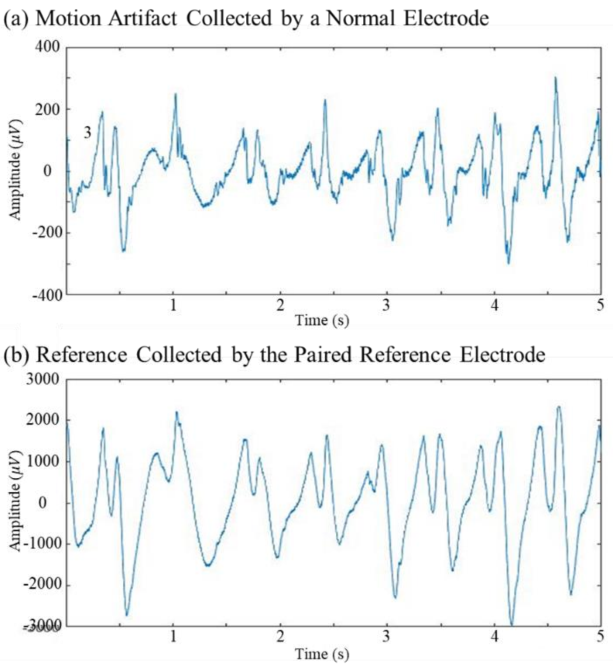


*Figure 7. Motion artifact and its reference*

## Conclusions

Mobile EEG empowers us to understand construction workers' mental processes related to their work in the field through their brain activities, thereby planning effective interventions for improving their jobsite safety, health, and productivity. Despite such a unique capability of EEG, current mobile EEG is still subject to motion artifacts caused by workers' dynamic body movements. Paired electrodes-based reference recording has great potential to alleviate motion artifacts in EEG signals collected by a mobile EEG device in the field. However, existing frequency-based dichotomous reference subtraction algorithms might not be effective in alleviating motion artifacts induced by real workers' motions during their field work because workers' irregularal motions spread the motion artifacts over a wide range of frequencies including frequency ranges of meaningful brain activities-induced EEG waves. To address this limitation, this study proposes a more adaptive denoising technique that conducts a constraint independent component analysis (cICA)-based reference subtraction. To compare the denoising performance of the proposed technique with an existing frequency-based dichotomous technique, the authors collected pure EEG motion artifacts by applying a construction task (i.e., material handling task)-induced real human motions on a mobile EEG-equipped phantom head and generated semi-simulated motion artifact-contaminated EEG signals by linearly combining the collected motion artifacts with clean ground truth EEG signals acquired from a publicly available EEG dataset. Then, three denoising metrics that quantify similarity between the ground truth and denoised EEG signals (i.e., $SNR_{dB}$, RMSE, and CC) were measured and compared between the two denoising techniques. The results showed that the proposed technique's denoising performance is statistically higher than the existing technique. The proposed denoising technique can significantly improve the field applicability of mobile EEG, thereby enabling us to monitor construction workers' brain activity during their ongoing work. The EEG-based field brain activity monitoring can provide useful understanding of workers' psychophysiological responses to work environments, so that their safety, health, and productivity can be better managed.

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