Available online at 2019.creative-construction-conference.com/proceedings/

CCC 2019

Proceedings of the Creative Construction Conference (2019) 055

Edited by: Miroslaw J. Skibniewski & Miklos Hajdu

https://doi.org/10.3311/CCC2019-055

Creative Construction Conference 2019, CCC 2019, 29 June - 2 July 2019, Budapest, Hungary

Monitoring Distraction of Construction Workers Using a Wearable Electroencephalography (EEG) Device

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Abstract

Distraction is a major cause of unsafe behaviors and decreased safety performance in a high-attention demanding construction environment. However, few studies have drawn attention on cognitive characteristics of distraction and the method to detect it quantitatively. To fill the gap, this study investigates the correlation between distraction and mental activity using EEG device, aiming to provide a real-time approach to monitor the worker's distraction objectively. In this study, sustained attention to response task (SART) has been employed to induce the occurrences of distraction in the simulated construction safety inspection tasks. The recorded EEG data was divided into two groups corresponding with task performance: focused and distracted. By analyzing the data through pre-processing and feature extraction methods, the objective is to examine indices that enable to distinguish these two statuses based on time and frequency domain. The metrics proposed are estimated to be associated with cognitive functions like attention deficit and attention allocation, herein serve as an objective assessment of an individual's sustained attention degrees and cognitive failures. Accordingly, this study facilitated the development of cognitive features of distraction theoretically and made it possible to detect and control the inner distraction leading to unsafe behavior or decreased task performance in practice.

Peer-review under responsibility of the scientific committee of the Creative Construction Conference 2019.

Keywords: distraction; EEG; sustained attention; unsafe behavior; job site safety

1. Introduction

Although construction safety management has been largely enhanced over recent years, the high incidence of accidents and huge financial cost recorded at construction projects among all industry sectors still highlight safety management to deserve discussed. In the United States, fatal occupational injuries in the construction industry have the largest proportion from 2003 to 2016, more than transportation and over twice than manufacturing [1]. Across the European Union, the construction sector accounts for 21% of fatal accidents in 2015 [2]. Catastrophic accidents undoubtedly mean tragedies to both families and construction program, causing irreversible damage to the health of suffers, and impeding smooth project running. A large body of research pays attention to investigate common and fundamental contributors to injury and fatality rates[3,4]. Evidence suggests that 88% of the accidents of construction programs among proximal factors were caused by inappropriate safe behavior [5]. Workers' unsafe behavior depends on a variety of factors, among which external factors include site conditions, safety culture, and climate, training and education,

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supervision and management, internal factors related to individual conditions such as safety incentives, attitudes working experience, social relations, attention allocation, alertness, emotion, fatigue and stress [6] .

Individual internal factors such as stress, fatigue, alertness that play a significant role in shaping the safety behavior of workers have been studied [7,8]. However, research addressing the link between mind-wandering and safety behavior remain inadequate in spite of ubiquitous distraction sources at the site. Not only the work quality decrease with distraction but also the likelihood of improper operation, careless accidents, and fall accidents increases, even impact on project cost and schedule [9]. Dynamic environments and potential safety hazards everywhere require construction workers to keep vigilant. Thirty-four workers were interviewed at the site about the causes of high-altitude falls and found that 33 workers agreed that negligence and distraction were one of the major causes of the fall [10]. Employees with repetitive and monotonous tasks like heavy machinery operators, signalmen, rebar tying workers are more prone to make poor safety judgment because of stuck in distraction. Distraction potentially derives from environmental or personal-related factors, like noise, moving vehicles, conversation with colleagues and safety incentives, body discomfort, fatigue, depressed mood or family bothering.

As various sources of distraction cannot be identified and eliminated completely within complex construction context, especially personal-inner interference, more important is to capture distraction state and manage properly than recognize each potential source. Although brain waves of distraction have been studied within medical and cognitive science domains, such findings cannot fit well in the construction industry practically for the nature of task and context. Therefore, it is yet not clear how to monitor the mind-wandering of workers real-time to avoid unsafe outcomes caused by distraction. To fulfill the research gap, an objective measurement approach with wearable EEG device is proposed to detect workers' distraction, aiming to inhibit frequency and address the occurrence of mind-wandering at actual sites. The paper provides insight into quantitation of distraction utilizing sustained attention to response task (SART). More specifically, the authors attempt to build correlates between brain state and behavior performance and discover indices regarding distraction after analyzing EEG data. In addition to enrich knowledge body, understanding of detecting distraction can help minimize adverse effect on work quality and avoid unexpected safety outcomes.

2. Literature Review

2.1. Distraction

In fact, many versions of distraction definition can be found in the literature, and what they have in common is divert the attention of primary task to something else and cannot pay full attention to perform the task at hand safely and efficiently [11,12]. Distraction usually displays in forms of yawn, drowsiness, eyes wandering, talking with colleagues, playing mobile phones, texting message, eating or drinking, looking around, or mind-wandering despite look like focused. Distraction can be into two types: mental and physical, also known as internal and external distracted, the main difference of which lies in the existence of physical changes and external events [13]. At present, there has been an enormous increase in the number of studies examining distraction in the area of education, transportation, medicine, cognition, and neuroscience by emerging physiological technologies but lack research in the area of construction safety. Combined with physiological measurement, students' neurofeedback to distinct learning content and media is useful to facilitate improving the quality of learning and teaching [14]. Likewise, drivers urgently need sustained attention than students due to distraction is confirmed that account for substantial crashes and traffic accidents [15]. The construction safety department gradually recognized the adverse effect of distraction and Occupational Safety and Health Administration (OSHA) set up special regulations to restrict the distraction of mobile phones aiming at crane operators. A recent study of workers has unveiled that distraction indeed impede hazards recognition levels and the rationality while perceiving safety risk through an experimental attempt [16]. Chukwuma Nnaji conducted extensive literature and a survey to summary distraction sources and ranked the impact of each distraction factor, which construction personnel agreed that poor attitudes, lack of safety resources, lack of familiarity with equipment, site crowding play a vital role in work safety and quality [9]. However, the issue of distraction and its impact on safety performance, and its sources and countermeasures have been under-researched from a scientific and systematic perspective in the field of construction. With respect to solutions, Seli claimed that different countermeasures should respond to different types of mind-wandering [17]. Except for eliminating sources of distraction, capturing distraction state is crucial to control the phenomenon and subsequent results.

The tools to assess cognitive state in the current study (alertness, tension, distraction, anxiety, cognitive overload) are divided into two categories: traditional subjective ratings and objective measures. Subjective response primarily consists of self-reports, and objective measures mainly contain performance measures (reaction time, error rate, task accuracy) as well as psychophysical methods. Mindful Attention Awareness Scale, Cognitive Failures Questionnaire (CFQ), Mind Wandering Scale (MWS), Attention-Related Cognitive Errors Scale (ARCES) and Karolinska Sleepiness Scale (KSS) were put forward to estimate the level of attention and mind-wandering. However, the retrospective method belongs to post-evaluation, which lost timeliness and affected by individuals' understanding deviation of questions to a large extent. Behavioral metrics in driving contain speed variability, lane deviation, the standard deviation of lateral position (SDLP) and steering reversal rate (SRR), to serve as a performance method to seize distraction. Nevertheless, these metrics cannot be applied to construction personnel for the nature of task and scenarios at the workplace. Emerging psychophysical technologies has been adopted in recent years, namely, endogenous eye blinks (EOG), heart rate activity (HRV), Electromyogram (EMG), wearable electroencephalography (EEG) devices, functional near-infrared spectroscopy (fNIRs) and functional magnetic resonance imaging (fMRI). EEG outperforms other wearable devices to record brain activity on account of its non-invasive, high time resolution and portable characteristics.

2.2 EEG Application

The reliability of wearable EEG devices to assess mental state has been validated by considerable research. Results of a breath counting task suggested a significant reduction of alpha-band activity combined with a diffuse increase in theta band activity, and the researcher found there was a similar increase in theta band as that reported by a study measuring frontal sites during mind wandering [18]. Conversely, the research conducted by Carryl L. Baldwin et al., combined driving task performance with EEG detection and the findings suggest periods of mind wandering were associated with increased power in the alpha band of the electroencephalogram (EEG), as well as a reduction in the magnitude of the P3a component of the event-related potential (ERP) in response to the auditory probe [19]. However, many articles reach a consensus that oscillatory activity in the alpha band of the EEG is suggested to be related to attention processes specifically the degree to which attention is allocated internally vs. externally [20]. In addition, research suggested alpha power is associated with lapses of attention to external stimuli [21]. A recent study also proposed EEG to detect mind-wandering and aimed to predict the mind-wandering state of a person, the results of which revealed reduced electrodes can also achieve prediction effect and the non-linear Support Vector Regression (SVR) model showed significantly better precision than linear SVR model [22]. However, specific metrics to recognize if a worker is distracted has not been built, and whether it can apply in the area of construction remain unclear. Up to now, EEG has been proposed to be utilized at construction sites to assess mental workload, stress and vigilance levels [23,24]. The construction workers' perceived risk level can be effectively reflected and quantified by EEG signals such as frequency, power spectrum density, and the relationship between vigilant attention and forehead EEG was identified most close [25]. In a word, EEG is plausible enough as an estimator of construction workers' cognitive state through extracting and processing features of different brain states.

3. Methodology

3.1 Experiment

Ten healthy postgraduate students completed the SART experiment, of which half is male, and the other half is female. The age range from 20-30 years old and all participants have normal or corrected-to-normal vision. The stimuli were presented in the form of pictures against a grey background on a computer screen, which includes two types of pictures appearing on the screen randomly. They are pictures workers wearing with and without hardhat. Those pictures are collected from Google search engine, namely, non-target and target stimuli, of which the proportion of non-target and target trials is 11:1. To detect internal and external distraction, two groups of experiments were designed. Each trial in the first experiment is only a picture associated with the construction site, but in the second set of experiment, two pictures are presented including a picture related to hardhat judgment and the other is interference irrelevant with construction. The EEG device used in this research is Emotiv-EPOC with 14 electrodes as shown in Figure 1. The experiment is supported by Paradigm, one of psychology software and the version is free trial version: v2.5 for Windows.

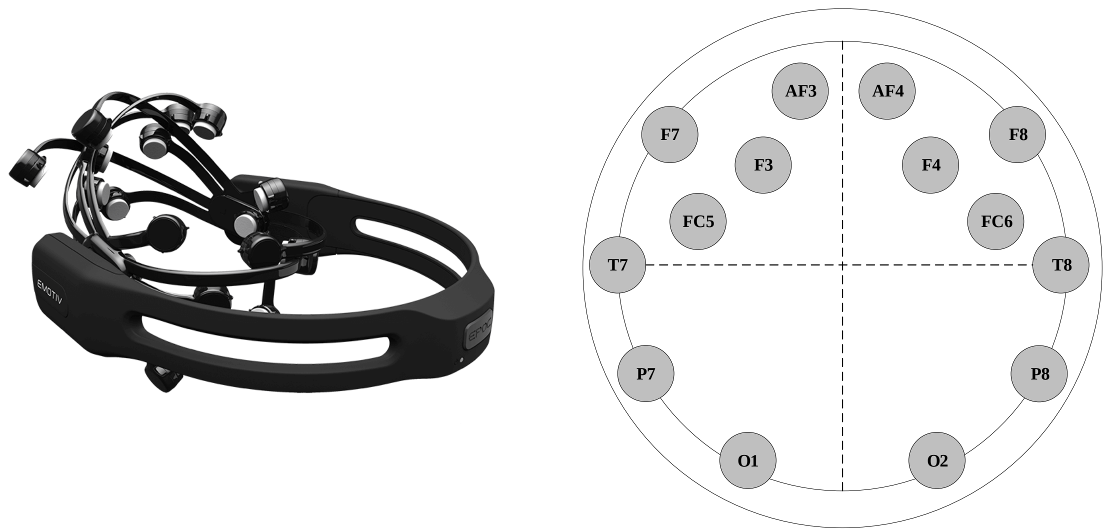

Fig. 1. EEG Headset/Sensors Location

Initially, participants were informed of the experimental procedure and were required to rest for 5 minutes. Then participants were instructed to respond to pictures including hardhat as quickly and focused as possible when the stimuli appear on the screen. If the worker wears a hardhat, called non-target stimuli, participants need to press the left arrow button on the keyboard; otherwise the right arrow button when the target appears. Meanwhile, the participant's behavior response and EEG brain activity were registered synchronously. Each trail just last 1000 milliseconds on the screen until a timeout occurred. A block consisted of 60 trials, so each participant is required to complete 4 blocks during each group, that is 480 trials totally. After they complete each block, participants will be asked: "Are you distracted just now?" The participants need to answer from 1 (very focused) to 5 (always distracted). "Are you aware that you are distracted?" The participants need to select from 3 options: very focused, intentionally distracted and unintentionally distracted. The duration of each question is about 5 seconds. The whole experiment procedure is demonstrated as Figure 2. Given that sufficient time is provided to perform each trail in 1000 ms, so participants are required to keep sustained attention to react in the limited duration, or they were identified distracted at the moment when giving an error response.

3.2 Data Processing

Data collected during the experiment include self-ratings, behavior performance and brain waves. Self-ratings serve as a subjective response of distraction degrees, and the role of behavior data is to provide an objective benchmark and label synchronous brain data. The purpose of analysing data is to find credible indices associated with a state of distraction. Behavior data recorded by Paradigm automatically contains reaction time (millisecond) and error labels (binary number) of each trial, as well as a self-rating of each block. Recorded data are analyzed by the statistical approach utilizing SPSS software, and the Spearman coefficient is selected to calculate the correlation between self-assessment and actual error rate.

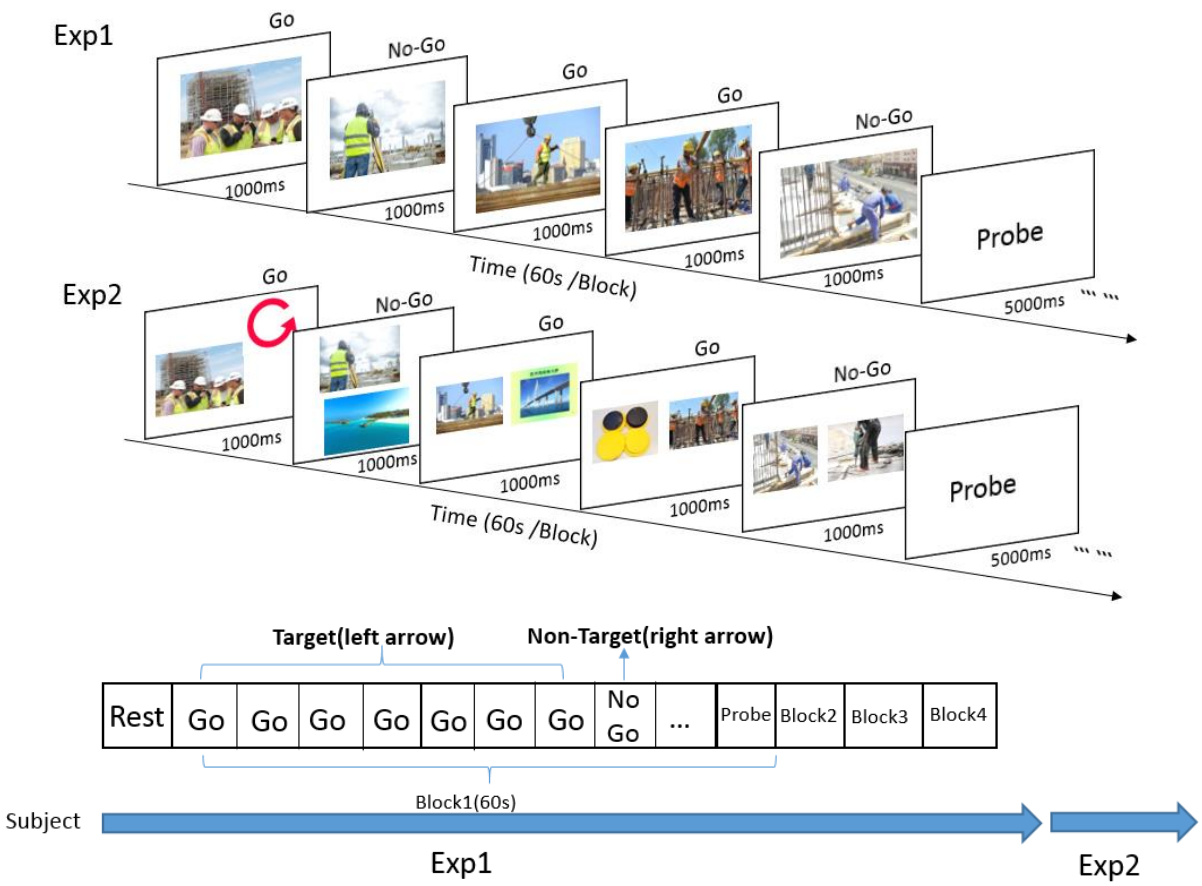

Fig. 2. Experiment Stimuli/Procedure

The most important stage is how to extract the features of EEG signals and validate the reliability of indices. The proposed EEG signal processing method consists of three phases: pre-processing, feature extraction, classification, as illustrated in Figure 3. EEG pre-processing is vital because EEG raw data is susceptible by various artifacts such as white noise, line noise, eye blink, eye movement, muscle artifacts, sweat pollution, motion interference and electrocardiogram (ECG). The main methods are Finite Impulse Response (FIR) band-pass filter from 1-60Hz to filter noise, and a notch filter at 50Hz was applied to eliminate power line interference. Independent component analysis(ICA) method supported by EEGLAB was used to reject eye movement and muscle artifacts. In the actual preprocessing, several subjects showed ECG artifacts, which were also removed by ICA. Then data were segmented into epochs as trail duration and regrouped into 'distracted' and 'focused' according to error labels. After pre-processing, signals can be analyzed in time, frequency or time-frequency domains to extract significant metrics. Feature extraction methods include Fast Fourier transform (FFT) to do frequency analysis, short-time Fourier transform (STFT) to extract time-frequency information, and wavelet decomposition to focus on frequency bands of interest. To validate the reliability of indices, support vector machine (SVM) is suitable for the binary classification problem in this experiment.

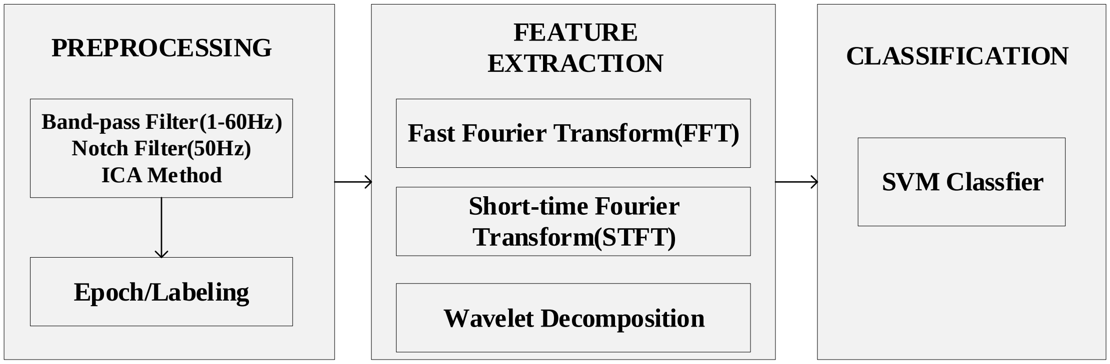

Fig. 3. EEG Data Processing Framework

4. Preliminary Results

In both sets of experiments, response time in Table1 when making mistakes (735.54 ms vs. 740.15 ms) was markedly longer than that of correct judgment (553.67ms vs. 588.98 ms). Participants cannot perform the task effectively as usual when distracted despite enough time. Comparing two groups, the correct response time in the second group with unrelated interference (588.98ms) is longer than that in the first group (553.67 ms), but the incorrect response time in two groups make no difference (735.54 ms vs. 740.15 ms). When the workers are disturbed by visual images unrelated to the primary task, it will take longer to process the task. Likewise, the proportion of error rate in the second group was significantly higher than the first group, 11.08% and 7.08% in Table 2 accordingly. Surprisingly, the correlation between subjective judgment and accuracy rate is lower than 0.6 excluding subject 6, so subjective judgment of distraction degrees has great deviation in the evaluation of the actual error rate.

Table 1. Mean response time of each block in two experiments.

Response time (ms)	Exp1		Exp2	
	Correct	Incorrect	Correct	Incorrect
Block1	560.76	763.68	607.94	784.19
	(150.04)	(301.12)	(159.60)	(316.97)
	563*	37*	555*	45*
Block2	561.09	658.23	602.42	790.80
	(139.35)	(336.67)	(153.38)	(334.38)
	572*	28*	540*	60*
Block3	560.15	763.71	580.54	725.83
	(154.17)	(288.54)	(161.78)	(318.15)
	543*	57*	518*	82*
Block4	532.31	726.28	563.25	691.45
	(158.23)	(291.23)	(164.68)	(296.10)
	551*	49*	521*	79*
Total	553.67	735.54	588.98	740.15
	(150.88)	(300.03)	(160.63)	(316.23)
	2230	170	2134	266

Note: Standard deviation is in brackets. * is the total number of correct and incorrect trials in each block.

Table 2. The error rate of two experiments and correlation with self-reports.

Subjects	Exp1	Exp2	Spearman coefficient
1	1.25%	6.67%	NaN
2	7.5%	11.67%	0.279
3	7.5%	10%	0.323
4	9.58%	15.83%	0.201
5	10%	18.75%	0.567
6	5.83%	7.5%	0.689
7	5.83%	12.5%	0.446
8	7.08%	5%	-0.394
9	7.92%	8.75%	0.399
10	8.33%	14.17%	0.028
Average	7.08%	11.08%	0. 047

5. Conclusions

It can be concluded that monitoring sustained attention subjectively exist assessment bias and cannot be implemented continuously in construction activities. Under the premise without hindering work, real-time detection by wearable EEG is able to response personal attention-related changes immediately than preventive measures like safety training and job hazards analysis. Compared with the causation analysis of distraction, detection is a straightforward intervention. In addition, the application range of findings are not limited in construction but drivers, surgeons, pilots and other jobs demanding sustained alertness. The main drawback of the experiment is that it is performed in a contained environment instead of a real construction job site. However, it was confirmed that wearing an EEG device at a construction workplace is completely practicable [26]. Moreover, the task in the experiment merely simulates one of the construction activities, sorts of safety activities are supposed to be considered in future works. Excluding visual interference, the distraction of workers is caused by various factors like fatigue, bad mood or noise around in daily work, yet it remains unclear whether the extracted features can be applied to all scenarios. Moreover, subjects participating in the experiment are not real workers, so it is still needed to examine that the difference between postgraduates and workers. Beyond this, it is necessary to explore the effect of demographic features like gender, age, and working experience on workers' sustained attention.

With regard to research about cognitive behavior by EEG, improving the accuracy of filtering is essential due to vulnerability during EEG signal acquisition. In addition, further research is needed to improve the accuracy of feature extraction because brain waves exist strong latent ability, and cannot be purely interpreted into corresponding cognitive behavior from a few features. In other words, forward reasoning from behavior to features does not promise the reliability of backward chaining from features to represent behavior.

Acknowledgments

This work was jointly supported by the National Science Foundation of China Grant # 51778553 and Research Grant Council Grant # 21206415 and 11214518. The conclusions herein are those of the authors and do not necessarily reflect the views of the sponsoring agencies.

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