Investigation of Changes in Eye-Blink Rate by VR Experiment for Incident Detection at Construction Sites

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Abstract -

Productivity and safety are in a trade-off relationship, and the improvement of the safety management system of construction sites is a pressing issue. Therefore, it is important to know and analyze information about incidents at real construction sites. However, it is difficult to gather information about these incidents from workers' self-reports. Therefore, in this research, we take an approach to view the workers as the sensors distributed in construction site and detect these incidents with the reaction of the workers. Biological signals such as heart rate, sweating, and muscle activity are the signals generally used to detect an emotional reaction; however, requiring workers to attach electrodes to their body during work is not suitable. Thus, we focused on blinks since they can be detected without electrodes attached to the skin. This study aims to investigate changes that occur in human blinks during an incident at a construction site. For safety purposes, this study used VR technology to simulate an incident at a construction site. During the simulation, an image of the subject's eyes was taken by the camera installed in the head-mounted display. The results of this study suggest that humans who face an incident have lower blink rates because they gaze at the cause of the incident.

Keywords -

Blink; Construction sites; Head-mounted display; VR

1 Introduction

Focusing on current industrial accidents in Japan, the number of fatalities in the construction industry accounts for more than 30% of fatal accidents in all industries. The number of fatalities due to accidents in construction industries has been on a downward trend; however, the decline has stagnated over the last decade. This shows that ensuring the safety of workers at construction sites is an important and urgent theme. On the other hand, improvement in labor productivity is also an urgent challenge. In many situations, productivity and safety are in a trade-off relationship. For instance, the areas, where workers and construction machines are active, are often separated for safety reasons in construction sites. However, restricting

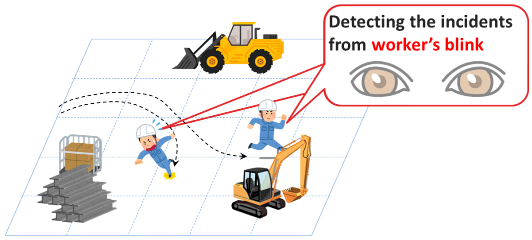


Figure 1. Concept of the final goal

movable ranges too narrowly for safety reasons would adversely affect work efficiency. This means development of technologies for improving safety without lowering efficiency is necessary.

To improve safety without lowering efficiency, identifying when danger occurs at the construction site is of utmost importance. It is also generally said that there are many "incidents" behind the serious accidents that cause fatalities. Thus, the motivation for our study is to collect information on these incidents. At many construction sites, these incidents are currently collected through reports from workers. However, these are uncertain methods because they are subjective on the worker's memory.

There are two possible methods for detecting incidents from construction sites. One is by observing the entire construction site using cameras or LiDAR, and the other is through the measurement of workers. In this study, we focused on the latter method.

A previous study detected incidents through the measurement of workers via heart rate variability. This method is also actively conducted, especially for detecting stress [1], sleepiness and fatigue[2], and the feeling of "traffic near-miss" (surprising)[3, 4] among car driver subjects using heart rate and other indicators. Heart rate is related to a person's mental state. During tension, the sympathetic nervous system is more dominant resulting to higher heart rates. However, it is generally known that the heart rate increases not only during mental tension but also during exercise and work. Furthermore, attaching many electrodes to field workers is not considered as a suitable method. Therefore, we focused on the element of eye blinks.

Blinking is associated with various factors such as prevention of corneal dryness, eye purification, eyelid muscle refreshment, and mental conditions such as anxiety and tension/attention[5]. A study relates blinking to stress in driving and using a personal computer[6, 7]. Blinking is not only measured by electrodes attached to the skin, but a method has also been developed for measuring it from images, which is suitable for this study since it is a non-contact procedure.

The aim of this study is to detect incidents that occur at construction sites. We aim to detect them by measuring blinks of workers when faced with dangerous incidents. Figure 1 shows our concept. As the first step, it is necessary to investigate what kind of changes human blink shows when human experiences a dangerous incident. This study uses VR technology as a safety precaution during the simulation of such incidents.

2 Method

VR technology was used to simulate the incident. Specifically, the subject wore a head-mounted display while viewing the VR image. A small camera was also installed in the head-mounted display to observe the state of blinking during the experiment.

Simple image processing was performed to detect the state of blinking. Since the camera was fixed to the head-mounted display, the position of the eyes can be easily specified manually. First, the brightness and contrast were adjusted for the obtained image, including the eye region. Next, the edges of the upper and lower eyelids were clearly visualized by bilateral smoothing and adaptive binarization. After image processing, the number of blinks was counted visually. Similarly, the high-speed opening and closing of the eyelids that occurred during 100-200 ms was considered to be a "blink". Figure 2 shows an example of this simple image processing.

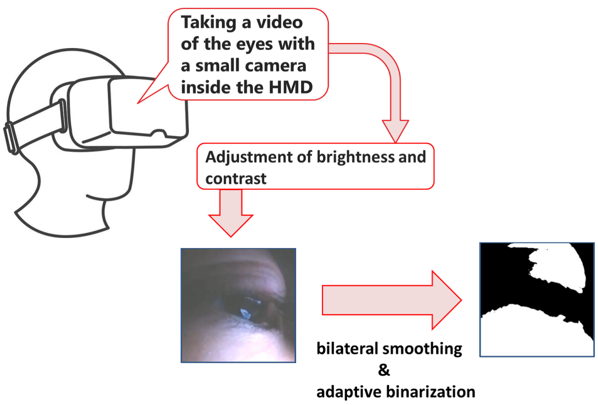


Figure 2. Simple image processing to blink detection

For comparison, we calculated the blink rate, which represent the number of blinks per minute. We compared the blink rate both when the incident is occurring and not occurring.

3 VR Experiment

3.1 Outline of Experiment

In this experiment, participants watched the simulation environment of the construction site through a VR video. During the simulation, an image of the subject's eyes was taken by the camera installed in the head-mounted display. In order to know the scene where the subject perceived danger, a gamepad was used and the subject was instructed to press a button during a dangerous scene.

3.2 VR video

The videos shown to the subject in the VR experiment must reproduce the incident. We focused on incidents related to collision of construction machines and humans, which is a very common accident at construction sites. To prepare videos that are impressive to the subjects, we used reverse playback. We carefully brought the construction machine and the 360-degree camera close to each other and shot a video of the construction machine moving away from the high-speed 360-degree camera.

We prepared the following four types of incident VR videos:

- Two types of incident videos in which the hydraulic excavator goes backwards without noticing the presence of the worker and almost comes into contact with the worker. There are two types of stop positions: (i) long-distance backward and (ii) short-distance backward.

- Two types of incident videos in which the hydraulic excavator turns unaware of the presence of the worker, and the tip of the bucket almost comes into contact with the worker. There are two types of distances to the excavator: (i) Long-distance turning and (ii) Short-distance turning.

For that incident VR video, we compared the blink rate before and after the incident occurs. However, discrepancies may arise when subjects expect that an incident will occur.

Therefore, we prepared four types of VR videos where incidents do not occur.

- One type of non-incident scene where the hydraulic excavator is stationary at a sufficient distance from the worker (stand by).

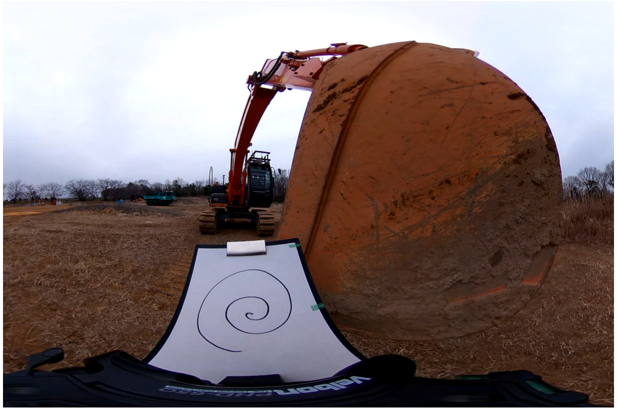


Figure 3. Sample Scene of a VR Video

Figure 4. Two cameras installed inside the head-mounted display

- One type of non-incident scene where the hydraulic excavator turns in the opposite direction from the worker (non-accidental turning).
- One type of non-incident scene where the hydraulic excavator moves forward and away from the worker (forward).
- One type of non-incident scene where the hydraulic excavator crosses at a distance far enough from the worker (crossing).

In addition, we prepared the videos so that the subject could see the paper near the subject's hand. This replicates a scene where the subject is working at the site while looking at the paper, such as progress schedule charts. The subjects were instructed in advance to look at the paper in front of them while paying attention to the construction machines as if they were in a construction site. These eight types of images were about one-minute long each and presented to the subjects in random order. An example scene of the prepared VR videos is shown in Fig. 3.

All these VR videos were shot at the Public Works Research Institute. We used Theta V from Richo and ZAXIS120 from Hitachi Construction Machinery as the 360-degree camera and hydraulic excavator, respectively.

3.3 Experimental Equipment

The head-mounted display used in the experiment was Vive COSMOS from HTC. This included headphones for the audio output of the virtual environment.

The two small cameras installed inside the head-mounted display were Raspberry Pi Camera Module V2. To capture a wider area inside the head-mounted display, the lens of the cameras was replaced with a 195 属 wide-angle lens. Two cameras were controlled by the Raspberry Pi 3B with a frame rate of 30 fps. This frame rate was selected since blinks are generally captured between 150 and 200 ms. To synchronize the VR video presentation and camera control, an integrated experimental environment was constructed using Unity.

The inside of the head-mounted display is shown in Fig. 4 where the two red circles are the cameras. Since the inside of the head-mounted display is sufficiently dark, the camera does not interfere with the subject's VR watching.

3.4 Participants

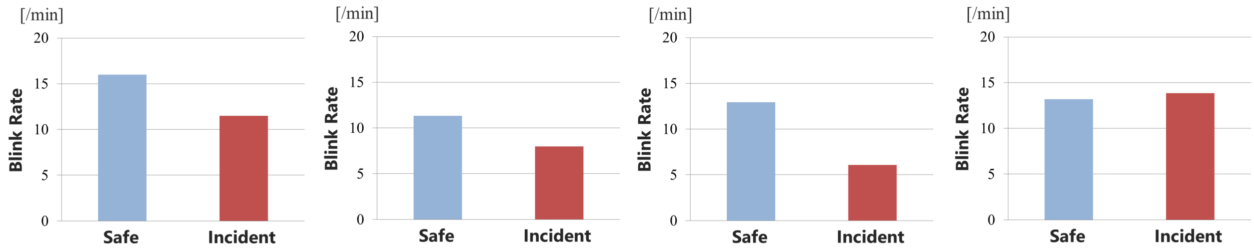
Three healthy male volunteers took part in the experiment and supplied informed consent. This study was approved by the research ethics committee of the University of Tokyo.

4 Results and Discussion

The results of the VR experiment are shown in Fig. 5. The blue bar stands for the average of subjects' blink rate before the incident occurs, while the red bar stands for the average of subjects' blink rate during the incident. The timing of the incident was determined from the video once the heavy equipment started to move.

Three results excluding short-distance backward revealed that the blink rate during the incident tended to be lower than that in the safe state. First, we must consider the reason why the blink rate did not decrease in Short-distance backward. Interestingly, the blinks that seemed to be voluntary were concentrated in the results of one subject which shows the higher blink rate. This is considered to be the reason for the higher average of blink rate in Short-distance backward. Voluntary blinks caused by some reasons unrelated to VR incidents such as eye itching become noise in this experiment. Hence, increasing the number of subjects and performing statistical processing are recommended to potentially eliminate noise unrelated to VR incidents.

Next, we discuss the decreasing tendency observed in



(a) Long-distance turning (b) Short-distance turning (c) Long-distance backward (d) Short-distance backward

Figure 5. Blink rate during incident and safe time

the three graphs. The first possibility is that the blink rate gradually decreases while watching a VR video for one minute. In other words, the blink rate is high until subjects adjust to the brightness of the VR image, and it decreases as they adjusted to it. Therefore, we calculated the blink rate in the "stand-by" condition where subject is farthest from the incident by dividing one minute into 10 seconds each (0-10 s, 10-20 s, 20-30 s, 30-40 s, 40-50 s, and 50-60 s). According to the results of the calculation, the blink rate under the stand-by condition remained almost constant. Therefore, this consideration was excluded. From this, it was considered that the decrease in the blink rate shown in the three graphs is related to the incident.

Another possible cause for the decreasing trend is that the subjects gazed at the cause of the incident (excavator). It is well known that the blink rate of a person who is gazing at something decreases, and this can explain the decreasing trend properly. The purpose of this study was to examine changes that occur in human blinks when humans experience an incident at a construction site. The results of this research suggest that humans during an incident have lower blink rates because they gaze at the cause of the incident.

During application of this approach for incident detection at construction sites, it is necessary to make a distinction between blink rate reduction due to incidents from those due to gaze irrelevant to incidents. In this case, a combination of saccades and facial expressions is considered effective.

5 Conclusion

In this study, we investigated the changes that occur in human blinks when humans experience an incident at a construction site. The VR experiment was performed using a VR video simulating an incident scene. Our results suggest that humans during an incident have lower blink rates because they gaze at the cause of the incident. However, increasing the number of subjects is recommended to further verify the suggestions obtained in this study.

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