Labor Vulnerability Assessment through Electroencephalogram Monitoring: a Bispectrum Time-frequency Analysis Approach

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Abstract: Detecting and assessing human-related risks is critical to improve the on-site safety condition and reduce the loss in lives, time and budget for construction industry. Recent research in neural science and psychology suggest inattentional blindness that caused by overload in working memory is the 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 and dangerous construction tasks. Therefore, detecting the risk perception abilities of workers could help to identify vulnerable individuals and reduce unexpected injuries. However, there are no available measurement approaches or devices capable of monitoring construction workers' mental conditions. The research proposed in this paper aims to develop such a measurement framework to evaluate hazards through monitoring electroencephalogram of labors. The research team developed a wearable safety monitoring helmet, which can collect the brain waves of users for analysis. A bispectrum approach has been developed in this paper to enrich the data source and improve accuracy.

Keywords: Construction Management, Vulnerablilty, Safety Management, Mental Workload, EEG

I. INTRODUCTION

Construction industry in Hong Kong has one of the worst safety records compared to all other industries. In 2013, there were 3,332 injuries and 37 fatalities, which accounts for 19.68% of fatalities across all industries [1]. 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%) [1]. Although the safety can be significantly improved through proper hazard detection and reporting [2], it extremely achieve accurate detection due to the dynamic environment of construction jobsites and workers' unpredictable behavior [3]. Many research suggests safety climate analysis [4] and training program [5] could greatly import jobsite safety. However, risks cannot be assessed, controlled and avoided if managers are not aware of the hazards in the first place [6]. Instead of find out all potential hazards, finding the potential victims or identify the vulnerable individuals on site provide us a new perspective for safety management. With or without training, every worker has certain level of ability to perceive and escape from the potential hazards. The classic psychological theories suggest people's decision on risk-taking behavior is negatively correlated with their risk perception [7]. Incapable of perceiving risk signals, vulnerable workers yield to higher chance of getting injured. Therefore, if the risk perception ability of workers can be measured, the vulnerability of individuals also could be identified and evaluated.

There are many factors could impact people's risk perception ability, mental condition is the most important one among them. In many psychological research, one of the most widely accepted indicator of ability of risk perception is mental workload [8, 9] Thus the measurement of individuals' mental workload equivalent to assess the perception ability of human brain. Then it could be extremely useful to find out vulnerable workers in a construction job site. Base on this logic, this research aims at developing a quantitative approach to assess construction worker's mental workload and find out the vulnerable individuals.

II. RESEARCH BACKGROUND

A. *Psychological Monitoring in Construction Industry*

In construction industry, the psychological conditions of workers plays an import role in both psychological and physical safety of workers. Construction work is an inherently dangerous occupation and exposure to various psychological stressors, such as constraint schedule, complicated tasks, and physical and chemical hazards. Tixier et al. (2014) conducted an experiment on 69 construction workers and observed that the emotionally negative group (sad, unhappy, fearful, anxious and disgusted) subject to more risks than the positive group (happy, amused, joyful and interested) [10]. ue to the tight project budgets and schedules, construction personals are predominately production-oriented and suffer huge physical and mental pressures [11], which will exacerbate the level of danger and increase the possibility of injury. In addition, even if the safety hazards have been identified, workers still have to involuntarily behave unsafely, since most of construction tasks inherently associate with various level of risks [12]. Therefore, targeting at more vulnerable workers are more practical than merely detecting hazards.

B *Mental Work Load*

According to Endsley's research, there are three steps for people who experience risks, including (1) detection of

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hazardous signals, (2) perception and comprehension of risks, and (3) projection of the consequences associated with decision options [13]. Many researchers conclude that as the very first step of risk avoidance, rick perception is the most critical for safety management [14, 15].

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 stimuli, which means lower ability for risk perception. 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 [16]. Therefore, when some tasks consume too much attention, people expose to the danger of inattentional blindness [17]. One direct result of inattentional blindness is when the workers focus too much on their work, they have less risk perception ability and vulnerable to dangers. Since every worker has the ability to avoid accidents, successful risk avoidance will result in near-miss accidents. Therefore, same event could results in different severity level in accidents (FIGURE 1).

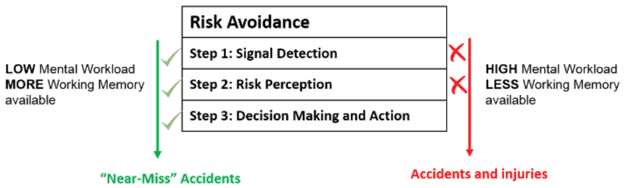

Figure 1. Mental Workload and Risk Avoidance

Another issue that related to the mental workload is work complexity [18]. 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. 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 quantitative and direct monitoring approach that can estimate the mental workload of construction workers are necessary.

C Quantitative Neural Time-frequency Analysis

In order to develop a measurement of mental workload, direct and quantitative monitoring technologies are necessary. In recently years, neuroimaging techniques, such as functional magnetic resonance imaging (fMRI) and electroencephalography (EEG) become the major tools for mental workload assessment [19]. EEG is suitable for construction implementation, since the monitoring device is light weighted and wearable. In addition, the brain rhythms of EEG signal processing shows a strong correlation with the human mental workload [20].

Time-frequency-based analysis has the most potential for such purpose, and able to decompose brain waves into frequency bands which suggest different mental activities of human [21]. In this research, a bispectrum approach was proposed to explore the ability of applying the brain electrical system to assess the vulnerability of construction workers.

III. Methodology

A Electroencephalography (EEG) Signals

Compare to other physiological signals, EEG has great advantages [22]. First, EEG can capture temporal cognitive dynamics of human activities. High temporal-resolution of EEG is suitable to capture these fast and fluctuate brain signals. Second, EEG one of the few direct measurement of human activities. The oscillations patterns of EEG signals can be interpreted reasonably. Third, EEG signal is multidimensional in term of time, magnitude, frequency, power and phase. Such multidimensionality provides a plentiful data resources and possibilities for sophisticated data analysis.

Based upon their center frequencies and frequency widths of brain wave, these rhythms that grouped into distinctive bands, such as 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). The grouping is not arbitrary but results from neurobiological mechanisms of brain oscillations, such as synaptic decay and brain signal transmission [23]. The EEG data analysis involve computation of power spectral densities (PSD) of above frequency bands. Suggested by Zhou et al. (2007), EEG raw signals based upon their bispectrum are suitable for classification and filtering [24].

PSD could be calculated for each rhythm band and be used for activity identification. Higher order of PSD also provide an extensive opportunity to detect various patterns for classification. The first order of spectral moment of the PSD at time t can be expressed as :

$$M_1(t) = \sum_{\omega=1}^{N} \omega \cdot H_\omega(t) \qquad (1)$$

Where ω is the frequency of the power spectrum; N is the maximum frequency to be considered. $H_\omega(t)$ is the PSD. The second-order spectral moment of PSD is

$$M_2(t) = \sum_{\omega=1}^{N} (\omega - M_1(t))^2 \cdot H_\omega(t) \qquad (2)$$

The calculation of bisepctrum is able to evaluate the inter correlation between different frequency band, which is extremely useful to classify the human activities based on multiple frequency bands. Both the amplitudes of first order and second bispectrum can be calculated through:

$$B_1 = \sum_{\omega_1,\omega_2 \in F,\ k=1}^{N} k \cdot \log(|B_0(\omega_k, \omega_k)|) \qquad (3)$$

$$B_2 = \sum_{\omega_1,\omega_2 \in F, k=1}^{N} (k - B_1)^2 \cdot \log(|B_0(\omega_k, \omega_k)|) \qquad (4)$$

Where,

$$B(w_1, w_2) = \sum_{m=-\infty}^{+\infty} \sum_{n=-\infty}^{+\infty} E[x(k)x(k+m)x(k+n)] \cdot e^{-i2\pi(m\omega_1 + n\omega_2)} \qquad (5)$$

$B(w_1, w_2)$ 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. Equation (3) is first order of bisepctrum PSD; Equation (4) calculates the second order of bisepctrum PSD.

B Experiment Setup

One 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.

Four sensoring locations are selected refer to the 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). The experiment results is reported in following FIGURE 2.

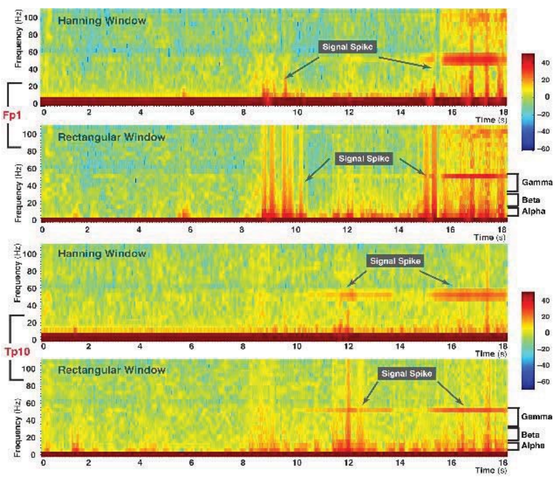

Figure 2 Brain Signal Spectrum of Preliminary Experiment

Bispectrum analysis also applied based on the approach discussed in this paper. Following FIGURE 3 suggest the PSD of the bispectrum cross multiple frequency bands.

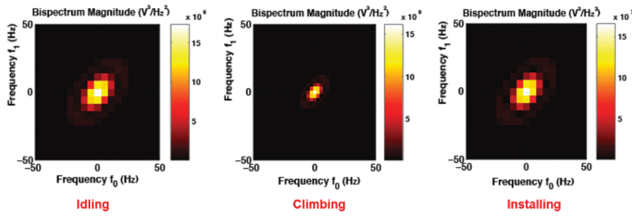

Figure 3 PSD of bisepctrum cross frequencies

IV. Results and Discussion

Results shown in Figure 2 suggest a clear pattern in single spike when the experiment subject change their behavior. For example, from both the spectrum of Fp1 and TP10, when the subject climbing up the ladder (around the 8th second), there is a surge on multiple frequency bands, which suggest more energy are focused on the climbing activing compare to the idling activity (before 8th second). When the subjects select nuts for installation and working (10th second to 14th second) at height (14th second to 18th second), there is a clear spike on gamma band (30-50Hz) from Tp10 channel. Since there are obvious distinctions between data pattern, EEG could be a novel approach to estimate the mental workload in various construction activities.

In addition, the bispectrum of average PSD at each different activity also suggest the inter-correlation as show in FIGURE 3, idling and installing activities has a highly intensive energy pattern between different energy bands. However, for climbing the magnitude of cross frequency PSD is relatively low. Such pattern is extremely helpful to differentiate the climbing activity and installing activity which looks similar form the data pattern from Fp1. Also, the intensity also can be used for the mental workload estimation with proper formulation. For example, Prinzel et al. introduced an engagement index to assess the level of mental workload through the electrical power of beta (13-30 Hz), alpha (8-12 Hz) and theta (5-7 Hz) waves [25].

Since the level of concentration or mental work load are good indication of the vulnerability of individual worker. Combining with positioning technologies, project managers can create a protection zone for workers who expose to hazards and restrict machineries' interference. Through utilizing pattern recognition and unique combinations of the frequency bands, the EEG data could be helpful in activity detection and productivity measurement, since each type of task has its own mental load and cognitive requirements. Therefore, the proposed measurement in this research could supplement other activity detecting metrics through various sensors, such as IMUs [26], camera [27], Kinect [28] and etc.

However, this very preliminary research currently still has some limitations. First, the experiment scale is not large enough and the collected data for each individual are dissimilar to each other. The personal difference should be discussed for future development. Second, the data collected from the system still yield to random errors. Especially, the physical movement of body could results is variation in the EEG signals. Third, the electrodes placement need to be optimized. There are more than 30 potential applying locations for EEG electrodes suggested by international 10-20 system, each of them indicate different brain functions. These applying location should be future tested to find the most robust and reliable data source.

V. CONCLUSION

Measurement of workers' mental workload provide an alternative indication of construction safety. Such approach is able to find out the vulnerable individuals through EEG signal processing. In this proposed research, a bispectrum approach is proposed to be used for classification of construction activities. Based on the complexity and working memory requirements of these activities, the proposed approach is able to identify the individuals who has higher mental work load and exposes to potential hazards. The preliminary experiment suggests it is feasible of using brain waves to quantify and differentiate the mental workload of activates in construction.

REFERENCES

[1] HKOSH, "Occupational Safety and Health Statistics 2014", 2014.
[2] T. E. McSween. "Values-Based Safety Process: Improving Your Safety Culture With Behavior-Based Safety", John Wiley & Sons, 2003.
[3] R. E. Levitt, "Construction Safety Management", John Wiley & Sons, 1993.
[4] P. X. Zou and R. Y. Sunindijo, "Skills for managing safety risk, implementing safety task, and developing positive safety climate in construction project." *Automation in Construction*, vol. 34, pp. 92-100, 2013.
[5] O. Abudayyeh, T. K. Fredericks, S. E. Butt and A. Shaar. "An investigation of management's commitment to construction safety", *International Journal of Project Management*, vol. 24, no. 2, pp. 167-174, 2006.
[6] G. Carter and S. D. Smith, "Safety hazard identification on construction projects", *Journal of Construction Engineering and Management*, vol. 132, no. 2, pp.197-205, 2006.
[7] B. Mills, V. F. Reyna and S. Estrada, "Explaining contradictory relations between risk perception and risk taking", *Psychological Science*, vol. 19, no. 5, pp. 429-433, 2008.
[8] N. Meshkati and P. Hancock, "Human Mental Workload", Elsevier, 2011.
[9] N. Moray, "Mental workload: Its theory and measurement", Plenum Publishing Corporation, 1979.
[10] A. Tixier, M. Hallowell, A. Albert, L. van Boven and B. Kleiner, "Psychological Antecedents of Risk-Taking Behavior in Construction", *Journal of Construction Engineering and Management*, vol. 140, no. 11, pp. 04014052, 2014.
[11] P. Mitropoulos, T. S. Abdelhamid and G. A. Howell, "Systems model of construction accident causation", *Journal of Construction Engineering and Management*, vol. 131, no. 7, pp. 816-825, 2005.
[12] B. Zimolong, "Hazard perception and risk estimation in accident causation", *Trends in Ergonomics and Human Factors II*, pp. 463-470, 1985.
[13] M. R. Endsley, "Measurement of situation awareness in dynamic systems" *Human Factors: The Journal of the Human Factors and Ergonomics Society*, vol. 37, no. 1, pp. 65-84, 1995.
[14] P. E. Slovic, "The Perception of Risk", Earthscan Publications, 2000.
[15] E. M. Peters, B. Burraston and C. Mertz, "An Emotion-Based Model of Risk Perception and Stigma Susceptibility: Cognitive Appraisals of Emotion, Affective Reactivity, Worldviews, and Risk Perceptions in the Generation of Technological Stigma", *Risk Analysis*, vol. 24, no. 5, pp.1349-1367, 2004.
[16] S. Newnam, R. Tay and C. Mason., "Using psychological frameworks to inform the evaluation of fleet safety initiatives". *Safety science*, vol. 44, no. 9, pp.809-820, 2006.
[17] I. Rock, C. M. Linnett, P. Grant and A. Mack, "Perception without attention: Results of a new method", *Cognitive Psychology*, vol. 24, no. 4, pp.502-534, 1992.
[18] C. D. Wickens, "Multiple resources and mental workload", *Human Factors: The Journal of the Human Factors and Ergonomics Society*, vol. 50, no. 3, pp.449-455, 2008.
[19] K. Ryu and R. Myung, "Evaluation of mental workload with a combined measure based on physiological indices during a dual task of tracking and mental arithmetic", *International Journal of Industrial Ergonomics*, vol. 35, no. 11, pp. 991-1009, 2005.
[20] D. A. Valentino, J. Arruda and S. Gold, "Comparison of QEEG and response accuracy in good vs poorer performers during a vigilance task", *International Journal of Psychophysiology*, vol. 15, no. 2, pp. 123-133, 1993.
[21] M. X. Cohen, "Analyzing Neural Time Series Data: Theory and Practice", The MIT Press, Cambridge, Massachusetts, 2014.
[22] M. X. Cohen, "It's about Time", *Frontiers in human neuroscience*, vol. 5, pp. 1-15, 2011.
[23] G. Buzsaki, "Rhythms of the Brain", Oxford University Press, 2006.
[24] S. M. Zhou, J. Q. Gan and F. Sepulveda, "Classifying mental tasks based on features of higher-order statistics from EEG signals in brain–computer interface", *Information Sciences*, vol. 178, no. 6, pp. 1629-1640, 2008.
[25] L. J. Prinzel, F. G. Freeman, M. W. Scerbo, P. J. Mikulka and A. T. Pope, "A closed-loop system for examining psychophysiological measures for adaptive task allocation", *The International journal of aviation psychology*, vol. 10, no. 4, pp. 393-410, 2000.
[26] C. Ahn, S. Lee and F. Peña-Mora, "Application of Low-Cost Accelerometers for Measuring the Operational Efficiency of a Construction Equipment Fleet", *Journal of Computing in Civil Engineering*, vol. 29, no. 2, pp. 04014042, 2015.
[27] M. Memarzadeh, M. Golparvar-Fard and J. C. Niebles, "Automated 2D detection of construction equipment and workers from site video streams using histograms of oriented gradients and colors", *Automation in Construction*, vol. 32, pp. 24-37, 2013.
[28] V. Escorcia, M. Dávila, M. Golparvar-Fard and J. C. Niebles, "Automated Vision-based Recognition of Construction Worker Actions for Building Interior Construction Operations Using RGBD Cameras", Proceedings of Construction Research Congress 2012, West Lafayette, IL, USA, pp. 879-888, 2012.