Revealing the "Invisible Gorilla" in Construction: Assessing Mental Workload through Time-frequency Analysis

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ABSTRACT

Construction companies suffer huge 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 holds the key to improve the safety condition of construction industry. Many research reveals the psychological and emotional conditions of workers could contribute to the fatalities and injuries. More recent observations in the area of neural science and psychology suggest inattentional blindness is one major cause of unexpected human related accidents. Due to the limitation of human mental workload, labors are vulnerable to unexpected hazards while they are focusing on complicated construction tasks. Therefore, detecting the mental conditions of workers could indicate the hazards level of unexpected injuries. However, there is no available measurement can monitor construction workers' mental condition and related hazards. This proposed research aims at proposing a measurement framework to evaluate such hazards through a neural time-frequency analysis approach. At the same time, the researchers also developed a prototype wearable Electroencephalography (EEG) safety helmet to enable the neural information collection.

Keywords –

Construction Safety; Mental Workload; Electroencephalography (EEG)

1 Introduction

Construction is one of the most dangerous industrial sector 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 3,332 injuries and 37 fatalities in the construction industry in Hong Kong, 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]. If the safety hazards are properly detected and reported, the workplace safety can be significantly improved [2]. However, the biggest challenge of identifying hazards and recording accidents are the dynamic environment of construction jobsites and workers' unpredictable behavior patterns [3]. Many research suggests through a safety analysis or safety climate analysis, the potential safety hazards could be identified [4]; together with proper safety programs, the safety condition could be significantly improved [5]. Although safety programs, such as training, inspections, motivation, enforcement, and penalties, are successfully implemented in the construction practices, there still are a great amount of unexpected accidents happened on job site. However, risks cannot be assessed, controlled and avoided if managers are not aware of the hazards in the first place [6]. Since preventing these unexpected accidents merely through safety programs is impossible, identifying and protecting vulnerable individuals instead of finding out all possible hazardous events provide us an alternative option to further improve on site safe conditions.

Every worker on site has the ability to perceive hazards, this ability could help them escape from dangerous events, sometimes results in near-miss accidents. The classic psychological theories suggest people's decision on risk-taking behavior is negatively correlated with their risk perception [7]. Thus, individuals who are weak in risk perception or tend to misestimate the risks are vulnerable to safety hazards. Therefore, if the risk perception ability of workers can be monitored, the vulnerable individual could be identified and protected.

Many factors could impact people's perception ability, mental condition is the most important one among them. In psychological research, mental workload has been proved as one of the best indicator of people perceptional ability [8, 9], 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 an approach to quantitatively estimate mental workload, and then vulnerability of construction workers.

2 Background

2.1 Psychological Issues and Construction Safety

In the labor-intense industry like construction industry, the psychological condition plays an extremely critical role in safety issues. 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]. According to Endsley's findings (1995) [11], 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. Many psychological researchers conclude that emotions greatly influence signal detection, rick perception and process of risk-based decision [12, 13]. 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, since most of construction tasks inherently associate with various level of risks [14]. Due to the tight project budgets and schedules, construction personals are predominately production-oriented and suffer huge physical and mental pressures [15], which will exacerbate the level of danger and increase the possibility of injury.

2.2 Risk Perception and Mental Workload

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. 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]. Inattentional blindness is a psychological phenomenon that an individual fail to identify stimuli due to the lack of attention. One of the most well know study demonstrates inattentional blindness is the Invisible Gorilla Test, designed by Daniel Simons [18]. 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.

One direct result of inattentional blindness in construction industry is when the workers focus too much on their work, they have less risk perception ability and vulnerable to dangers. Also, when a work has too less mental workload, for example he or she is repeating a daily work, which can also lead to the person to missing the unexpected accidents. 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. 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 work complexity [19]. 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 quantitative and direct monitoring approach that can estimate the mental workload of workers could help project managers to find the vulnerable workers and implement safety policies or approaches to avoid accidents.

2.3 Quantitative 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 [20]. Among these methods, EEG is the best candidate for construction implementation, since it can be applied outside of specialized laboratory; 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 [21].

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 [22]. 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.

3 Research Methodology

3.1 Electroencephalography (EEG)

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 [23]. 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 [24]. In this research, EEG will be introduced to assess the mental workload of workers. There are several advantages of EEG to study neurocognitive process: as suggested by Cohen (2011) [25] 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.

(3) 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.

3.2 Data Processing

The data collected and analysed 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 [26].

The EEG data 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 [27]. In this research, the engagement index developed by Prinzel et al. will be introduced [28]. The calculation of EEG-engagement index (EN) is based on beta power (13-30 Hz) divided by alpha power (8-12 Hz) plus theta power (5-7 Hz) and can be represent in following equation:

$$\mathrm{EN}(\mathrm{t}) = \frac{\mathrm{P}_\beta(\mathrm{t})}{\mathrm{P}_\alpha(\mathrm{t}) + \mathrm{P}_\theta(\mathrm{t})} \tag{1}$$

Where $\mathrm{EN}(\mathrm{t})$ is the EEG-engagement index at time t ;

$\mathrm{P}_\alpha(\mathrm{t})$, $\mathrm{P}_\beta(\mathrm{t})$, and $\mathrm{P}_\theta(\mathrm{t})$ are the power of alpha rhythm, beta rhythm and theta rhythm at time t.

Another useful mental workload assessment framework is based on a hybrid brain–computer interface (BCI) model that characterized by the temporal and frequency information of EEG data. 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 a useful tool for EEG signal classification and filtering [29]. 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:

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

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,

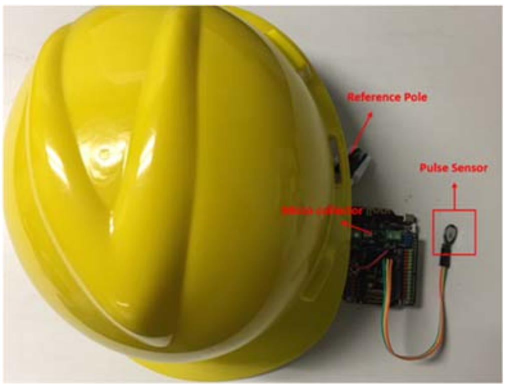
$$B(w_1, w_2) = \sum_{m=-\infty}^{+\infty} \sum_{n=-\infty}^{+\infty} E[x(k)x(k+m)x(k+n)] \cdot e^{-i2\pi(m\omega_1 + n\omega_2)} \tag{8}$$

$B(w_1, w_2)$ 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.

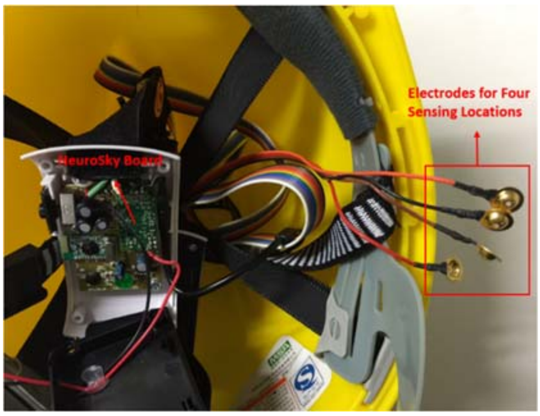
3.3 Preliminary Test and Equipment

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 a EEG monitoring safe helmet with Neurosky TGAM [30] 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, PulseSensor [31], also attached to the microcontroller for reference, but will not be discussed in this paper. Following Figure 1 shows the developed monitoring helmet.



(a) Micro controller and pulse sensor



(b) NeuroSky Board and Electrodes

Figure 1. Design of the wearable EEG monitoring safety helmet

Four sensor sites are 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 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.

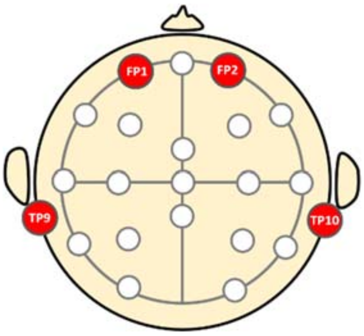


Figure 2. Electrodes installing locations refer to 10-20 system

Since 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.

4 Experimental Results and Mental Workload Assessment

To simplify the data analysis for the preliminary experiment, this manuscript only discuss the signal pattern of FP1 and focus on the first 13 seconds of the experiment, which includes three type of activities (idling, climbing, and installing). Figure 3 presents the spectrum of brainwaves of four different locations during the preliminary experiment.

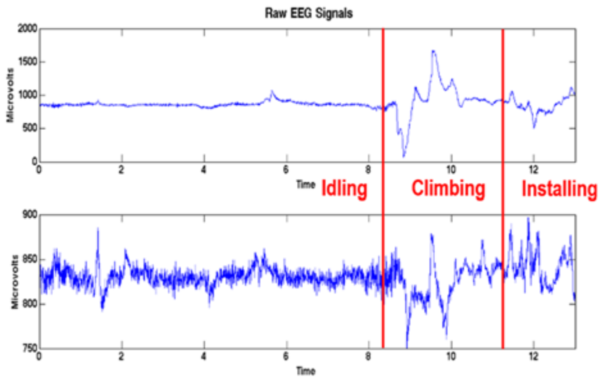


Figure 3. Raw singles form FP1(above) and FP2(below)

The raw data displayed in Figure 3 shows clear distinctions in signal magnitude and frequency among three activities. To visualize the difference between activates in the target rhythms, the data is projected into the frequency domain as shown in Figure 4.

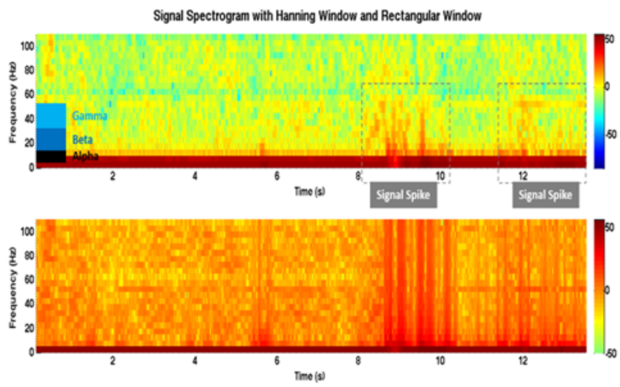


Figure 4. Signal spectrogram from FP1 with Hanning window (above) and rectangular window (below)

There are clear single spikes in Alpha, Beta and Gamma rhythms when the subjects begin to climb the ladder and start to fasten the bolts. These spikes is directly associate the mental workload. Through estimates the spike magnitude the mental workload could be quantitatively estimated.

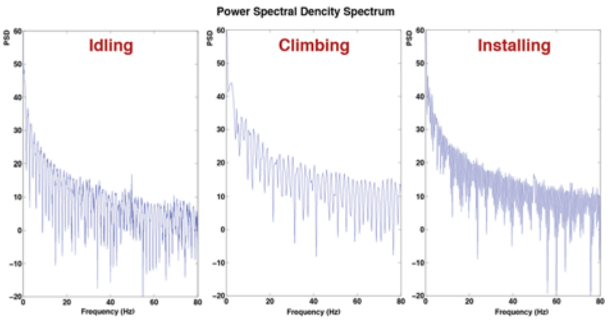


Figure 5. PSD Spectrum for activities

Above Figure 5 is the PSD spectrum, which show the power distribution in various frequency bands. It is clear that most of the power concentrates on the low frequency bank, which suggests the estimation could be improved and simplified by filtering out the high frequency part.

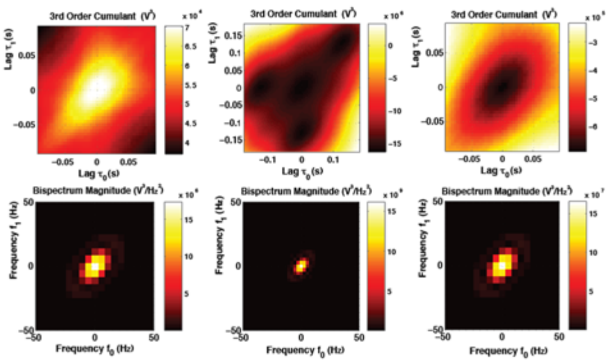


Figure 6. Bispectrum magnitude (below) and 3rd order cumulant (up) of idling (left), climbing (middle) and installing (right)

As discussed before the bispectrum analysis could be applied in the pattern recognition on the level of mental workload under different activities. Such differences in 3rd order cumulant also not only can help us to quantitative assess the attention level of the worker, but also could server as the features of activity detection for workers.

5 Safety/Vulnerability and Mental Workload

Data from the preliminary experiment suggests that EEG is an effective measurement to monitor the dynamic fluctuation of the mental load when workers engage in construction tasks. Since there are obvious distinctions between data pattern, EEG could be a novel approach to estimate the mental workload in various construction activities. More specifically, the metrics proposed in this research is able to differentiate the activities through a series of quantitative features. The estimated level of mental workload is good indication of the vulnerability of individual worker, since many psychological research [32, 33] shows when people subject to heavy mental workload could cause inattentional blindness and results in sever accidents. Therefore, by knowing who is concentrating on works, project managers are able to identify vulnerable employees and provide sufficient protection. Combining with positioning technologies, project managers can create a protection zone for workers who expose to hazards and restrict machineries' interference.

Also, another potential usage of the EEG data is activity detection. Observing from the experiment results, when the subjects conduct different types of jobs, the signal pattern of brain waves are varied. 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 [34, 35], camera [36], Kinect [37, 38], and etc.

One limitation of current injury reporting system required OSHA is that all accidents are self-reported after the accidents occurred. However, there are a great amount of near-miss accidents also can help project managers to improve the safety management practice but neglected because these accidents are extremely difficult to detect and monitor. The EEG monitoring system provide an innovative perspective to realize near-miss accidents by monitoring the mental condition when people percept danger. Some frequency bands of EEG signal, such as gamma wave, could indicate the mental condition of workers when they are experiencing accidents. Together with other sensors, such as IMU, camera or RFID, an automatic near-miss accident recording system could be created and dramatically increase the accident database for project managers to refer to.

6 Conclusion and Limitations

Measurement of workers' mental workload provide an alternative source of information about the safety condition on site. Instead of detecting hazards, the EEG assessment enable project managers find out the vulnerable individuals from a unique and innovative perspective. This research 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 suggests it is feasible of using brain waves to quantify and differentiate the mental workload of activates in construction. Since this research is a preliminary study, it still subject to several.

First, the experiment scale is not large enough. Since the equipment designed by the research team is still a prototype. Thus, the experiment cannot be conducted in a large and practical scale. In future research, the research team will try to improve the equipment design and data quality to testify the validity of the assessment model in a larger scale.

Second, the data collected from the system still yield to random errors. Although filters have been applied to eliminate the white noise in the retrieved data, the reliability of the sensing system still need to be tested and specific filers need to be designed.

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. To optimize the detecting accuracy and wearing convenience, the hardware need to expanded and optimized. In future research, the research team will connect more electrodes and sensing channels to resolve this limitation.

Acknowledgement

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