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Detection of Unconscious Movements With RGB-D Camera for Objective Ride Comfort Evaluation

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ABSTRACT

This paper presents a measurement system to evaluate objective ride comfort in vehicles. For participants' subjective ride comfort evaluation, the frequencies of the unconscious movements in vehicles have been focused. Then, we have tried to develop other techniques that facilitate the digitization of participants' movements. For example, the method using a body pressure distribution measurement system, or flex sensors have been reported. As these were instrument contact-constrained methods, this paper developed a measurement system that automatically extracts and classifies unconscious movements in a non-contact and non-constraint manner. In the accuracy evaluation experiment, the participants were asked to drive a driving simulator for 60 minutes and were captured with the developed system and a conventional video camera. As a result, the accuracy needed to be improved, and there were two error types. The first error (false positive) was a case in which the program falsely detected the occurrence of a motion even though no unconscious movement occurred. The second one (false negative) was the opposite error, where the result incorrectly indicates the absence of movements. By applying the proposed countermeasures to reduce these errors, the recognition accuracy of unconscious movements will be improved and applied to the objective evaluation of riding comfort.

Keywords: Ride comfort evaluation, Image processing, Skeleton pose estimation, Driving simulator, Fidget

INTRODUCTION

Whole-body vibration exposure to occupants while riding in a vehicle affects ride comfort. Therefore, automobile manufacturers and seat suppliers have conducted research and development that can reduce whole-body vibration. In judging new products or technologies, they have utilized sensory evaluations, in which the subjective senses of skilled persons are used. However, as for sensory evaluations, since it takes a long time to train skilled workers, it takes a lot of work to hand down the skills to the next generation. Although there is a questionnaire targeting general drivers as an alternative evaluation method, a certain number of samples is necessary considering the data variation due to individual differences. From this background, it is desired to develop objective evaluations of ride comfort.

On the other hand, it was reported that the frequency of unconscious movement during seated in the vehicle was effective as objective evaluation index of ride comfort (Sammonds et al. 2014). Then, unconscious movements were considered to be carried out to release blood flow obstruction caused by muscle compression. This study suggests a strong correlation between the frequency of unconscious movements and the subjective discomfort level of participants. This method has been applied to evaluating vehicle seats in a driving simulator environment (Tatsuno et al. 2017). In this research, measurers visually checked the recorded movements of participants after the experiment. Then, it was found that this method had a high workload. Hence, the previous studies tried to develop other techniques to digitize participants' movements. Specifically, the studies using motion capture systems (Tatsuno et al. 2018), flex sensors (Tatsuno et al. 2019), and body pressure distribution measurement system (Tatsuno et al. 2020) were reported. Since these were instrument contact-constrained methods, there was an unquenchable concern. Thus, this study developed a measurement system that automatically extracts and classifies unconscious movements in a non-contact and non-constraint manner.

System Development

Outline

Figure 1 shows the configuration and processing flow of the system proposed in this research. In this research, an RGB-D camera (Intel, RealSense D435i) was used to construct a non-contact and non-constraint system. The RGB-D camera has a built-in RGB sensor and depth sensor. Applying the pose estimation technology Openpose (Cao et al. 2021) to images captured by the RGB sensor could calculate the two-dimensional coordinates (x, y) of joints. Moreover, adding the depth data z measured by the depth sensor could obtain three-dimensional coordinates (x, y, z). By processing the time series of angular change data of the body part, we could identify which part of the body moved. Subsequently, unconscious motions were classified into three types based on the combination of the body parts identified as causing the movement.

Motion Detection

The 3D coordinates of the joints would change when the participant moved any body parts consciously or unconsciously. Therefore, in order to detect each body part motion, we programmed to sequentially calculate the changes in six directional vectors connecting the joints and two normal vectors to the plane composed of the two shoulders and the hip joints, as shown in Fig. 2.

In the subsequent process, we detected the occurrence of motion with the time-series data of the vector changes. This paper tried to utilize a change

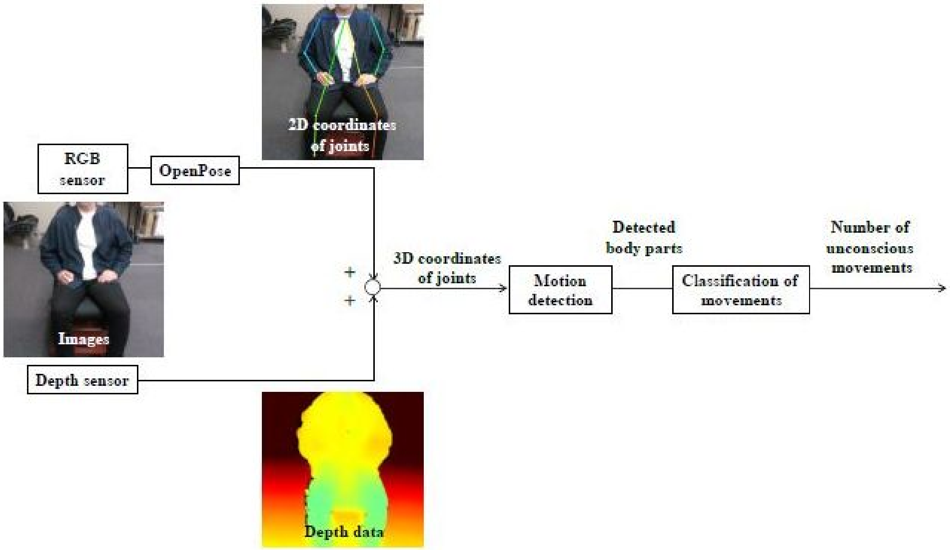


Figure 1: Signal flow of our proposed system.

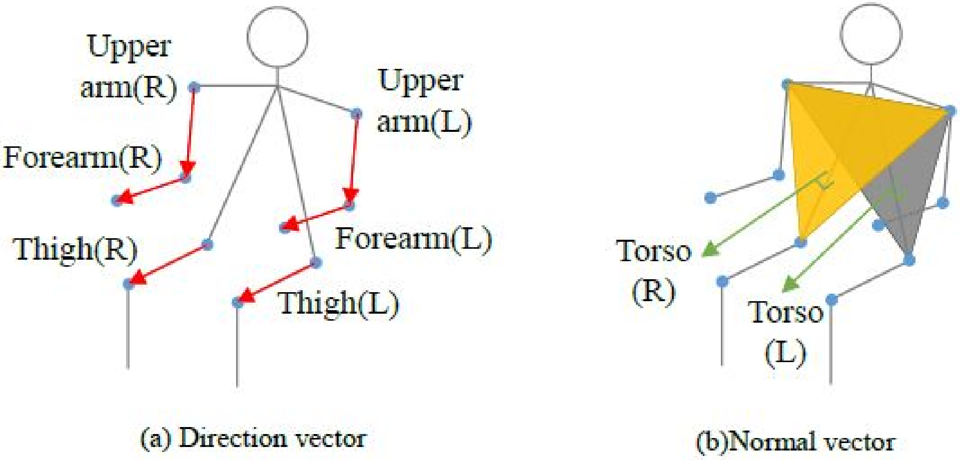


Figure 2: Vectors of targeted body parts in the experiment.

points detection engine named ChangeFinder (Takeuchi and Yamanishi, 2006). ChangeFinder is an anomaly detection algorithm that can detect change points in time series data. So, we recognized the vector changes caused by the motion as an anomaly applied ChangeFinder to a motion detection program.

Figure 3 shows the angle variation of the vector and the change point score calculated by ChangeFinder. A larger change point score means a significant change occurred in the time series data. Then, the time when the change point score output by ChangeFinder exceeded the threshold value were recorded by the program. Here, the values of the threshold were determined by trial and error. The sample graph in Fig. 3 shows the change point score exceeds

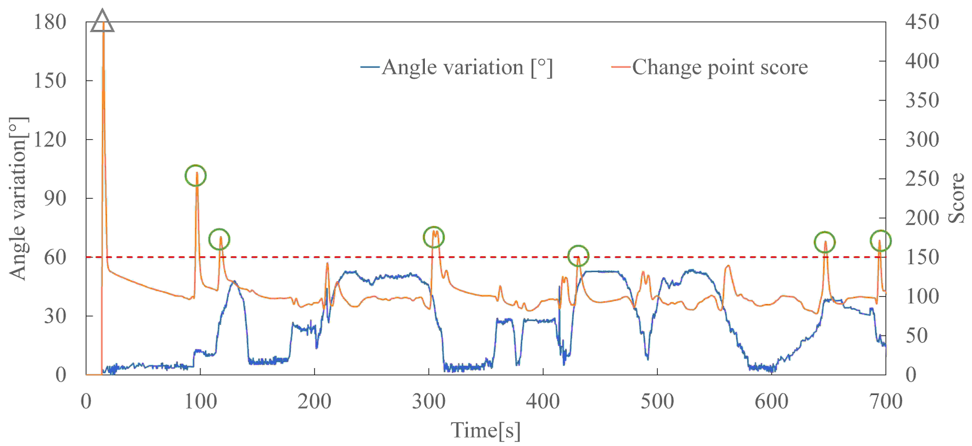


Figure 3: Sample graph to illustrate the change point score.

the threshold value seven times during the measurement period. Besides, the first point at which the threshold value is exceeded must be ignored due to the characteristics of the algorithm.

Classification of Movements

Next, we created a program that can classify which of the three unconscious movements, Type 1 (upper and lower limb movements), Type 2 (torso movements), and Type 3 (whole-body movements), from the recorded data. Figure 4 shows the classification algorithm based on the combination of body parts extracted by the motion detection program.

First, the detection window was slid, and body parts within the window area were listed. Second, after determining whether any body parts movement occurred in the window, the system returns to the window sliding step if there is no motion. Next, the window edge was shifted so that the motion that occurred earliest in the window became the first. After that, all body parts detected in the window were recognized as a single movement. That movement was classified according to the combinations of body parts, as shown in Table 1.

We incorporated a function to cancel the motion classification when we extracted any change in the direction vector connecting both wrists, in order to avoid false detection of conscious actions such as driving or instrument panel operation.

Evaluation of the Developed System

A driving simulator experiment was conducted to evaluate the developed system (Figure 5).

A test course created in the VR environment is approximately 8 km long and has 18 vibration exposure sections with speed bumps. As connected virtually to the end and beginning terminals, participants could drive the vehicle as a circuit. In addition, there were two intersections where participants made right or left turns after a temporary stop. Participants in the experiment were

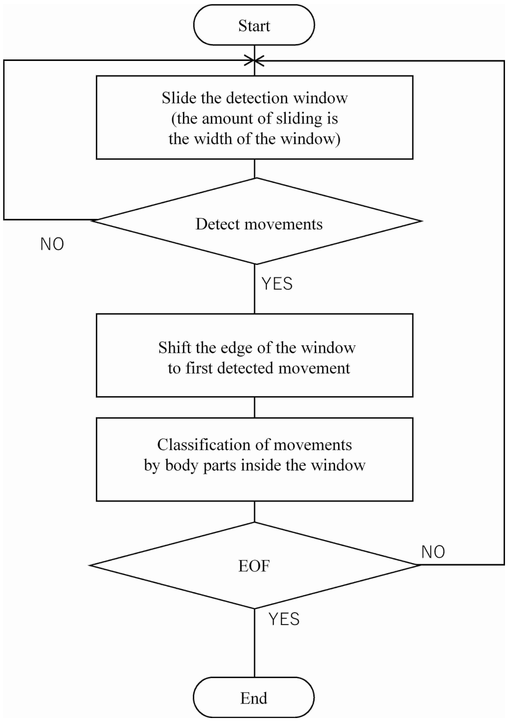


Figure 4: Flow chart of classification function.

Table 1. Relationship between body part and movement type.

Type	#	Torso (R)	Torso (L)	Thigh (R)	Thigh (L)	Upper arm (R)	Upper arm (L)	Forearm (R)	Forearm (L)
1	1					√		√	
	2						√		√
	3			√					
	4				√				
	5			√	√				
2	1	√							
	2		√						
	3	√	√						
3	1	√		√					
	2	√			√				
	3	√		√	√				
	4		√	√					
	5		√		√				
	6		√	√	√				
	7	√	√	√					
	8	√	√		√				
	9	√	√	√	√				

asked to drive the DS for 60 minutes, and the experiment was filmed using the RGB-D camera installed on the top of the DS and a video camera set down on the side of the DS. After the experiment, we compared the frequency of unconscious movements measured by the developed system with that using the visual observation of the video images.

In the experiment, healthy male university students with driver's licenses were asked to participate. Before the experiment was designed, we obtained

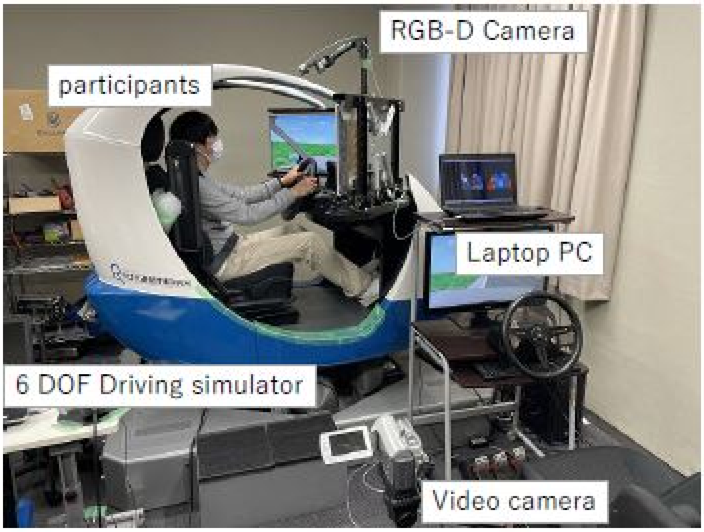


Figure 5: Appearance of the experimental environment.

approval from the Bioethics Committee of the Faculty of Engineering, Kindai University (approval number: KUBE1404).

Table 2 shows the experimental results for three subjects. Precision and Recall were calculated as indicators of the detection accuracy of the program, and can be calculated using the following equations.

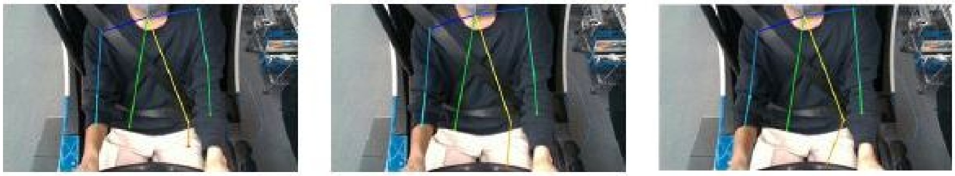
$$\text{Precision} = \frac{TP}{TP + FP} \tag{1}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{2}$$

As a result of calculating the total values, Precision and Recall became 28% and 41%, respectively. The reasons could be classified into two main categories. The first is a case in which the program falsely detected the occurrence of a motion even though no unconscious movement occurred (false positive). The second case is that the program did not notice the event of a movement even though the movement was happening (false negative). It was considered that the cause of the false positives was a recognition error by Openpose. As shown in Fig. 6, the position of the left knee joint recognized by Openpose changed even though the participant hardly moved his

Table 2. Evaluation results of our developed program.

	TP (True Positive)	FP (False Positive)	FN (False Negative)	Precision	Recall
P1	4	23	6	15%	40%
P2	6	9	10	40%	38%
P3	9	18	11	33%	45%
total	19	50	27	28%	41%



(a) 1665 s (b) 1672 s (c) 1679 s

Figure 6: Sample snapshots of participant when false positive occurred.

left thigh. Such a phenomenon would cause the program to detect unconscious movement of the left thigh. A possible countermeasure was modifying the code to skip processing when the length between joints is short, like in Fig. 6(a). On the other hand, it was found that the cause of the false negative was due to the threshold setting of the change point score. Therefore, we recognized the necessity of investigating the characteristics of the change point score in each body part.

CONCLUSION

This paper reported the development of a non-contact and non-restraint method to detect and classify unconscious movements that occur while riding in a vehicle. In this system, a commercial RGB-D camera was used as the optical system. A program installed skeleton estimation and change point detection as key software elements was developed. Specifically, change point scores were calculated from time series angular changes of body parts, and threshold processing was used to identify which body parts moved unconsciously. In addition, detected movements were classified into three types based on the combination of body parts. The results of a driving simulator experiment suggested the possibility of detecting and classifying unconscious movements with our developed system, although the accuracy needed to be improved. Thus, we proposed some improvements to decrease false positives and false negatives.

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