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How to Measure Alert Fatigue by Using Physiological Signals?

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Abstract: This paper introduces alert fatigue and presents methods to measure alert fatigue by using physiological signals. Alert fatigue is a phenomenon that which an individual is constantly exposed to frequent alarms and becomes desensitized to them. Blind spots are one leading cause of struck-by accidents, which is one most common causes of fatal accidents on construction sites. To reduce such accidents, construction equipment is equipped with an alarm system. However, the frequent alarm is inevitable due to the dynamic nature of construction sites and the situation can lead to alert fatigue. This paper introduces alert fatigue and proposes methods to use physiological signals such as electroencephalography, electrodermal activity, and event-related potential for the measurement of alert fatigue. Specifically, this paper presents how raw data from the physiological sensors measuring such signals can be processed to measure alert fatigue. By comparing the processed physiological data to behavioral data, validity of the measurement is tested. Using preliminary experimental results, this paper validates that physiological signals can be useful to measure alert fatigue. The findings of this study can contribute to investigating alert fatigue, which will lead to lowering the struck-by accidents caused by blind spots.

Key words: alert fatigue, physiological signal, EEG, EDA, construction equipment safety

1. INTRODUCTION

The construction industry is known as one of the most dangerous industries. Accidents related to vehicles and equipment are one of the leading causes of fatal injuries in the construction industry [1]. The blind spot of construction equipment is one common danger on construction sites [2]. To prevent accidents caused due to blind spots, backup and proximity alarms are installed in construction equipment. As the construction site is a confined place and various resources such as materials, equipment, and workers-on-foot need to work in such a congested area, the work path of equipment and workers-on-foot can overlap. The circumstances lead to frequent alarm emissions.

Alert fatigue is a phenomenon that happens when a person or a group is exposed to frequent alarms and becomes desensitized to alarm [3]. As an alarm is designed to prevent accidents due to the blind spot by alerting the equipment operators and workers and informing them about the impending danger, desensitization toward the alarm can lead to a higher possibility of accidents.

There have been some research studies investigating the alarm systems to improve the effectiveness of alarms by reducing the rate of false alarms [2, 4]. Even though the effectiveness of the alarm system has been improved, due to the work path overlapping on the construction site, the frequent alarm is inevitable. Therefore, operators of the construction equipment still experience alert fatigue, and the possibility of accidents due to the blind spot remains high.

The objective of this paper is to introduce alert fatigue and present the methods of measuring alert fatigue of construction equipment operators via physiological sensors. As alert fatigue means decrement of alertness due to certain alarms repeated, by measuring alertness via physiological signal and observing the changes of alertness as the alarm is repeated, alert fatigue can be measured quantitatively. Electroencephalography (EEG) and electrodermal activity (EDA) sensors are used to measure the physiological signal of the subject in the experiment. The raw data is filtered and processed into alertness data measured by EEG, EDA, and event-related potential (ERP) which is extracted from the raw EEG data. By observing the changes of alertness as the alarm is repeated, alert fatigue can be measured.

There has been no study investigating alert fatigue in the construction industry even though alert fatigue can be one major causal factor of an equipment-related accident on the construction site. By introducing alert fatigue and presenting the methods of measuring alert fatigue quantitatively, this study can contribute to the current body of knowledge of construction equipment safety and improve the safety performance of the construction industry.

2. LITERATURE REVIEW

2.1. Alert fatigue

Alert fatigue is usually studied in the medical sector [5, 6]. Edworthy (2013) proposes that as individuals adjust their reaction rate to the accuracy of the alarm (i.e., false alarm), the overwhelming alarm can lead to a slower reaction, which can lead to a dangerous decision [6].

The everyday safety tailgate talks of Cornell University is the only article that proposes the concept of alert fatigue in the construction industry. In the article, safety alert fatigue was defined as a phenomenon that occurs when an individual or a group is constantly exposed to an alarm or warning sound and becomes desensitized to the alarm which can lead to a slower reaction and a dangerous situation [7]. In this study, alert fatigue is defined as a phenomenon that which an individual is constantly exposed to frequent alarms and becomes desensitized to alarm [3, 7].

2.2. Physiological and behavioral features

Physiological signals are widely used to measure the mental status of individuals quantitatively in many research areas [8-10]. Alert fatigue means decrement of alertness as certain alarms are repeated. Decrement of alertness can be conceptualized as a change in mental status. Therefore, by measuring alertness via physiological signals and observing the changes in alertness as alarms are repeated, alert fatigue can be measured with physiological signals quantitatively.

EEG is an electrical signal generated due to the activation of neurons. EEG is collected on the surface of the scalp by using electrodes [10]. As EEG can reflect the activation of the brain due to the stimulus, EEG has been widely used in many research areas, including construction safety research [11, 12]. Alpha and beta frequency ranges are widely used to measure the stress level or arousal status of an individual in many studies [9, 10, 13]. Alertness due to alarm sound can be conceptualized as arousal status due to auditory stimulus, therefore, alpha and beta frequency ranges are used in this study to measure alertness. Alertness measured by EEG signal is reported in terms of the absolute power spectral density (PSD) values. However, using absolute PSD values can lead to an inter-individual difference of results due to the difference of the conductance of the scalp of each individual. To deal with this issue, this study uses the relative PSD value as well. Relative alpha and beta PSD values can be obtained by dividing absolute alpha and beta PSD values by absolute PSD values of the overall frequency range (i.e., delta, theta, alpha, beta, and gamma), respectively [14]. In summary, a total of four different EEG features are used in this research to measure alertness. As the alpha frequency range is related to the relaxed state, increments of absolute and relative alpha PSD values with time indicate reduced alertness, i.e., alert fatigue. In the case of the beta frequency range, as the beta range is related to the arousal state, decrements of absolute and relative beta PSD values with time indicate alert fatigue. To measure EEG data, Emotiv EPOC+ device is used in this study. EPOC+ has 14 electrodes for different electrode locations and collects data at 128Hz. Details about processing EEG data are discussed later.

EDA is skin conductance data collected on the surface of the skin (e.g., wrist, finger) by passing a small amount of current through the electrodes [15]. EDA is affected by the autonomic nervous system, especially the sympathetic nervous system (SNS). Activation of SNS occurs due to stimuli and leads to sweating. Sweat on the skin can induce higher skin conductance, which leads to higher EDA values. Therefore, higher EDA values mean arousal status or alertness [10]. EDA is considered as a robust measurement method as sweating is only affected by stimulus in controlled situations [15]. EDA data can be classified into two according to their timely aspect. Phasic skin conductance response (SCR) is the rapidly changing peak in EDA data. SCR data represent the response of the body to short-term events or discrete stimuli. As alertness is measured by EDA data is recorded for each alarm, which is discrete stimuli, hence, SCR data can measure alertness. Tonic skin conductance level (SCL) is the slow change of EDA data. SCL data represent the mental status change in a long period of time, such as tiredness, or numbness [12]. Decrement of alertness can be related to numbness, therefore in this research, both SCR and SCL data are used to measure alertness and alert fatigue. In this paper, the continuous decomposition analysis (CDA) method and the convex optimization-based EDA model (cvxEDA) are used to decompose EDA data. Two different methods are widely used to decompose EDA data [12, 16-18]. By using the cvxEDA method, SCR and SCL data from the cvxEDA method can be obtained. By using the CDA method to decompose EDA data, not only maximum-SCR and mean-SCL data but also SCR area data and mean-SCR data can be obtained. SCR area data is obtained by calculating the area of SCR peak via time integral. Mean-SCR values are obtained by calculating the average value of every SCR value in the SCR peak. In summary, a total of six different EDA features are used to measure alertness. As aforementioned, increasing EDA values indicates alertness. Therefore, a decrement of any of the six EDA features with time indicates that alertness decreases, which is alert fatigue. Measuring EDA data is conducted with the Empatica E4 device. E4 device is a widely used off-the-shelf physiological sensor that collects EDA data from the wrist at 4Hz [10, 17]. Details about processing EDA data are presented later.

ERP is a small electrical signal collected from the scalp with electrodes in response to the activation of a large number of neurons due to a stimulus [19]. As ERP is data that is time-locked to a specific event or stimulus, ERP has been widely used to study the physical response to discrete external stimuli (e.g., alarm) [20]. ERP can be obtained from EEG data. Each ERP wave represents the positive or negative potential detected after a certain time has passed after an event, and each wave indicates different mental status. For example, the P300 wave refers to a positive peak detected after 250-400ms has passed from the event. This wave is related to the attention to auditory stimuli of a subject [19]. As attention toward certain auditory stimuli can be related to alertness towards alarm, P300 is used in this study. If P300 values decrease with time, it indicates lowered alertness, which is alert fatigue. Details about processing ERP data are discussed later.

For the research studies about human responses to external stimuli, the response time has been widely used as behavioral data [21]. In addition, individuals react slowly because of alert fatigue, as mentioned above. Therefore, reaction time can be a good measure for alert fatigue. If reaction time increases with time, it indicates lowered alertness, i.e., alert fatigue. Alertness measured with reaction time can be used to verify the performance of the physiological signal of measuring alert fatigue quantitatively. As reaction time is more directly related to alert fatigue, if both experiment results from certain physiological features and reaction time indicate that a subject experiences alert fatigue, then it is reasonable to conclude that such physiological features can successfully measure alert fatigue. In summary, including reaction time, a total of 13 physiological and behavioral data are used to measure alert fatigue.

I) 3. RESEARCH METHODOLOGY

3.1. Experiment Design

To emulate the circumstances of the construction equipment operation, a driving simulation is used. Subjects of the experiment will play a driving simulation that simulates the construction site and construction vehicle while wearing both EPOC+ and E4 sensors. While playing simulation, alarm sounds will be emitted from the speaker at a random interval. The volume of the alarm sound is 75dB and background noise (e.g., engine sound from the driving simulation) is 55dB. The alarm sound used in this experiment is the complex tone that consists of 500, 1000, 2000, and 3000Hz, representing the conventional alarm sounds [22]. Subjects are ordered to push the brake pedal in front of their feet in response to the alarm sound before the experiment. The action of pushing the brake pedal when the alarm sound was heard is the simulation of the action of the construction equipment operator, and reaction time is recorded through such actions. After 25 alarms are emitted, the experiment is completed.

3.2. Data processing

As EEG and EDA sensors use sensitive electrodes, the physiological signals can be disrupted with many different physical features such as breathing and heart beating. Thus raw EEG and EDA data contain intrinsic and extrinsic artifacts (i.e., noise) [10, 12]. Therefore, before feature extraction, raw data should be filtered. In this section, the detailed methods of processing data, including filtering and feature extraction are presented. Figure 1 shows the data processing procedure for both EEG and EDA data.

The extrinsic artifacts are noise due to mechanical or electrical interference or interference occurring outside of the body. The intrinsic artifacts are noise that occurred inside of the body or occurred due to physical movements.

The extrinsic or intrinsic artifacts in EDA data can be removed with a high-pass filter and rolling filter. As the artifacts are noise from unintended interference or movement of the body, the frequency ranges or amplitude of the artifacts differ from such information of the physiological signals. Therefore, by using a high-pass filter and rolling filter, the artifacts within EDA data can be removed [12]. EDA data filtering process is conducted with Ledalab software [18].

Unlike the EDA signal, intrinsic artifacts of EEG data are related to the internal signal (e.g., organ) rather than unintended physical movement. Therefore, the frequency ranges of the intrinsic artifacts within EEG data are not different from those of EEG data [10]. Hence, intrinsic artifacts within EEG data need to be processed with a different method. The independent component analysis(ICA) method is a method for signal processing that has been widely used for removing intrinsic artifacts of the EEG data [10, 11]. The ICA method assumes that collected EEG data is a sum of independent components and can be decomposed into independent components [13]. By decomposing the EEG data into independent components, each independent component can be classified as intrinsic artifacts or the clean EEG data. The process of filtering and applying the ICA method to EEG data is conducted with EEGlab software [23].

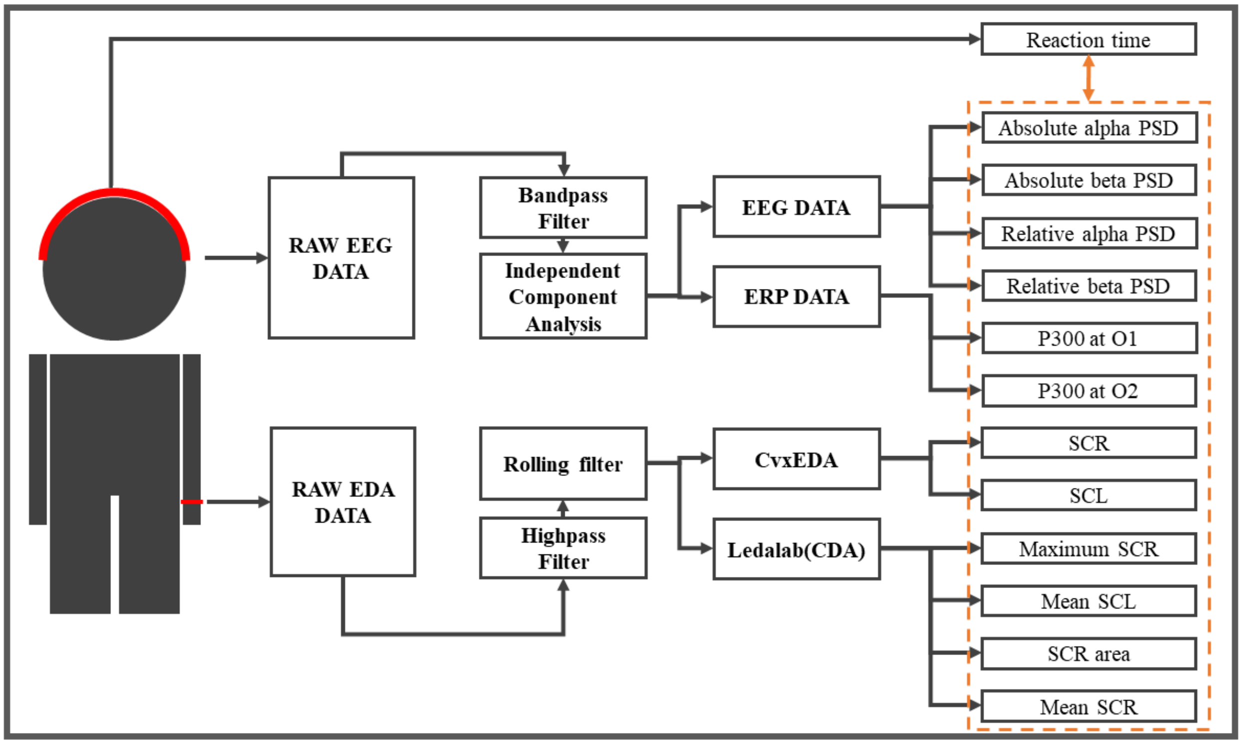

Figure 1. Data processing procedure

After removing the artifacts from both EEG and EDA data, physiological features can be calculated from each data. From the EEG data, absolute alpha and beta PSD values, and relative alpha and beta PSD values can be extracted. PSD values for four EEG features are obtained by calculating the average values for the overall region of the scalp [24]. From the EEG data, ERP data can be obtained. Research shows that the P300 wave from the occipital lobe (i.e., O1 and O2 electrode location) is well performed [25]. Therefore, the P300 value from O1 and O2 is extracted from the EEG data.

SCR and SCL features of EDA data can be obtained by using two different decomposition methods. The cvxEDA method suggested by Greco et al. (2016) is a relatively new, and robust method of decomposing the EDA data. By using the method, SCR and SCL values can be extracted from the EDA data [16]. Compared to the cvxEDA method, the CDA method is a relatively traditional method of decomposing the EDA data. With the CDA method, extra features such as the SCR area feature and Mean SCR feature can be extracted [23].

Each physiological feature, as well as reaction time, will be calculated for each alarm emitted during the experiment. To verify whether subjects experience alert fatigue or not, 25 physiological data for each physiological feature and 25 reaction time data will be measured in the early phase and the later phase of the experiment with one data overlapped for each phase. If alertness of the early phase is higher than the later phase, it can be said that alert fatigue is detected. By comparing the results of physiological features to the results of reaction time, the performance of detecting alert fatigue of the physiological features can be verified.

3.3. Preliminary result

This section presents the preliminary experiment results. One female and four male subjects participated in the experiment. The average age of the subjects is 27.6, the oldest subject was 31 and the youngest subject was 26. No subject experienced the nervous system or brain-related diseases. As EEG records the activation of the brain, such diseases disrupt the data. In addition, no subject experienced hyperhidrosis. As EDA collects the skin conductance level of the hand, hyperhidrosis can affect the EDA data [10]. Table 1 shows the results of measuring alert fatigue with behavioral or physiological features for five subjects. The “Detected” tab means that a subject experienced alert fatigue and the “Not detected” tab means that a subject did not experience alert fatigue. For the features related to arousal states, such as EDA, beta frequency range, and ERP, if the value of the later phase is lower than the early phase, which means lowered alertness, the result is considered as alert fatigue. For other features such as behavioral features, and alpha frequency range, if the value of the later phase is higher than the early phase, it is considered as alert fatigue.

Table 1. Preliminary result

Features	**Subject A**	**Subject B**	**Subject C**	**Subject D**	**Subject E**
Behavioral	Detected	Detected	Detected	Not detected	Detected
SCR(cvxEDA)	Not detected	Not detected	Detected	Not detected	Detected
SCL(cvxEDA)	Detected	Detected	Detected	Detected	Not detected
SCR(CDA)	Detected	Not detected	Detected	Detected	Detected
SCL(CDA)	Not detected	Not detected	Not detected	Detected	Detected
SCR area(CDA)	Detected	Not detected	Detected	Detected	Detected
Mean SCR(CDA)	Detected	Not detected	Detected	Detected	Detected
Absolute alpha	Detected	Detected	Not detected	Not detected	Detected
Absolute beta	Not detected	Not detected	Detected	Detected	Not detected
Relative alpha	Not detected	Detected	Detected	Not detected	Not detected
Relative Beta	Not detected	Detected	Not detected	Not detected	Not detected
P300(O1)	Detected	Detected	Detected	Not detected	Not detected
P300(O2)	Not detected	Not detected	Not detected	Not detected	Not detected

As shown in the table, all of the subjects except subject D experienced alert fatigue according to the behavioral feature. This result can indicate that alert fatigue of the construction equipment operator due to alarm repetition may exist. In addition, the performance of the physiological features to detect alert fatigue is verified for each feature. P300(O1) feature is the best performing feature among 12 physiological features. P300(O1) feature can detect the same result as behavioral data for four subjects. All of the rest physiological features, except four features (i.e., SCL(CDA), absolute Beta, relative Beta, P300(O2)) show the same results as behavioral data for three subjects.

4. DISCUSSION

Through the preliminary experiment results, this paper proposes that construction equipment operators experience alert fatigue due to repeated alarms, and some features such as reaction time and P300(O1) can measure alert fatigue quantitatively. This result shows that repeated alarms can affect the alertness of the construction equipment operator, therefore emphasizing the importance of managing alert fatigue in construction equipment safety. As there has been no research about alert fatigue, this paper can contribute to the current body of knowledge by verifying one major causal factor of construction equipment-related accidents, which is one of the major causes of fatal accidents on the construction site.

However, this study is not free from limitations. First, as the sample size of this study is too small, findings from the results cannot be generalized yet. It is still unknown whether alert fatigue is real, and the construction equipment operator truly experiences alert fatigue when they work. In addition, it is still unknown which physiological feature is most suitable for measuring alert fatigue. The higher number of sample size is encouraged to generalize the result. Second, this study only shows that there may exist alert fatigue which can be one major causal factor in the construction equipment-related accident, and do not show or suggest any methods for managing alert fatigue. Thus, in future study, methods for controlling or managing alert fatigue should be investigated.

For future studies, more physiological signals or physiological features can be used to measure alert fatigue. For example, in this study, only the EDA sensor of the Empatica E4 device is used. However, as the Empatica E4 device can record photoplethysmography and skin temperature, more physiological features can be investigated. Research about measuring alert fatigue with more various kinds of physiological features with a larger sample size, and suggestions for managing alert fatigue can contribute to reducing accidents caused by blind spots.

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