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Revealing the “Invisible Gorilla” in construction: Estimating construction safety through mental workload assessment

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ABSTRACT

Construction companies can accrue losses due to labor fatalities and injuries. Since more than 70% of all accidents are related to human activities, detecting and mitigating human-related risks hold the key to improving the safety conditions within the construction industry. Previous research has revealed that the psychological and emotional conditions of workers can contribute to fatalities and injuries. Recent observations in the area of neural science and psychology suggest that inattentional blindness is one major cause of unexpected human related accidents. Due to the limitation of human mental workload, laborers are vulnerable to unexpected hazards while focusing on complicated construction tasks. Therefore, the ability to detect the mental conditions of workers could reduce unexpected injuries. However, there are currently no available measurement approaches or devices capable of monitoring construction workers' mental conditions. The research proposed in this paper aims to develop a measurement approach to evaluate hazards through neural time–frequency analysis. The experimental results show that neural signals are valid for mental load assessment of construction workers, especially the low frequency bands signals. The research also describes the development of a prototype for a wearable electroencephalography (EEG) safety helmet that enables the collection of the neural information required as input for the measurement approach.

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1. Introduction

Construction is one of the most dangerous industrial sectors in every country. In Hong Kong, the construction industry has one of the worst safety records compared to all other industries. In 2013, there were 3332 injuries and 37 fatalities in the construction industry in Hong Kong, which accounts for 19.68% of fatalities across all industries [29]. Most of these accidents (including injuries and fatalities) were related to labor activities (75%), including slipping (24.0%), lifting (14.7%), falling (13.1%), striking against stationary objects (9.3%), operating tools (2.8%) and other human-related activities (10%) [29]. If safety hazards are properly detected and reported, workplace safety can be significantly improved [40]. However, the biggest challenge in identifying hazards and recording accidents is the dynamic environment of construction jobsites and workers' unpredictable behavior patterns [34]. Many researchers suggest that safety hazards could be identified through a safety analysis or safety climate analysis [75]. Together with proper safety programs [3] and prospective safety performance evaluation [71], safety conditions could be significantly improved. Although safety practices such as training, inspections, motivation, enforcement, and penalties, are successfully implemented in construction projects and achieved some improvements [28], there still are a large number of unexpected accidents that occur on job sites. However, risks cannot be assessed, controlled and avoided if managers are not aware of the hazards in the first place [12]. Since preventing accidents purely through safety programs is not possible, focusing on identifying and protecting vulnerable individuals rather than attempting to identify all possible hazardous events for all possible individuals who could be impacted provides an alternative option to further improve on site safe conditions [6]. In other words, construction site safety interventions can be improved by strategically targeting individuals who are more susceptible to accidents.

A workers' ability to perceive hazards can help him or her to escape from dangerous situations, which can result in near-miss accidents. Classic psychological theories suggest that people's decision making on risk-taking behavior is negatively correlated with their risk perception [46]. Thus, individuals who are weak in risk perception or tend to misestimate the risks are vulnerable to safety hazards, which can result in injuries instead of near-miss accidents. Therefore, a worker's ability to perceive risk is an excellent indication of a worker's vulnerability. If such an ability can be quantified and monitored, more vulnerable individuals could be identified and better protected.

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Among the many factors that could impact a worker's perception ability, his or her mental condition is most important. In psychological research, mental workload has been determined to be one of the best indicators of perceptional ability [45,49] especially for people who usually conduct complicated tasks. Therefore, the measurement of individuals' mental workload can help to assess their perception ability, which in turn can then be used to identify vulnerable workers on a construction job site. The research described in this paper aims to propose an approach to quantitatively estimate mental workload and then apply the resulting estimates to identify potentially vulnerable construction workers.

2. Background

2.1. Psychological issues and construction safety

In labor-intensive industries like construction, the psychological condition of workers plays a central role in safety performance. Construction work involves inherently dangerous tasks and exposure to various psychological stressors associated with pressure due to constraints on schedules and physical hazards [38]. According to Endsley's findings (1995) [19], there are three steps that people who experience dangerous events proceed through, including (1) detection of hazardous signals, (2) perception and comprehension of risks, and (3) projection of the consequences associated with decision options. Many psychological researchers conclude that emotions greatly influence signal detection, risk perception and process of risk-based decision making [51,60]. Different from other industries, in construction, risk perception is more important because even if the hazards are identified, workers still may involuntarily behave unsafely, since most construction tasks are inherently associated with various level of risks [74]. Due to tight project budgets and schedules, construction personnel are predominately production-oriented and can suffer from high levels of physical and mental pressure [47], which can exacerbate the level of danger and increase the possibility of injury. Tixier et al. (2014) conducted an experiment on 69 construction workers and observed that the emotionally negative group (i.e. those workers who were sad, unhappy, fearful, anxious and disgusted) were subject to more risks than the positive group (i.e. those workers who were happy, amused, joyful and interested) [63]. For example, in masonry work, heavy load lifting and awkward posture requires significant physical demands. In additional to physical demands, temporal demands and mental demands play critical roles in workers' performance [43] and safety [41]. Therefore, the demands of construction tasks could be indicators of safety risk. In 2010, Mitropoulos and Namboodiri proposed a novel task demand assessment (TDA) approach to measuring construction safety based on how difficult it was to safely perform an activity [48]. With the help of wearable biological sensors, the physical demands of tasks can be detected and measured, however, there is still no meaningful quantitative assessment framework on the mental demands of construction tasks [2]. This research aims at proposing such an approach to assess the mental demands through analyzing human brain rhythms.

2.2. Risk perception and mental workload

Mental workload or cognitive load refers to the total amount of human mental effort or memory that is required for the execution of a task [62]. When a person places too much attention on one task, he or she will have less attention to focus on other stimuli. One classic example is talking on the phone while driving [55]. In these cases, when a driver's attention is mostly allocated to the phone conversation, less attention is allocated for driving, which can result in higher accident rates [50]. Therefore, when a task consumes too much attention, people can be exposed to the danger of inattentional blindness [56]. Inattentional blindness is a psychological phenomenon where an individual fails to identify stimuli due to this lack of attention [39]. One approach to studying inattentional blindness is known as the Invisible Gorilla Test [13]. In this test, subjects are asked to count the number of ball passes between several participants in a video, while a person wearing a full gorilla suit walks through the scene. After watching the video, the subjects are asked to indicate whether they saw the gorilla. Most results demonstrate that 50% of subjects did not report seeing the gorilla. Failure to see the gorilla is attributed to the high mental engagement of the counting task and results in inattentional blindness [18].

In the construction industry, when workers focus too narrowly on their work, they become inattentionally blind, which decreases their perception ability and makes them more vulnerable to dangers. Also, repetitive tasks that require a very low cognitive load can lead to accidents. Another possible issue that affects the risk perception is hazard expectation. When workers conduct certain construction activities, they expect certain things to happen and tend to block out other possibilities. For example, when a worker installs a roof, he or she knows from standard training that falls are major hazards. Because they are focused on avoiding a fall, they may not be aware that they may be also hit by an object. These types of distractions and lack of focus on safety may also lead to inattentional blindness. These examples highlight why, even though workers may participate in safety training, they still could be injured.

Another issue that is related to the mental workload of workers is work complexity [69]. Workers often face rising cognitive demands when they execute increasingly complex tasks. In these cases, their cognitive skills are more important than physical skills [16]. In the construction industry, workers obtain a considerable portion of information directly from the cognitive task, while they are concurrently performing physically demanding work [17]. For instance, in the case of electrical installation, workers not only need to accurately attach wires, but they may need to do so on top of a ladder while holding their arms up for long periods of time. In these types of situations, understanding how the physical workload impacts the mental workload is required to estimate the safety condition of the worker in executing the task. However, due to differences between individual workers, it is difficult to predict the risk level from the task complexity and individual proficiency. Therefore, a quantitative and direct monitoring approach that can estimate the mental workload of workers can help project managers to identify vulnerable workers and implement safety policies or approaches to help avoid accidents.

2.3. Quantitative neural time–frequency analysis

In order to develop a measurement of mental workload, various behavioral and physiological tests have been developed since the 1980s [27,70]. Although subjective and inaccurate, such measurements can provide a relatively continuous data record over time without obstructing execution of the task [68]. In recent years, new neuroimaging techniques such as functional magnetic resonance imaging (fMRI) and electroencephalography (EEG) can provide direct and quantitative alternatives for the assessment of mental workload [57]. Among these methods, EEG is the best candidate for construction implementation because it can be applied outside of a specialized laboratory. Other methods require cumbersome devices, large medical teams and immobile subjects [23]. Moreover, many studies have found a correlation between brain rhythms collected by an EEG and mental workload [52,61,66].

One popular quantitative analysis for brain rhythms of mental workload is Event-Related Potentials (ERPs). ERPs is a valid approach because it requires fewer assumptions or parameters, possesses higher temporal precision and accuracy, has been well studied, and provides fast and easy computational results [14]. However, the results of ERPs are difficult to interpret and link the continuous data to physiological mechanisms. To resolve these difficulties, a time–frequency-based analysis adopted from digital signal processing theory has been introduced for use in the analysis of brain rhythms [26,64,65]. In the research method described below, time–frequency analysis will be adopted to assess the mental workload of subjects when they focus on construction tasks. A preliminary experiment is described, which is designed to collect the brain rhythms of experimental subjects, and then estimate their mental workload and their vulnerability to accidents.

2.4. Physiological load of construction workers and the scope of this research

Another valid approach of improving workforce productivity and safety is through monitoring workers' physiological conditions. Gatti et al. conduct a comparative experiment and found that vital signs, such as heart rate and breathing rates, are valid signals for monitoring workers' physiological conditions [22]. Those physiological signals have been used as predictors of physical strain for productivity measurement [20, 21]. One critical observation suggested by Tixier et al. (2014) is the existence of an interrelationship between physiological and mental conditions [63]. Both perspectives have a complicated interrelationship and have to be monitored separately and distinctively. Although such issues have not been thoroughly studied in the construction industry, to simply the research question, the research described in this paper will focus on exploring the feasibility and validity of applied time–frequency analysis on mental perspectives through monitored EEG signals. A study on interrelationship between physiological and mental conditions for construction activities will be discussed in future research.

3. Research methodology

3.1. Electroencephalography (EEG)

In recent years, research has led to new methods for collecting workers' physiological information with the end goal of enhancing construction safety. For instance, Jebelli et al. employed inertial measurement units to detect the body motion of steel works to protect them from falls [30]. Gatti et al. measured two physiological parameters (i.e. heart rate and breathing rate) to monitor the health condition of construction workers when they conduct various construction activities [22]. In the research described in this paper, EEG will be introduced to assess the mental workload of workers.

There are several advantages of using EEG to study neurocognitive processes [15] including:

1) EEG can capture cognitive dynamics over time. Most cognitive events occur in a temporal sequence and in a scale of milliseconds or seconds. High temporal-resolution techniques such as EEG are suitable to capture this rapid information on a temporal scale.
2) EEG is a direct measurement of neural activities. The voltage fluctuations detected by EEG are the most direct observation method compared to other measurement devices. Although the mechanism is not fully known by researchers, the oscillating patterns of EEG signals are well-studied and can be modeled fairly accurately [10,67].
3) The EEG signal is multidimensional. Different from regular time series data, EEG signals are multidimensional because they include time, magnitude, frequency, power and phase. Such multidimensionality provides plentiful data resources and possibilities for sophisticated data analysis.

3.2. Data processing

The data collected and analyzed through EEG will capture brain rhythms that will be grouped into bands based upon their center frequencies and frequency widths. These brain rhythm frequency bands include delta waves (1–3 Hz), theta waves (4–7 Hz), low alpha waves (8–9 Hz), high alpha waves (10–12 Hz), low beta waves (13–17 Hz), high beta waves (18–30 Hz), low gamma waves (31–40 Hz), and high gamma waves (41–50 Hz). Such a grouping is not arbitrary but results from neurobiological mechanisms of brain oscillations, such as synaptic decay and brain signal transmission [9].

The EEG data analysis involves computation of power spectral densities (PSD) for the above frequency bands. These rhythms can be used to identify and classify cognitive states such as mental workload, engagement, execution, and verbal or spatial memory [7]. In this research, the engagement index developed by Prinzel et al. will be used [53] to measure the attentional resource allocation. This index has been successfully applied by NASA's Langley Research Center and reported to be sensitive to increases in task load. In the study, the engagement index will be compared across tasks with different levels of complexity. The calculation of an EEG-engagement index (EN) will be based on beta power (13–30 Hz) divided by alpha power (8–12 Hz) plus theta power (5–7 Hz) and can be represented in the following equation:

$$EN(\mathrm{t}) = \frac{P_\beta(\mathrm{t})}{P_a(\mathrm{t}) + P_\theta(\mathrm{t})} \tag{1}$$

where EN(t) is the EEG-engagement index at time t;$P_\alpha(t)$, $P_\beta(t)$, and $P_\theta(t)$ are the power of alpha rhythms, beta rhythms and theta rhythms at time t.

An engagement index is a time–frequency indicator based on the power and energy of alpha, beta and theta frequency bands. Bandpass filters were applied to isolate each frequency band from the raw signal. A higher engagement index suggests higher mental workload. Since people have limited memory sources (or working memory), higher mental workload spent on tasks means fewer resources will be allocated to risk perception. Therefore, the engagement index describes to which level the memory resources have been allocated to risk perception. In other words, a higher engagement index suggests lower risk perception ability and higher vulnerability.

Another useful mental workload assessment framework is based on a hybrid brain–computer interface (BCI) model that is characterized by the temporal and frequency information contained within the EEG data. As suggested by Zhou et al. (2007), eight quantitative features can be derived from EEG raw signals based upon their bispectrum, since bispectrum has been proven to be a useful tool for EEG signal classification and filtering [73]. These features are:

(1) Peak frequency of the power spectral density (PSD), $H_1(t)$.
(2) Peak value of the PSD, $H_2(t)$
(3) The first order spectral moment of the PSD at time t:

$$H_3(t) = \sum_{\omega=1}^{N} \omega \cdot H_{1,\omega}(t) \tag{2}$$

where ω is the frequency of the power spectrum; N is the maximum frequency to be considered.

(4) The second-order spectral moment of the PSD:

$$H_4(t) = \sum_{\omega=1}^{N} (\omega - H_3(t))^2 \cdot H_{1,\omega}(t) \tag{3}$$

(5) The sum of logarithmic amplitudes of the bispectrum at time t:

$$H_5 = \sum\nolimits_{\omega_1,\omega_2 \in F} \log(|B(\omega_1, \omega_2)|) \tag{4}$$

(6) The sum of logarithmic amplitudes of diagonal elements in the bispectrum

$$H_6 = \sum_{\omega \in F} \log(|B(\omega, \omega)|) \tag{5}$$

(7) The first-order spectral moment of the amplitudes of diagonal elements in the bispectrum

$$H_7 = \sum_{k=1}^{N} k \cdot \log(|B(\omega_k, \omega_k)|) \tag{6}$$

(8) The second-order spectral moment of the amplitudes of diagonal elements in the bispectrum:

$$H_8 = \sum_{k=1}^{N} (k - H_7)^2 \cdot \log(|B(\omega_k, \omega_k)|) \tag{7}$$

where,

$$B(\omega_1, \omega_2) = \sum_{m=-\infty}^{+\infty} \sum_{n=-\infty}^{+\infty} E[x(k) \cdot x(k+m) \cdot x(k+n)] \cdot e^{-i2\pi(m\omega_1 + n\omega_2)}. \tag{8}$$

$B(w_1, w_2)$ is the bispectrum of the 2D Fourier transform of the third-order cumulant of $x(t)$, which is a non-Guassian third-order stationary random process.

The estimation of the bispectrum is based on the calculation of moment as Eq. (2). The moment of PSD suggests how power is distributed across frequencies, whereas higher frequencies provide higher leverage and results in exponential increment in moment. Since high frequency signals normally are caused by random noise and low frequency signals are reflection of brain activities, the moment indicates whether the collected data is dominated by noise or valid signals. The bispectrum calculation in Eqs. (3) to (8) describes the non-linear relationships across frequency bands. A high bispectrum value suggests high interdependency between frequency components and invalidates the linear estimation, such as regression, of these frequency bands. The logarithm of bispectrum aims at rescaling the output for more robust comparison.

3.3. Preliminary test and equipment

A preliminary experiment was designed to validate the feasibility of mental workload measurement. Five subjects were invited to wear an EEG monitoring helmet to perform an installation task. The subjects were asked to relax for 5 s, climb up a ladder (1 m tall and 3–4 s to climb), conduct an installation (4–5 min), climb down the ladder and then rest. The installation task requires each subject to choose suitable nuts and fasten them to bolts with a screwdriver. The task is repeated three times by the subjects. The task includes four types of activities with various risk levels: idling, ladder climbing, nut selection and bolt fastening. The risk level is recorded based on the subjects' perception through a post experiment survey as bolt fastening (high risk) > ladder climbing (high risk) > nut selection (medium risk) > idling (low risk). During the experiment, a monitoring safety helmet was connected to a laptop via Bluetooth to stream data. At the same time, a camera was used to record the activities and events and was synchronized with the EEG data collection. Then, event tags were associated with raw EEG data based on analysis of the video.

The research team developed a EEG monitoring safety helmet with a Neurosky TGAM model [10]. Since Neurosky TGAM only has one channel for raw data collection, the research team expanded it to four channels by stacking four TGAM boards and connected them with a DFRduino UNO R3 and a Bluetooth module. An electrocardiography (ECG) sensor, PulseSensor [1], was also attached to the microcontroller for reference. Fig. 1 shows the instrumentation of the monitoring helmet.

The four sensor sites that were selected refer to the 10–20 system or international 10–20 system, which is a method that describes the application locations of scalp electrodes. Four selected locations in this research are left ear (TP9), left forehead (FP1), right forehead (FP2) and right ear (TP10). These locations are presented in Fig. 2. The FP1 location is related to logical attention and other brain functions, such as interaction planning, decision making, task completion and working memory [8]. The FP2 location relates to emotional attention and other brain functions, such as judgment, sense of self and restraint of impulses. Because of proximity to auricular and mastoid, TP9 and TP10 are suggested to be the reference points by a 10–20 system. One practical issue of wearing the helmet is to fix the application locations of each electrode. Conductive paste was applied to a stick, which connected electrodes to the skin. Another potential issue arose because of sweating. For instance, the sweat could potentially decrease the conductivity of skin which could result in faulty data. During the preliminary experiment, the researchers ensured that the subjects did not sweat by keeping the work load low and operation duration short. For applications in the field, the problems introduced by sweating must be more robustly addressed.

Since the raw data contains rich information with unavoidable noise, it is important to determine the best signal for mental load estimation. Comparing across the spectrum of all frequencies, alpha waves (8–12 Hz), beta waves (13–30 Hz), and gamma waves (31–50 Hz) are the best candidates [9] for the following reasons. Alpha brainwaves are present when people have quietly flowing thoughts. They are associated with relaxed wakefulness and aid with mental coordination, calmness, and alertness. *Beta* brainwaves dominate normal waking states of consciousness when people engage in tasks, i.e. they are associated with attentiveness, selective attention, concentration and anticipation. Gamma brainwaves are high frequency waves relate to simultaneous information processing involving multiple brain areas and are associated with higher mental activities, perception, problem solving, fear and consciousness.

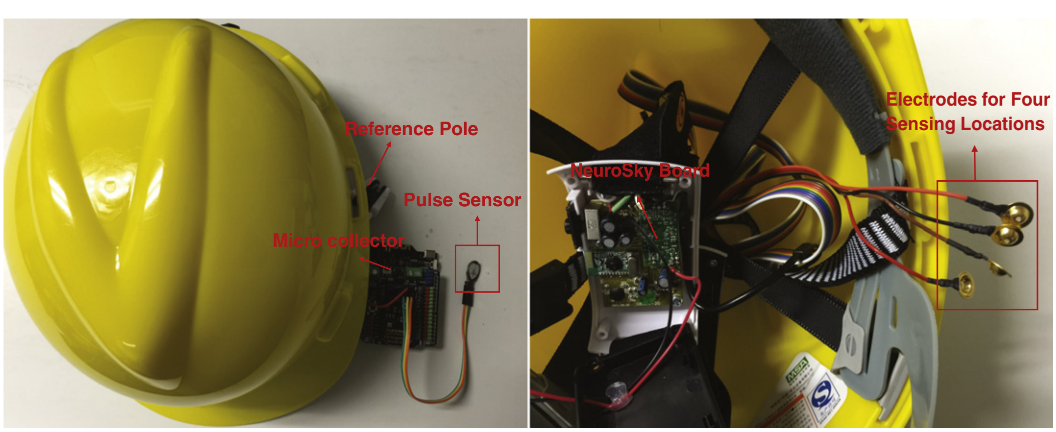

Fig. 1. Design of the wearable EEG monitoring safety helmet: Micro controller and pulse sensor (left); NeuroSky Board and Electrodes (right).

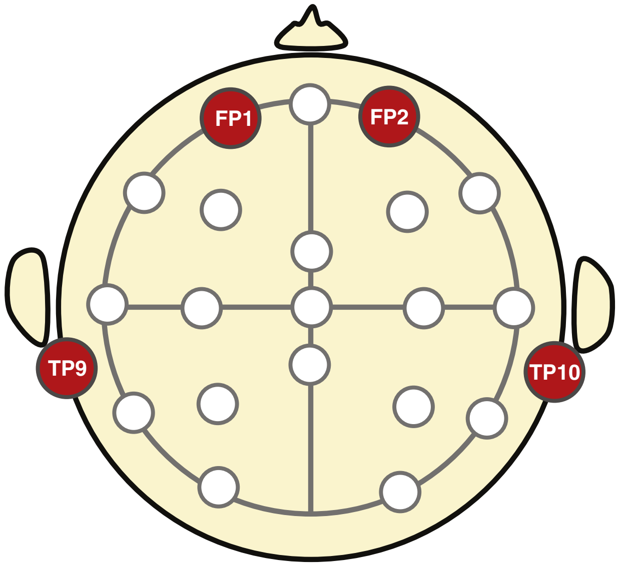

Fig. 2. Electrodes installing locations refer to 10–20 system.

4. Experimental results and mental workload assessment

4.1. Time–frequency analysis results

Since the engagement level indicates the vulnerability of a worker, the interrelationship between the risk level of tasks and engagement level is critical to validate the feasibility of the mental workload assessment model and the EEG monitoring helmet. Fig. 3 presents the raw data of brainwaves from the four electrode installation locations during the first 18 s. Event tags were associated with the raw signal by referring to videos recorded during the preliminary experiment. All data reported here is recorded from a single subject in one experimental round.

To simplify the data analysis for the preliminary experiment, this manuscript only discusses the signal patterns of FP1 and TP10, since FP1 and TP10 have less fluctuation. The temporal data analyzed in this study includes the first 18 s of the experimental window, which includes all four major activities (idling, climbing, nut selection and bolt fastening). Since the EEG signals have plentiful information with random noise, by focusing on two channels and a short time window, it improves the computational efficiency by removing redundant information. Multiple electrode channels and longer time windows will be discussed in future research. The raw data displayed in Fig. 3 shows distinctive patterns in signal magnitude and frequency among the four different activities. Although the output voltages are different in magnitude, the frequency patterns are similar across all four channels. To visualize the performance of the target rhythms, the data is decomposed into frequency domains as shown in Fig. 4.

Fig. 4 shows the energy distribution across the whole frequency spectrum. The time–frequency analysis was applied to understand the raw EEG signals. Two types of time windows were applied through the raw signal to remove white noise. The Hanning window is a bell-shaped window with decreasing weight for signals based on distance from the testing time point. A rectangular time window only takes into account the 0.2 s time period centered on the testing time point. Then a Fourier Transform was performed to isolate the frequency band based on the observed physiological indicators. Fig. 4 shows the frequency spectrum of the raw signals, which uses a heat map to highlight the power of each frequency level. There are clear signal spikes in the Alpha, Beta and Gamma rhythms when the subjects begin to climb the ladder and starts to fasten the bolts. These spikes are directly associated with the subject's mental workload and physical work. By

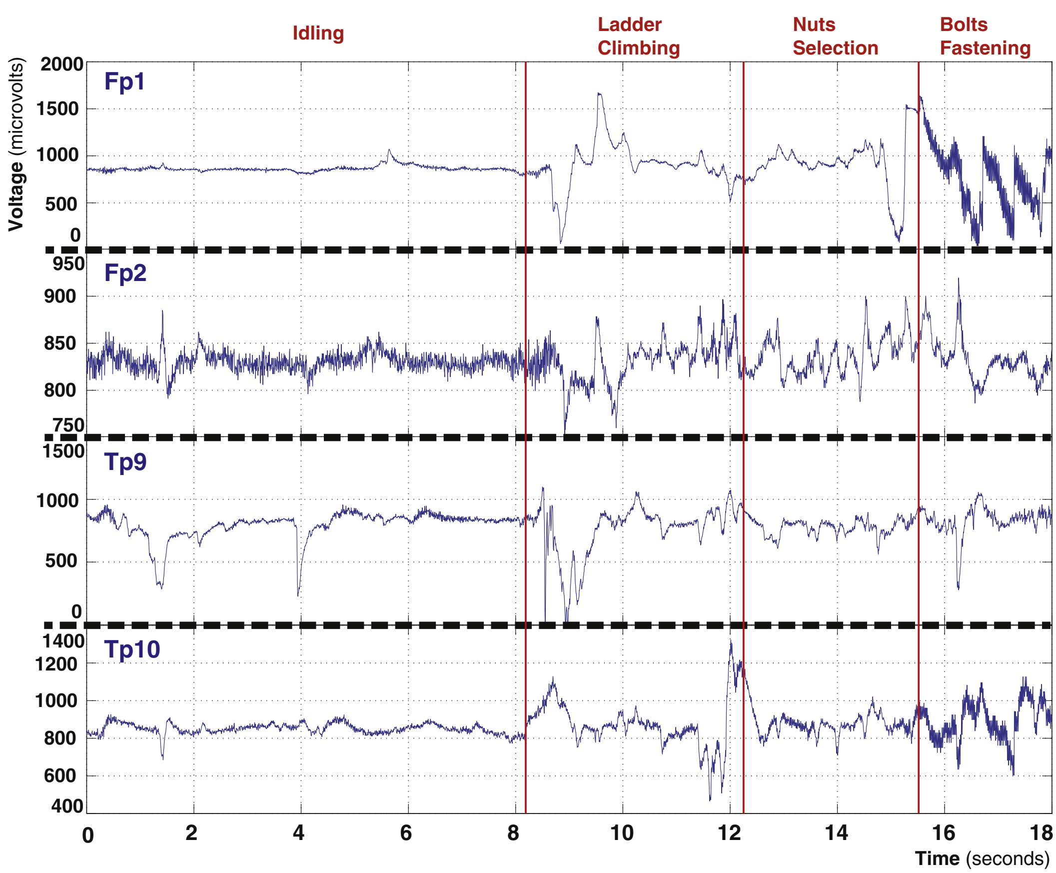

Fig. 3. Raw singles from channels of FP1, FP2, TP9 and TP10.

calculating the magnitude of the spikes, the mental workload can be quantitatively estimated. It is also important to note that the appearance of gamma waves occurs when the subject selects the nuts and fastens the bolts, but not when the subject is climbing the ladder. Neurologists believe that gamma waves implicate neural consciousness via the mechanism for conscious attention, which is relatively independent from physical movement [9]. Even if the ladder climbing involves a heavy physical load, the activity doesn't initiate a gamma spike. Therefore, gamma waves can be used to differentiate routine behaviors from behaviors that involve decision making, since both nut selection and bolt fastening require judgment, i.e. the subject needs to choose the right size nut and then fasten the bolts in the correct order.

To understand how signal power is distributed through the frequency domain, a Power Spectrum Density map is shown in Fig. 5. In various frequency bands, most of the signal power is distributed in low frequency bands, which include theta, alpha, beta and gamma waves. Also, the Power Spectrum Density map demonstrates that the Gamma band uniquely possesses a great amount of power compared to the other frequencies. This observation suggests that most the information within EEG signals are stored in low frequency bands, particularly in the Gamma band. Therefore, to achieve cleaner data, a Lowpass filter should be used to remove the irrelevant data contained in the higher frequencies. Combining the results from Figs. 4 and 5, it is also important to note that, although low frequency bands store more energy, their fluctuation is not as obvious as bands with relatively higher frequencies. Thus, to simplify single pattern identification and reduce computational complexity, a Bandpass filter should be employed to remove both low and high frequency components.

The results of the time–frequency analysis suggest that the monitoring helmet is able to capture the fluctuation of brain wave bands when the user engages in different tasks. Each type of task is associated with various levels of mental workload and risks, and shows distinctive patterns. Thus, it is feasible to estimate the mental workload through extracting, filtering and processing the EEG singles.

4.2. Mental workload estimation

To estimate the mental workload associated with the activities, an engagement index was calculated by deriving the power in each frequency band. Before the calculation, bandpass filters were applied to remove irrelevant frequency components and isolate the objective brain rhythms. Calculation of the engagement index uses a moving time window of 0.2 s. Since the sampling rate is 220 Hz, each time window includes 44 data points. Fig. 6 shows the temporal level of the engagement index using a sliding time window. Each value of the y axis is calculated based on its average PSD within a 0.2 s time window before that time point.

The engagement index significantly spikes when the subject climbs up the ladder. The bolt fastening activity also requires higher engagement with more intense frequency. The drawback of the engagement index is its neglect of information contained in the gamma band,

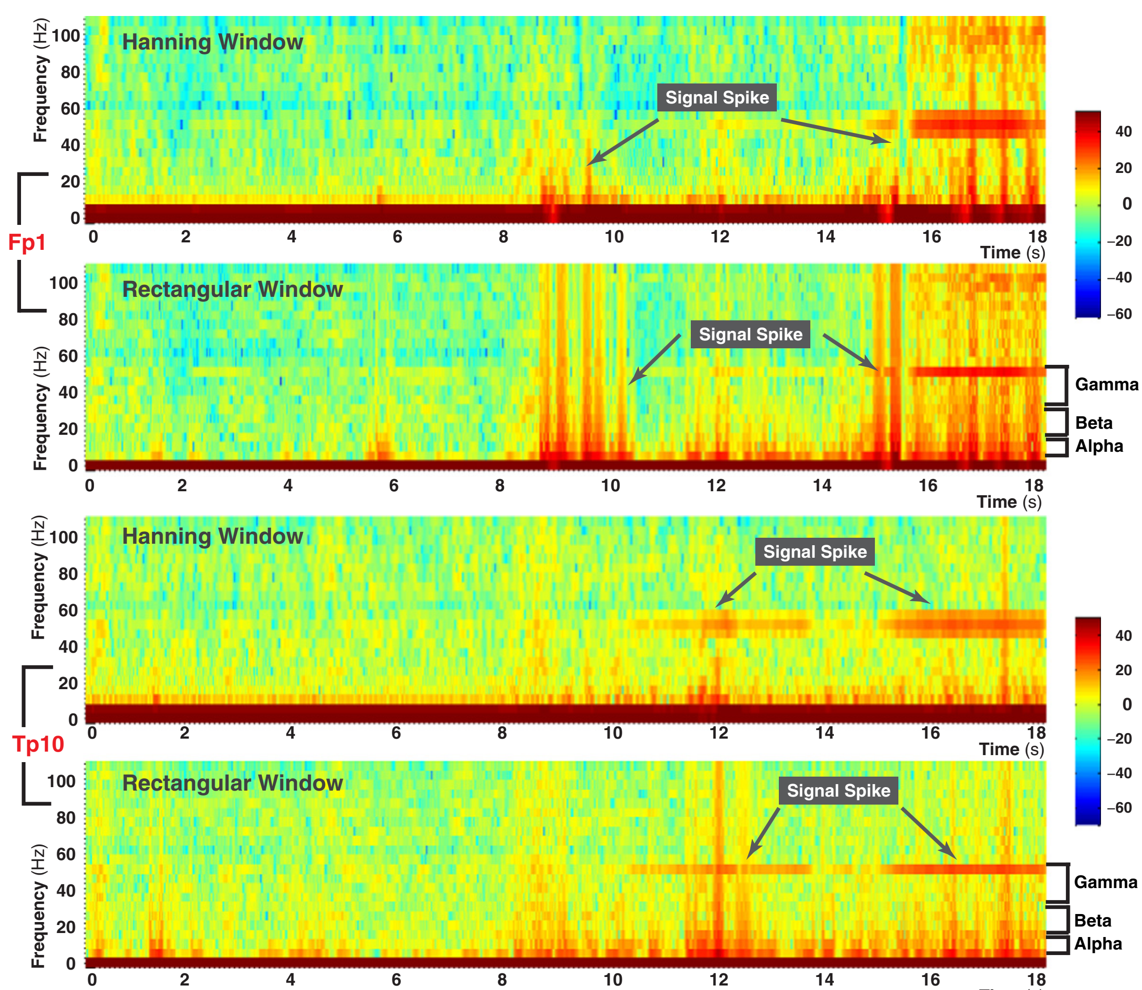

Fig. 4. Signal spectrogram of FP1 and TP10 with Hanning window and rectangular window.

which contains a great amount of energy in a single PSD. However, the engagement index is simple and accurate enough to reflect the mental workload for various activities. In the previous discussion on the relationship between mental workload and vulnerability, higher engagement suggests lower risk perception ability and higher probability for accidents. The results from this preliminary experiment in Fig. 6 show that the ladder climbing activity is the most dangerous activity (i.e. it has the highest engagement index value) of those investigated that may result in inattentional blindness. Although both the nut selection and bolt fastening activities also required the subject work at height, the subject is more vulnerable to inattentional blindness when working on the fastening activity (multiple engagement index spikes) and is more alert during the selection activity (lower engagement index).

In order to validate the conclusions suggested by the engagement index, a bispectrum signal is constructed to calculate the bispectrum feature indexes suggested by Zhou et al. [73]. Four time windows with a length of one second are selected for each activity. The 3rd order cumulant and bispectrum magnitude are calculated by Eq. (8). Instead of a fixed time lag in the original signal, a flexible time lag is compared on top of Fig. 6 to select the proper lag for large differences between 3 order cumulants so that the data pattern can be easily identified.

Through the bispectrum analysis, the bispectrum feature indexes can be calculated by Eqs. (2) through (7). The resulting combination of feature indexes is listed in Table 1, which indicates the mental workload of each activity type. H_3 has similar results to the engagement index, which shows that ladder climbing requires more mental load compared to bolt fastening. H_4 is similar to H_3 but in a reciprocal pattern. Both H_3 and H_4 are moments that describe energy distribution across the frequencies. Lower moments imply that the power is mainly allocated at low frequency bands, which requires more brain activity and working memory. Bispectrum indicators for H_5 to H_8 have the same conclusions relative to each other, even in varying scale, which suggests that bolt fastening requires more concentration and has a higher probability of triggering accidents compare to the other activities. The magnitude of bispectrum indicators reflects the non-linearity across frequencies. A more detailed magnitude through the whole spectrum is mapped in Fig. 7.

The bottom of Fig. 7 suggests which frequency pairs are most useful to differentiate the magnitude of different activities. High frequency regions have weak correlation with each other, which results in insensitive responses for different activities. In other words, the high frequency bands are relatively consistent for each task and not suitable to be used to differentiate different mental load levels. However, the frequency bands between 10 Hz and 15 Hz could provide larger distinctions among activities. One exception is idling, when all frequency bands are active and memory is less concentrated. The bispectrum magnitude of high frequency bands could be used to identify idling, since for other tasks, the magnitude is close to zero. This result is consistent with the conclusions that are suggested by the spectrogram in Fig. 4.

Although the engagement index provides us with a direct and simple interpretation of the intensity of mental workload, it is important to notice that each individual has his/her own brain responses when executing the same task. This could result in inaccuracy in risk detection and difficulty in generalizing the findings. Bispectrum feature indices offer more feature references to differentiate tasks and judge risk levels through non-linear changes across brainwave frequency bands. Therefore, bispectrum feature indices of EEG signals could supplement the engagement index and help to provide a more reliable estimation of individual vulnerability.

5. Safety/vulnerability and mental workload

Based upon the results from the preliminary experiment, we draw following conclusions. First, EEG is an effective measurement tool to monitor the dynamic fluctuation of mental workload when workers are engaged in construction tasks. From the monitored EEG signals, there are obvious distinctions in data patterns for each construction activity. As shown in Figs. 3 and 4, the magnitude and power spikes can be used to differentiate tasks with various levels of complexity and memory requirements. Second, the engagement index is a valid tool for

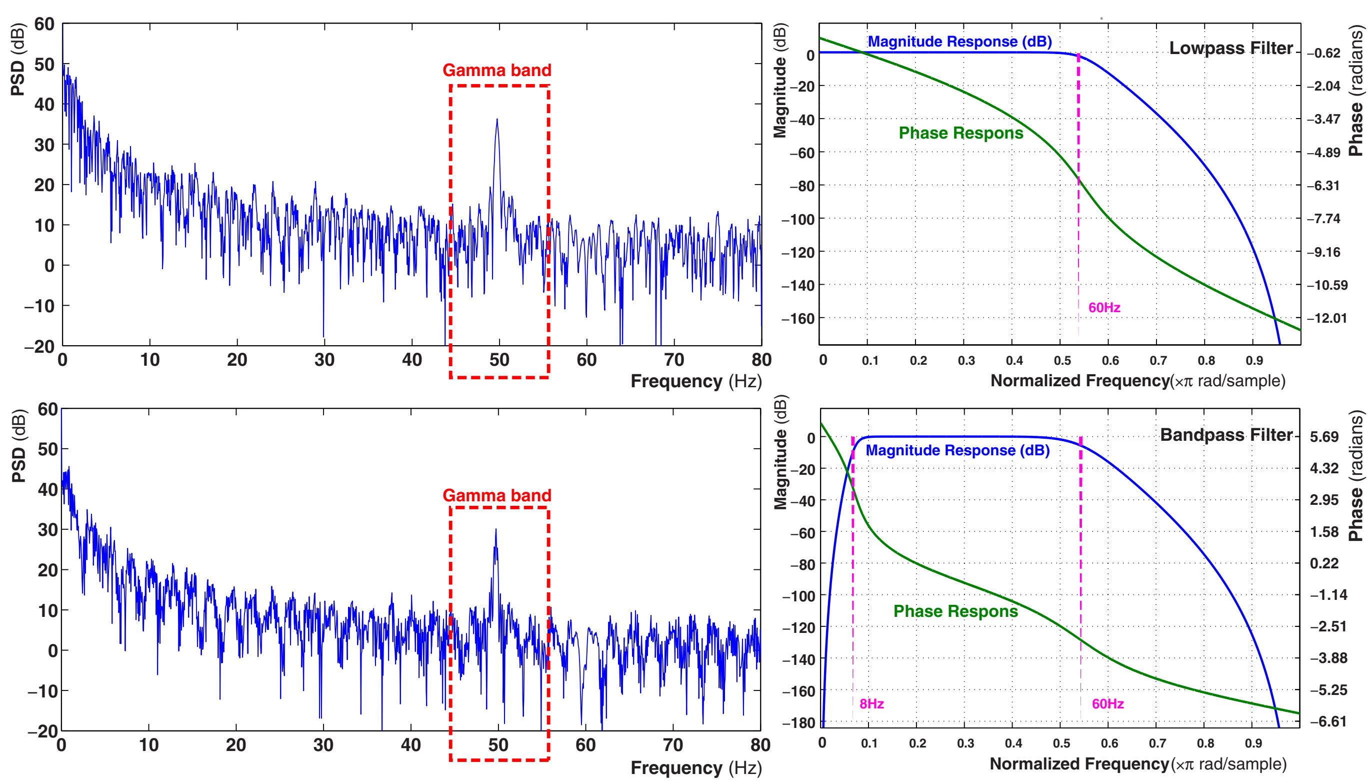

Fig. 5. PSD spectrum for FP1 (upper left) and TP10 (lower left) and filter design (lowpass filter on upper right; bandpass filter on lower right).

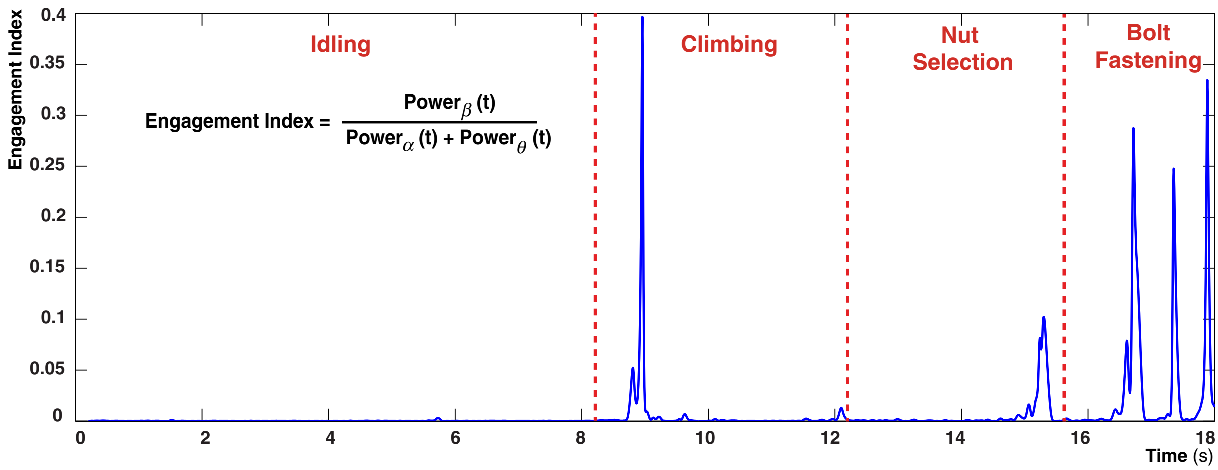

Fig. 6. Engagement index estimated from FP1 data.

mental workload estimation in construction. The derived engagement index (Fig. 6) aligns with the EEG spectrum and could be used to assess the mental workload of construction tasks based on their signal features, such as magnitude, frequency and phase. Third, the bispectrum analysis highlights that low frequency bands are more appropriate and sensitive to complicated work. "Idling" activities can be easily identified through the calculation of correlations between high frequency bands. In addition, some frequency bands, such as gamma waves, demonstrate independency with the subjects' physical load and could be used to mitigate the impact of subjects' movement.

Through this study, EEG shows promise as a novel approach to estimating the mental workload involved in executing various construction activities. More specifically, the metrics described in this paper are also able to differentiate the activities through a series of quantitative features. The estimated level of mental workload is a good indication of the vulnerability of an individual worker [18,39]. Previous research shows that when people are subject to heavy mental workload, it could cause inattentional blindness, which can result in accidents. Therefore, by knowing who is concentrating on work or conducting tasks that demand high levels of concertaration, project managers will be able to identify vulnerable employees and provide sufficient interventions. For instance, project managers can create protection zones for workers who are exposed to hazards by restricting their contact with machinery. EEG signals can also be an effective tool to diagnose workers' mental conditions, such as whether they are alert, relaxed or nervous. Also, field supervisors could use the abnormal signals patterns as an indicator of task overloading or inappropriate work shifting. In other words, the mental demands required by various construction tasks can be estimated to guide task allocation together a with TDA approach [48], especially for the use by a multi-skilled workforce [24]. Meanwhile, the boredom and lack of attention that results from task underloading can be partially relieved through better mental demands management.

Another potential use of the EEG data is activity detection. Based on the experimental results, the signal pattern of brain waves vary predictably when subjects conduct different types of activities. The EEG data can also be helpful in activity detection for productivity measurement since each type of task has its own mental load and cognitive requirements. At the same time, the proposed measurement in this research could supplement other activity detecting metrics through various sensors [58], such as IMUs [4,5], cameras [44], Kinect [31,54] or physiological sensors [21]. EEG monitoring provides a new data dimension that can help other sensory monitoring approaches make more accurate judgements. Occupational injuries and fatalities also can be attributed to poor task and work place design. Field supervisors could implement the collected multisensory data in construction production system design [42]. For example, quantitative demands of all construction tasks can be quantified by the signal strength of physiological and mental monitoring. Such information could help the field supervisors design more efficient and reliable construction production systems through measuring the productivity, determining the size of the crew, arranging night shifts and highlighting potential errors.

One limitation of the current injury reporting system required by OSHA is that all accidents are self-reported after they occurred. However, there is also a great number of near-miss accidents that are often neglectded in safety assessment [72] because such accidents are extremely difficult to detect and monitor. The EEG monitoring system provides an innovative way to identify near-miss accidents by monitoring the mental condition when people perceive danger. Some frequency bands of the EEG signal (such as gamma waves) could indicate the mental condition of workers when they are experiencing accidents. Also, with the development of information and communication technology in past decades, integration of technoglies among various disciplines could potentially create a significant synergy from multi-sensory data sources [37]. Together with other sensors, such as IMU [5], video camera, RGBD camera [25] or RFID [36], an automatic near-miss accident recording system could be created and dramatically increase the accident database for project managers to refer to.

Since the research described in this paper is based on a preliminary study, it is subject to several limitations. First, the scale is not large enough. Since the equipment (EEG safety helmet) was designed by the research team, it is still a prototype. Thus, the experiment cannot be conducted in larger, more practical scales. Also, the ground truth of risk level of each task is based on post experiment survey, which is relatively subjective. In future research, the research team will try to improve the equipment design and data quality and build more devices to test the validity of the assessment model on a larger scale. Motion sensors will be applied to collect more objective risk assessments. Second, the data collected from the system still yielded random errors.

Table 1
Bispectrum feature indices of time windows selected from four experimental activities.

Feature indexes	Window 1 (idling)	Window 2 (climbing)	Window 3 (nut selection)	Window 4 (bolt fastening)
Risk level	Low	High	Medium	High
H_3	8.44 e + 4	6.44 e + 4	7.49 e + 4	6.19 e + 4
H_4	3.62 e + 14	1.39 e + 14	2.67 e + 14	1.58 e + 14
H_5	1.28 e + 4	2.94 e + 4	1.85 e + 4	3.14 e + 4
H_6	247.82	635.22	397.50	675.51
H_7	1.51 e + 4	3.49 e + 4	2.18 e + 4	3.71 e + 4
H_8	0.62 e + 11	7.72 e + 11	1.89 e + 11	9.29 e + 11

Note: the values in table are the normalized magnitude calculated from Eqs. (2) to (7).

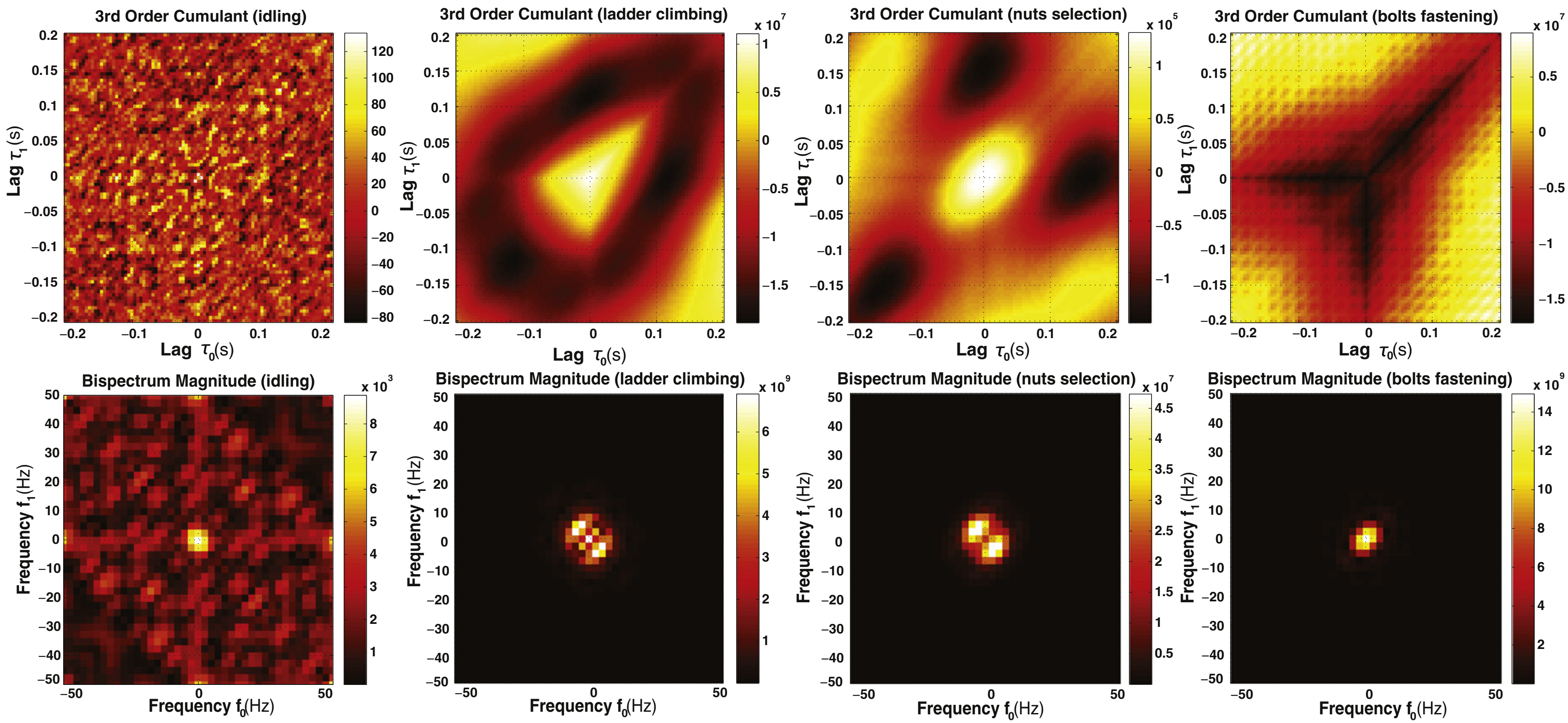

Fig. 7. 3rd order cumulant (up) and bispectrum magnitude (below) for activities of idling, climbing, nut selection and bolt fastening.

Although filters have been applied to eliminate the white noise in the retrieved data, the reliability of the sensing system still needs to be tested and specific filers need to be designed. One possible solution is make full use of reference monitoring points, such as TP9 and TP10, to develop a statistical filter and construct a stochastic process to estimate the confidential level. Third, the pacement of the electrodes within the helmet needs to be optimized. There are more than 50 potential locations for application of the EEG electrodes suggested by the international 10–20 system, each of which indicates a different brain function. To optimize the accuracy of detection and comfort for the wearer, the hardware needs to be expanded and optimized. Devices with multiple channels will be applied to compare across the electrode locations to find out the most senstive installing location and to minize the number of electrodes that need to be attached. Another critical limitation of this research is its narrow focus on mental load monitoring. Monitoring of human activities contains both physiological and mental information, which are clearly correlated to each other. Although this research studied the mental load independently, there exists a research gap to understand how researchers can fuse both types of information for higher accuracy and reliability.

The EEG measurement technique described in this paper enables the real-time direct monitoring on worker's mental conditions. It can revolutionize the construction industry not only in terms of making it safer, but also more measurable in terms of labor productivity. Combined with sophiticated building information systems [11,32,35,59] or social network [33] proposed by other researchers, EEG monitoring could create productive synergies in schedule management and quality control. Another potential future development to extend the current study is to better understand the relationship between physical load and mental load. A motion detection system such as one based on inertial measurement units could be applied and integrated with mental load data as the ground truth of physical load and complexity of tasks.

6. Conclusions

Measurement of workers' mental workload provides an alternative source of information about on-site safety conditions. The EEG assessment enables project managers to identify vulnerable individuals and thus supplement the on-site risk detection. Integrating both perspectives could help project managers to prioritize the safety resources to protect vulnerable individuals who are exposed to higher risks. The research described in this paper demonstrates how to utilize EEG data to indirectly measure the vulnerability of workers based on their mental load when they conduct various construction tasks. The preliminary experiments suggest that it is feasible for using brain waves to quantify and differentiate the mental workload of activates in construction. The proposed framework enables the possibility of quantitatively assessing the mental demands of construction activities, since nearly all complex construction work can be broken down into relative simple and interdependent tasks. Combining physiological and temporal demand estimation, future development in quantification of mental task demands could help field supervisors optimize workload allocation, production system design and project scheduling. In addition, due to the complexity of human biological systems, it is also critical to further investigate the interrelationship between the mental and physiological conditions of the workforce during construction activities.

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