Assessing Working Vulnerability of Construction Labor through EEG signal processing

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Abstract:
Many researches suggest the construction risks are highly associated with the job complexity. Recent developments in the area of neural science and psychology suggests many accidents caused by the lack of attention or attention distractions. Labors are vulnerable while they are focusing on complicated construction tasks, which consumes too much working memory. Therefore, assessing the level of working memory could help to determine the vulnerability of on-site construction labors. Through comparing multiple assessment metrics, this research aims at proposing a quantitative assessment approach to enable the assessment the concentration level and vulnerability of construction workers through analyzing Electroencephalography (EEG) signals.

Keywords: Construction Safety, EEG, Vulnerability, Safety Management

1. INTRODUCTION
The construction industry has one of the poorest safety records compared to all other industries. For example, in Hong Kong, there were 3,332 injuries and 37 fatalities in the construction industry and accounts for 19.68% of fatalities across all industries (HKOSH 2014). If the hazards can be properly detected and reported, the workplace safety can be significantly improved (McSween 2003). Safety analysis or safety climate analysis (Zou and Sunindijo 2013) with proper safety programs can greatly improve the safety performance of construction project to some extent (Abudayyeh et al. 2006), however, the major difficulties related to the dynamic nature of construction environment and unpredictability of workers’ behavior patterns (Levitt 1993). With regard of such difficulties, preventing unexpected accidents through safety programs is impossible to achieve. Instead, identifying and protecting vulnerable individuals rather than detecting hazards provide us an alternative option.

Every single worker has the ability to perceive hazards on site, with such ability they are able to escape from dangerous events. Therefore, sometimes workers are able to avoid accidents and report near-miss accidents. The classic psychological researchers believe people’s decision on risk-taking behavior is negatively correlated with their risk perception (Mills et al. 2008). Individuals who have insufficient risk perception ability are vulnerable to safety hazards. Therefore, the workers’ risk perception ability is an indication of their vulnerability.

There are many factors could impact people’s perception ability. In psychological research, mental workload as one of most critical factor to estimate people’s perceptual ability (Meskhati and Hancock 2011; Moray 1979), especially for people who usually conduct complicated tasks. Therefore, the measurement of individuals’ mental workload could help to assess their perception ability and then to find out vulnerable workers in a construction job site. This research aims to propose a framework that using computer to quantitatively estimate mental workload, and then improve the on-site construction safety management.

2. BACKGROUND
2.1 Mental Workload and Risk Perception
Mental workload or cognitive load refers to the total amount of human mental effort or memory that being used for task operation. When a person place too much attention on one task, he or she will have less attention to focus on other surrounding stimuli. One classic example is talking phone calls while driving, when driver’s attention is mostly allocated to the phone conversation, less attention is used for driving and results in higher accident rate (Newnam et al. 2006). According to psychological theory, when some tasks consume too much attention, people expose to the danger of inattentional blindness (Rock et al. 1992). Inattentional blindness is a psychological phenomenon that an individual fail to identify hazardous stimuli due to the lack of attention (Mack and Rock 1998). One of the most well know study demonstrates inattentional blindness is the Invisible Gorilla Test, designed by Daniel Simons (Chabris and Simons 2011). In the test, the subjects are request to count the number of ball passes in a video, while there will be a men wearing a full gorilla suit wall through the scene. After watching the video, the subjects are asked that if they saw a gorilla. In most of tests, 50% of subjects did not report of seeing the gorilla. The failure of seeing the gorilla attributes to the high mental engagement of counting task and results in
inattentional blindness. As the direct result of inattentional blindness in construction industry, when the workers focus too much on their current work, they have less risk perception ability and vulnerable to dangers. Another possible issue that affect the risk perception is the hazard expectation. When workers conduct certain construction activities, they expect certain things to happen and tend to block out other possibilities and allocate fewer mental load to potential stimulus. For example, when a worker installs a building roof, knowing from the training, he or she may assume fall is the major thing need to be worried, however, they may fail to predict the possibility of hitting by some random objects. Such imperfect predictions or expectations can also lead to inattentional blindness. This could explain why even if safety trainings are performed, workers are still injured in various accidents.

Another issue that related to the mental workload is task complexity (Wickens 2008). Workers have to face rising cognitive demands with increasing complexity in task operations where cognitive skills are more important than physical skills. In construction industry, workers obtain a consideration portion of information directly from the cognitive task, while workers have to perform physically demanding work concurrently. Such as the task of electrical installation, workers not only need to accurately attach wires together, sometimes also need to perform all the tasks on the top of a ladder and hold up their arms for long time periods. Under such situations, it is necessary to determine how the physical works may impact the mental workload, and then estimate the safety condition of the worker of performing these tasks. However, due to the differences between individual workers, it is extremely difficult to predict the risk level purely from the task complexity and workers’ proficiency. Therefore, a more direct and quantitative monitoring approach that can estimate the mental workload could help project managers to find out the vulnerable workers and implement safety policies or approaches to avoid accidents.

2.2 Construction Safety from Psychological perspective

In the labor-intense industry like construction industry, the psychological condition plays an extremely critical role in all types of accidents. Construction work is an inherently dangerous occupation and exposure to various psychological conditions and stressors, such as constraint schedule, complicated tasks, and physical and chemical hazards. These psychological conditions could strongly affect the risk perception ability of construction workers. According to Endsley’s findings (Endsley 1995), there is a three-step process for people who experience dangerous events, including (1) detection of hazardous signals, (2) perception and comprehension of risks, and (3) projection of the consequences associated with decision options. According to many psychological research, mental conditions greatly influence the risk signal detection, risk perception and process of risk-based decision (Peters et al. 2004; Slovic 2000). Different from other industry, in construction, risk perception is more important because even if the hazards are identified, workers still have to involuntarily behave unsafely while conducting their jobs, since most of construction tasks inherently associate with various level of risks (Zimolong 1985). Due to the tight project budgets and schedules, construction personals are predominately production-oriented and suffer huge physical and mental pressures (Mitropoulos et al. 2005) at same time, which will exacerbate the level of danger and increase the possibility of injury and fatality.

3. METHODOLOGY

3.1 Electroencephalography (EEG) and Vulnerability Estimation

In recently years, there are many research of collecting workers physiological information to enhance the safety condition of construction. Jebelli et al. employed inertial measurement unit to detect the body motion of steel works to protect them from fall accident (Jebelli et al. 2014). Gatti et al. measure two physiological parameters (heart rate and breathing rate) to monitor the health condition of construction worker when they conduct various constructing activities (Gatti et al. 2014). In this research, EEG will be introduced to assess the mental workload of workers. As a quantitative indication of mental and memory conditions of construction workers. The EEG data will used to assess the risk perception ability of workers in term of mental load, and then the vulnerability. The mechanism of vulnerability assessment based on mental load is shown in following Figure 1.

Meanwhile, there are several advantages of EEG to study neurocognitive process during construction process: as suggested by Cohen (Cohen 2011) for the reasons of:

1. EEG can capture cognitive dynamics in a time frame. Most cognitive events occurs in a temporal sequence and in a scale of milliseconds or seconds. High temporal-resolution techniques such as EEG is suitable to capture these fast and temporal information.

2. EEG is a direct measurement of neural activities. The voltage fluctuations detected by EEG are the most direct observations compare to other measurement devices. Although the mechanism is not fully known by researchers, the oscillations patterns of EEG signals are well studied and can be modelled fairly accurately.
EEG signal is multidimensional. Different from regular time series data, EEG signals is multidimensional, since it includes time, magnitude, frequency, power and phase. Such multidimensionality provides a plentiful data resources and possibilities for sophisticated data analysis.

Figure 1. Mental load estimation and construction accident

3.2 EEG data

The data collected and analyzed in this research is brain rhythms that grouped into bands based upon their center frequencies and frequency widths. These brain rhythm frequency bands include delta wave (1-3 Hz), Theta wave (4-7 Hz), Low Alpha wave (8-9 Hz), High Alpha wave (10-12 Hz), Low Beta wave (13-17 Hz), High Beta wave (18-30 Hz), Low Gamma wave (31-40 Hz), and High Gamma (41-50 Hz). Such grouping is not arbitrary but results from neurobiological mechanisms of brain oscillations, such as synaptic decay and brain signal transmission (Buzsaki 2006).

The brain rhythms analysis involve computation of power spectral densities (PSD) of above frequency bands. These rhythms can be used to identification and classification of cognitive states such as mental workload, engagement, execution, and verbal or spatial memory (Berka et al. 2007). The raw data has rich information with unavoidable noise; it is extremely important to find out the right signal for mental load estimation. Comparing through the spectrum of all frequencies, alpha wave (8-12 Hz), beta wave (13-30 Hz), and gamma wave (31-50 Hz) are the best candidates. Alpha brainwaves are present when people have quietly flowing thought; they associate with relax wakefulness and aids mental coordination, calmness, and alertness. Beta brainwaves dominate our normal waking state of consciousness when people engage in tasks; they associate with attentiveness, selective attention, concentration and anticipation. Gamma brainwaves are the high frequency waves relate to simultaneous information processing involves multiple brain areas; they associate with higher mental activities, perception, problem solving, fear and consciousness.

3.3 Neural Time-frequency Analysis

In order to develop a measurement of mental workload, various behavioral and physiological tests has been developed since 1980s. Although subjective and inaccurate, such measurements can provide a relatively continuous data record over time without obstructing the primary task performance. In recently years, new neuroimaging techniques, such as functional magnetic resonance imaging (fMRI), electroencephalography (EEG), and etc. provide a direct and quantitative alternatives for the assessment of mental workload of human brain (Ryu and Myung 2005). Among these methods, EEG is the best candidate for construction implementation, since it is portable for wearing; other methods require massive devices, large medical team and immobile subjects. Many research has found the correlation between brain rhythms that collected by EEG and mental workload (Valentino et al. 1993).

One popular quantitative analysis for brain rhythms of mental workload is Event-Related Potentials (ERPs). ERPs is a valid approach because it requires less assumptions or parameters, possesses higher temporal precision and accuracy, has been well studied, and provides a fast and easy computational results. However, ERPs is difficult to interpret the results and link the continuous data to physiological mechanisms. Adopted from the digital signal processing theory, a time-frequency-based analysis has been introduced in then analysis of brain rhythms (Cohen 2014). In this research, both approach will be adopted to analysis the mental workload of subjects when they focus
on their tasks. A preliminary experiment is conducted to collect the brain rhythms of workers, and then estimate their mental workload and their vulnerability to unexpected accidents.

4. PRELIMINARY EXPERIMENT SETUP

A preliminary experiment is designed to validate the feasibility of mental workload measurement. Five subjects was invited to wear an EEG monitoring helmet to perform an installation task. The subjects were requested to relax for 5 seconds, then walk onto a ladder (1 meter tall, cost 3-4 seconds to climb), conduct installation works (4-5 minutes), climb down the ladder and have a rest. The installation task requests each subject pickup suitable nuts and fasten bolts with a screwdriver and the subjects have to do so at height. The subjects have to repeat the task for three times. The task includes four types of activities: idling, ladder climbing, nuts selections and bolts fastening. During the experiment, the monitoring helmet was connected to a laptop via Bluetooth to stream data. At the same time, a camera was placed in scene to synchronize and record the activities and events. Then, the event tags was associated with EEG raw data based on video analysis.

The research team developed an EEG monitoring safe helmet with Neurosky TGAM model. 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 blue tooth module. Also, a Electrocardiography(ECG) sensor. Following Figure 2 shows the developed monitoring helmet.

![Figure 2. Wearable EEG monitoring safety helmet and sensing locations](image)

Four sensing sites are selected refer to the international 10-20 brain monitoring 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 the Figure 2. The FP1 location is related to logical attention and other brain functions, such as interactions planning, decision making, task completion and working memory. The FP2 location relates to emotional attention and other brain functions, such as judgement, sense of self and restraint of impulses. TP9 and TP10 serve as the references for further comparison.

5. RESULTS AND DISCUSSION

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. Figure 3 presents the raw data of brainwaves from the two of four electrode installation locations (TP9 and TP10) during the first 18 seconds. 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 TP10. The temporal data analyzed in this study includes the first 18 seconds 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 Figure 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 Figure 4. When pasting figures, especially, photographs, to your manuscript, please be aware of the size of the manuscript. Try to minimize the size of the graphic files, but not excessively so that they do not appear blurred.

Figure 3. Raw singles form TP9 (Red) and TP10 (Blue)

Figure 4. Power density spectrum of EEG signal (TP10 channel)

Above figure 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 second 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. Figure 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 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 gamma waves implicate neural consciousness via the mechanism for conscious attention, which is relatively independent from physical movement. 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.

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 (Berk et al. 2007). In this research, the engagement index developed by Prinzel et al. will be used. 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 following equation:

\[ EN(t) = \frac{P_\beta(t)}{P_\alpha(t) + P_\theta(t)} \]

where \( EN(t) \): the EEG-engagement index at time \( t \);
\( P_\alpha(t) \), \( P_\beta(t) \), and \( P_\theta(t) \): power of alpha rhythm, beta rhythm and theta rhythm at time \( t \).

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, 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 Figure 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).

![Figure 5 Engagement Index Estimated from TP10 data](image)

6. CONCLUSIONS

Measurement of workers’ mental workload provides an alternative source of information about on-site safety conditions. Instead of detecting hazards, the EEG assessment enables project managers to identify vulnerable individuals. The research described in this paper demonstrates how to utilize EEG data to indirectly measure the vulnerability of workers based on mental load when they conduct various construction tasks. The preliminary experiments suggest it is feasible for using brain waves to quantify and differentiate the mental workload of activates in construction. The system proposed in this research can potentially revolutionize the construction industry not only in terms of making it safer, but also measurable in labor productivity. Together with other technoglies, such as RFID, IMU, video camera and etc., the project manager will fully aware of the laborers’ condition and construction process.

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