Incident Detection at Construction Sites via Heart-Rate and EMG Signal of Facial Muscle

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Abstract -

Fatal accidents occur at construction sites. Incidents involving dangerous situations but not reaching the category of fatal accidents also take place. When an incident occurs, workers typically generate an on-site physiological reaction. In this paper, an automatic detection system is proposed to automatically identify incidents by measuring biological signals related to emotions of on-site workers, such as heart rate and the masseter muscle. In the first stage of this study, some virtual reality (VR) video-based experiments were conducted with some wearable sensors to confirm whether the aforementioned biological signals are suitable to detect incidents. While watching the VR videos, biological signals of the subjects were measured using different wearable sensors. The experimental results corroborated that the proposed sensing method is suitable to detect construction-site incidents.

Keywords -

Construction site, Safety, Biological signals, Incident detection

1 Introduction

According to a survey by the Ministry of Health, Labour and Welfare, there has been a slight increase in the number of occupational accidents in Japan. In particular, more fatal workplace accidents occur in the construction industry than in other industries [1]. The reasons for this are the shortage of workers caused by the decline in the population due to the low birth rate, and the aging of the on-site workers. Therefore, the need to establish a safer working environment is becoming urgent. To this end, we need to detect an “incident”, i.e., a situation in which there is a risk of an accident or other danger, and conduct an analysis of the cause of the problem.

There are two main methods for detecting incidents, as shown in Figure 1: detection from the external environment through devices such as a camera, and detection of hazards perceived by field workers. For the latter method, biological signals related to physiological responses are often used to detect and register dangerous situations perceived by the workers at the site. In this study, this method was used because we finally would visualize the hazards perceived by the field workers not only for incident detection but also for removing the mental burden of the workers in the future.

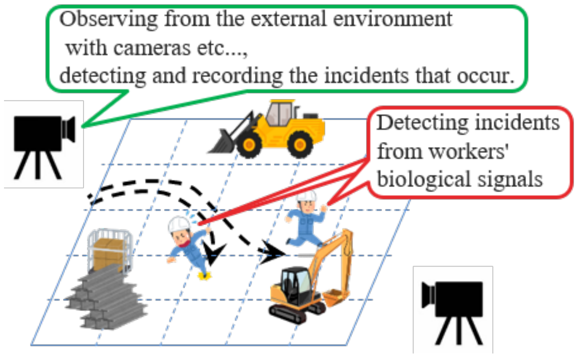


Figure 1: Two main methods for detecting incidents.

Previous studies related to ours reported a construction-site incident detection method based on the heart rate [2]. In this study, the subjects’ heart rate was measured using a chest-belt smartwatch, and incidents were detected using the measured heart-rate variability. There are also previous studies for traffic incidents, where the heart rate of drivers is used to detect incidents[3][4]. The heart rate varies according to the activity of sympathetic and parasympathetic nerves [5]. This is related to a person’s mental state. Remarkably, the sympathetic nervous system is dominant during tension, resulting in a higher heart rate. In other words, the heart rate is higher when the user feels in danger. However, it is generally known that the heart rate increases not only during mental tension but also during exercise[6]. At construction sites, workers often carry heavy materials and perform other tasks that require strenuous exercises. Therefore, the problem of uncertainty about whether an elevated heart rate is caused by exercise or worker ’ s unsafety feelings is expected to occur.

In this study, to solve the aforementioned problems, we aimed to detect incidents at construction sites by using various biological signals related to physiological responses in addition to heart rate. To achieve this, we created virtual reality (VR) videos that simulated incidents that can occur at construction sites. We also conducted experiments using the VR videos. Subjects were asked to watch the VR videos while their physiological responses were measured in terms of heart rate and electromyography (EMG) of the masseter muscle. The detectability of construction-site incidents using these biological signals was verified.

2 Proposed Method

2.1 Biological Signals Used

The final goal of this study was to detect situations where workers feel in danger in the field through a wearable sensor. The sensor measures their biological responses and correlates them with the work content. To achieve this, it is necessary to select the biological signals for detecting the scene where a worker feels in danger. Typical biological signals related to human emotions include the heart rate and the masseter muscle.

The heart rate fluctuates according to sympathetic and parasympathetic, i.e., autonomous, nervous activity [5]. This activity is related to the human psyche and is associated with a higher heart rate owing to the dominance of sympathetic nerves during tension. In other words, it is believed that the heart rate increases when the worker is in a tense state due to potential danger to himself.

Facial muscles, such as the masseter muscle, are known to be related to human emotions [7]. Therefore, it is possible to estimate workers' emotions toward danger by measuring the activity of the masseter muscle.

Overall, heart rate and EMG of the masseter muscle can constitute physiological indicators to detect situations where a worker feels danger. In this study, we used these indicators as candidates for the biological response. We conducted indoor VR experiments to test whether these candidate biological signals can be used to detect construction-site incidents.

2.2 Detection Method

In this study, heart rate and EMG of the masseter muscle were used as features, and a Gaussian naive Bayes classifier was used to detect construction-site incidents, as shown in Figure 2.

As in previous studies, we used the average heart rate h at a given time t as a feature of heart rate [2]. Given that the maximum amplitude is generally used for the evaluation of EMG, the masseter EMG feature in our study was the maximum amplitude f at a given time t. The feature vector $\mathbf{x}$ used in this study is expressed as follows:

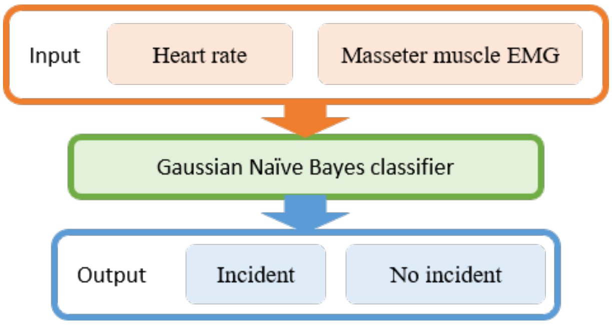


Figure 2: Outline of the proposed method.

$$\mathbf{x} = (h, f)^{\mathrm{T}}. \tag{1}$$

Using this $\mathbf{x}$ as inputs, a Gaussian naive Bayes classifier, which is often employed to classify time series data such as those generated in this study, was used to determine whether an incident occurs at a construction site or not. A Gaussian naive Bayes classifier assumes the independence of each feature and simultaneously estimates the probability from each feature. The label with the highest probability constitutes the output. The classifier is expressed according to the following formula:

$$\begin{aligned} \hat{y} &= \mathrm{argmax}[p(y|\mathbf{x})], && (2)\\ &= \mathrm{argmax}[p(y)\prod_{d=1}^{D} p(x_d|y)], && (3) \end{aligned}$$

where $\hat{y}$ is the output label, $p(y|\mathbf{x})$ is the posterior probability of correct label y given the input vector $\mathbf{x}$, $p(y)$ is the prior probability of correct label y, $p(x_d|y)$ is the likelihood, x_d is the feature in the d-th dimension, and D is the dimension of $\mathbf{x}$.

To use the classifier, we need a unique parameter for each probability distribution. The optimal value of the eigen-parameters is found by maximum likelihood estimation, with the feature matrix of the training data as $\mathbf{X}$ and the corresponding correct label vector as $\mathbf{y}$. The maximum likelihood function $L(\mathbf{X}, \mathbf{y})$ is expressed as follows:

$$\begin{aligned} L(\mathbf{X}, \mathbf{y}) &= \prod_{n=1}^{N} p(y_n)p(\mathbf{x}_n|y_n), && (4)\\ &= \prod_{n=1}^{N}[p(y_n)\prod_{d=1}^{D} p(x_{nd}|y_n)], && (5) \end{aligned}$$

where N is the number of training data, y_n is the correct label in the n-th training data, $\mathbf{x}_n$ is the feature vector in the n-th training data, and x_{nd} is the feature in the d-th dimension of the n-th data.

A Gaussian naive Bayes classifier assumes that the likelihood $p(x|y)$ follows a Gaussian distribution and finds the optimal value of the intrinsic parameters such that the likelihood function $L(\mathbf{X}, \mathbf{y})$ is maximized for each event. The Gaussian distribution is represented by the following equation:

$$p(x|y) = \frac{1}{\sqrt{2\pi\sigma^2}}\exp(-\frac{x-\mu}{2\sigma^2}), \tag{6}$$

where σ^2 is the distribution of the feature x when the correct label is y and μ is the mean of the feature x when the correct label is y. A Gaussian naive Bayes classifier estimates the correct label from the input features by computing the above equation.

In this study, the aforementioned methods were used to classify whether incidents occur at a construction site.

3 VR Experience

3.1 Outline of Experience

In this study, we conducted experiments in which subjects watched a simulated environment of a construction site through VR videos and simultaneously obtained biological signals from a wearable sensor. Subjects sat in a designated position in the laboratory, wore a wearable sensor for biometric measurements, and watched a VR video. To understand which scenes subjects felt as dangerous, we gave them a controller and instructed them to press the button on the controller when they felt a situation as dangerous; we recorded the time when they pressed the button. This experiment was conducted with the approval of the Ethics Committee of the University of Tokyo.

3.2 VR videos

In the construction industry, personal injuries involving contact between workers and construction equipment or machines such as automobiles are very common [8]. Therefore, in this study, we prepared VR videos of incident scenes where a subject and an excavator are likely to come into contact. Specifically, we prepared the following eight videos.

- Two types of incident scenes in which a hydraulic excavator moves backwards unaware of the presence of a worker and almost comes into contact with the worker, changing the stopping position (long-distance backward and short-distance backward)
- Two types of incident scenes where a hydraulic excavator turns unaware of the presence of a worker and the tip of the bucket almost comes into contact with the worker at different distances (long-distance turning and short-distance turning)

Figure 3: Example of VR image.

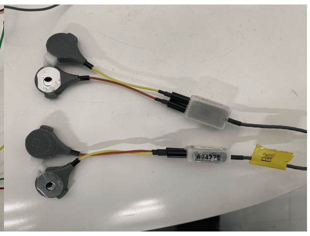
- One type of non-accident scene where a hydraulic excavator waits at a long enough distance from a worker (standby)
- One type of non-accident scene where a hydraulic excavator turns in the opposite direction with respect to a worker (non-accidental turning)
- One type of non-accident scene where a hydraulic excavator moves forward and away from a worker (forward)
- One type of non-accident scene where a hydraulic excavator crosses at a long enough distance from a worker (crossing)

In addition, we prepared videos so that the subject could see papers near the subject's hand, simulating that the subject is working at a site while looking at papers such as instructions. The subjects were instructed in advance to look at the papers before them and to pay attention to the construction machines in front of them, as if they were in a construction site. An example of such prepared VR images is shown in Figure 3. These VR images were filmed at the Public Works Research Institute using Ricoh Theta V, operated by Hitachi Construction Machinery ZAXIS120.

3.3 Devices

The wearable sensors used in this experiment are shown in Figure 4. The S&ME DL-310 was used to measure the heart rate, as shown in Figure 4a, and the S&M DL-140 was used to obtain the EMG, as shown in Figure 4b. The S&ME's DL-310 amplifies the R wave of the cardiac signal detected by the sensor with a filter amplifier, and outputs this pulse. EMG of the masseter muscle was measured by the S&M's DL-140 with electrodes attached to the temporal area of the face. The biological signals acquired

(a) S&ME DL-310



(b) S&ME DL-140

(c) S&ME DL-3100

Figure 4: Sensors employed in the experiments.

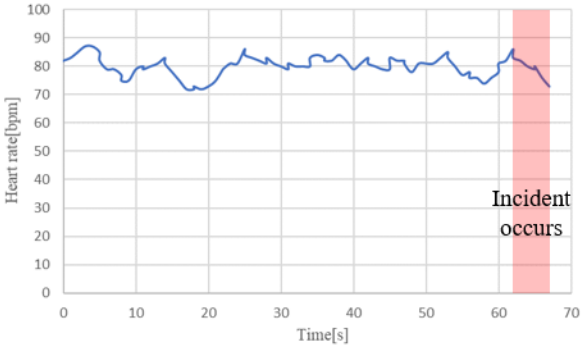
from these sensors were recorded in an S&ME data logger (DL-3100), as shown in Figure 4c. This S&ME DL-3100 has a sampling frequency of 1000 Hz and 16-bit A/D conversion resolution and can store measurement data in its on-board memory.

Vive Cosmos was used to present the VR videos. This head-mounted display is also equipped with headphones; thus, subjects could hear the sound recorded at the time of filming and watch the video.

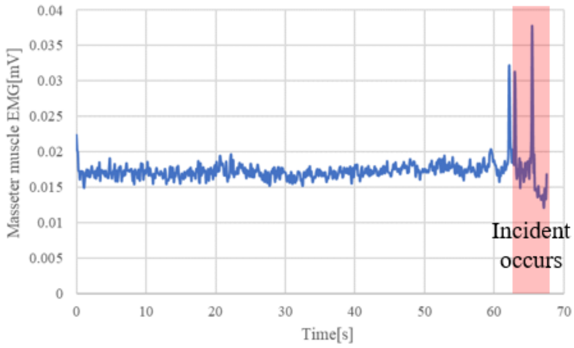
3.4 Biological Signals Processing

After applying a bandpass filter in the frequency range from 0.16 to 500 Hz to the cardiac telegraphic signal in the amplifier section, the biometric information was transmitted to the receiver and recorded in the device. Simultaneously, a pulse waveform synchronized with the R wave was generated in the amplifier section and was recorded in the biometric device concurrently with the cardiac signal. Given that the synchronized pulse rises at the time position of the R wave, the R-R interval was calculated from the time position of the rise of the pulse, and the heart rate was calculated from the inverse of the pulse. The time at the midpoint between consecutive R waves was used to record the heart rate.

In this study, the root mean square (RMS) method was used, which is commonly used for analyzing an EMG of the masseter muscle. Considering the frequency range of EMGs in previous studies, a 5-Hz high-pass filter was used to process the EMGs [9]. Given that humans usually chew in a range from 0.1 seconds to several seconds when they chew, the frame length in this study was set to 100 ms and the interval between frames was set to 1 ms. Denoting the value of RMS at sample point n as $S(n)$, we obtain the



(a) Heart-rate variability in subject A.



(b) EMG of the masseter muscle in subject A.

Figure 5: Biological signals of subject A.

following equation:

$$S(n) = \sqrt{\frac{1}{N}\sum_{i=0}^{N} f^2(n+i)}, \qquad (7)$$

where N is the frame length and f(n+i) is the signal of the masseter muscle at sample point n+i.

3.5 Result

Three male students in their twenties were the subjects of this study.

As an example of experimental results, the variations of heart rate and EMG of the masseter muscle for subject A while he was watching the short-distance turning VR video are shown in Figure5. Figure5a shows the heart rate of subject A. The horizontal axis represents the time of the VR video and the vertical axis represents the heart rate. Figure5b shows the variation of the EMG of the masseter muscle for subject A. The horizontal axis shows the time of the VR video and the vertical axis shows the amplitude variation of the EMG of the masseter muscle. The area in red in both Figure5a and Figure5b is the interval of the incident. Figure5 shows that the heart rate ranged from 73 to 86 bpm during the incident, and there was only a slight difference from the time before the incident occurred. In contrast, the amplitude of the EMG of the masseter muscle reached up to 0.38 mV, which is approximately twice as large as before the incident occurred. This suggests the possibility of detecting incidents from the EMG of the masseter muscle.

In this study, among the experimental data of 3 subjects watching 8 VR videos, 3 subjects watching 4 VR videos (short-distance backward, short-distance turning, standby, and crossing) were used as training data, and 3 subjects watching the remaining 4 videos (long-distance backward, long-distance turning, forward, and no-accident turning) were used as evaluation data. Correct labels were assigned for the experimental data as incidents at the time of the simulated incident in the VR video and no incidents otherwise.

The detection of construction-site incidents by the proposed method was evaluated using accuracy and recall. Accuracy was calculated by comparing the estimation results of the proposed method with the correct labels of the test data and dividing the number of correct answers by the total number of test data. Thus, it provides the percentage of correct estimation results. Recall is calculated by dividing the number of test data correctly detected as incidents by the proposed method by the number of test data actually labeled as incidents. Thus, it indicates the completeness of the incident detection. The equations for accuracy A and recall R are as follows:

$$A = \frac{D^C}{D^T}, \tag{8}$$

$$R = \frac{D_I^C}{D_I^T}, \tag{9}$$

where D^C is the total number of correct data, D^T is the total number of evaluated data, D_I^C is the number of correct data detected as incidents, and D_I^T is the number of data labeled as incidents.

The accuracy and recall of the proposed method are shown in Table 1. In addition, for comparison, the accuracy and recall obtained by the method of estimating only the heart rate as a feature are also shown in Table 1. Accuracy was 0.48 for the proposed method and 0.87 for the heart-rate-only method. Therefore, the accuracy of the heart-rate-only method was higher. By contrast, recall was 0.57 for the proposed method and 0 for the heart-rate-only method. Therefore, the recall of the proposed method was higher. The purpose of this study was to detect incidents, and it is important to detect incidents comprehensively for achieving a safe construction-site environment. Therefore, it is desirable to have a method with high recall and accuracy. Given that the recall of the heart-rate-only method is 0, it is assumed, according to such method, that no incidents were detected at all. The proposed method is more effective than the heart-rate-only method because the recall is higher and more comprehensive, even though the accuracy of the proposed method is lower than that of the heart-rate-only method. The reason why we could not detect an incident using the heart-rate-only method in these environments may be because heart rate responds after a short period of time after an incident occurs. Generally, the heart rate is known to respond about 10 to 20 seconds after an incident occurs, but in the VR video used in these experiments, the video ended within 10 seconds after the incident occurred. It is thought that we could not detect incidents using the heart-rate-only method. In the future, we will consider creating a VR movie with more than 20 seconds left after an incident and using it for experiments.

Table 1: Accuracy and recall of the proposed method and heart-rate-only method

Method	Accuracy	Recall
Proposed Method	0.48	0.57
Heart-Rate-Only	0.87	0

4 Conclusion

In this study, a method for detecting construction-site incidents through a Gaussian naive Bayesian classifier using heart rate and masseter EMG as features was developed. Indoor experiments in which subjects experienced the simulated environment of a construction site through VR videos were conducted to obtain biological signals. The performance of the proposed method was evaluated using the data obtained from the experiments. A comparison between the proposed method and a heart-rate-only method confirmed that the proposed method was more effective in detecting incidents comprehensively. In the future, we will aim to establish a method for detecting incidents in which workers and construction machines are close to come into contact with each other through verification of experiments using VR videos.

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