Assessment of the Detectability of Vulnerable Road Users: An Empirical Study

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Abstract: This study analysed the detectability of vulnerable road users (VRUs) as a function of time to the closest point of approach. We defined four patterns: Gradual Increasing Pattern and High Detectability Pattern as the safe situation, Immediate Increasing Pattern and Low Detectability Pattern as the dangerous situation and investigated empirically drivers' detection patterns. The results showed that motorbikes in the same direction showed the dangerous pattern, and pedestrians in the same direction also showed the dangerous patterns but influenced by the distance of closest point of approach. Bicycles in the same direction showed higher detectability due to their positioning in the driver's field of view for longer time. For the VRUs in the opposite direction, and those in the left and right direction, participants also showed high detectability. The results give implications for advanced driver assistance systems (ADAS) design.

1 INTRODUCTION

1.1 Traffic Accidents at Intersections

Urban safety is a pressing issue, and traffic accidents are one of its major concerns. Intersections have been identified as accident hotspots, and over half of all accidents occurred at or near them (Japanese police department, 2022). Drivers must be alert to the movement of vehicles, pedestrians, bicycles, and motorbikes from multiple directions. Hills (1980) found that driving at intersections requires large amounts of visual and cognitive resources to deal with high-density visual stimuli. As accidents at intersections occur frequently, and the resulting cognitive challenges are significant, it is imperative to promptly implement traffic safety measures.

One potential solution to the issue is to rapidly introduce advanced driver assistance systems (ADAS), which utilize numerous sensors and cameras to scan the surrounding environment, and which provide alerts and notifications to the driver. However, drivers may not always be receptive to these notifications. According to Lee et al. (2002), early alerts may be seen as bothersome, especially for vigilant drivers (Lee et al., 2002). Naujoks et al. (2016) revealed that warnings that urge drivers to respond quickly in urgent scenarios can be perceived as irritating. Therefore, it is crucial for ADAS to work effectively and match the attention levels of drivers.

Vulnerable Road Users (VRUs) refers to non-motorised individuals, including pedestrians, cyclists, motorbikes, and persons with disabilities. This study examines scenarios in which a moving vehicle approaches VRUs at intersections.

Intersections are significant meeting points for VRUs. Tay (2015) observes that the high complexity of traffic flow at intersections poses greater risks to VRUs. Furthermore, Cantin et al. (2009) found that driver's distractible attention at intersections threatens VRUs safety. Furthermore, Werneke and Vollrath (2012) found that driver distraction was the primary cause of accidents involving VRUs and vehicles. Driver distraction could lead to accidents as VRUs may not be detected successfully. Although there have been numerous studies on the detection of VRUs by drivers, most of them were mainly concerned with the detection characteristics of single VRUs. In this study, however, we developed a framework in which the detection characteristics of many types of VRUs can be examined based on a unified format.

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1.2 Objectives

This research aims to examine how detectability of VRUs is influenced by an increase in collision risk. Ascertaining the relationship between collision risk and VRUs detectability is crucial to enhance road safety for both drivers and other road users. When collision risk is high, drivers must detect it with concentration. Yoshitake et al. (2020) revealed that drivers direct their visual attention towards the surrounding of the intersection and detect pedestrians early enhances the likelihood of avoiding a collision when turning right at intersections. Such research emphasises the importance of recognising VRUs in high-risk collision situations. Further investigation is necessary to examine the effect of collision risk on detectability of VRUs. Understanding the relationship between such variability and detectability is crucial to improve traffic safety measures.

1.3 Relationship Between Detectability and Collision Risk

This study quantitatively measured detectability using d' based on the signal detection theory. A higher value of d' indicates better ability to distinguish target from noise. For the calculation of d', the current study used fuzzy signal detection theory (Parasuraman et al., 2000).

Fuzzy signal detection theory modifies the outcomes of hit, miss, false alarm, and correct rejection in signal detection theory by distributing each stimulus-response combination into categories where they can be partially assigned to multiple outcomes. In each trial, participants determine the presence of a VRUs by providing a score of 0-1. Hit rate, false alarm rate, miss rate, and correct rejection rate are employed to calculate d', following the procedure of traditional signal detection theory. The formula for d' is as (1):

$$d' = Z\,(\text{Hit rate}) - Z\,(\text{False Alarm rate}) \qquad (1)$$

On the other hand, collision risk is calculated based on *t*, until the driver and VRUs approach their closest point of approach to each other. A shorter *t* duration leads to a higher collision risk.

In the realm of shipping, objective index of potential collisions has been developed, one of which is the TCPA (Time to Closest Point of Approach) and DCPA (Distance of Closest Point of Approach) indicators (Chauvin and Lardjane, 2008).

TCPA corresponds to the time *t* to the reapproach point in this study. In this study, two moderator variables are assumed.

DCPA is considered the first moderator of this function. Along with DCPA, the degree of traffic congestion in the driving environment is considered as another moderator. Bao and Boyle (2009) found that high levels of traffic congestion led to an increase in leftward visual scanning when approaching an intersection to detect VRUs. Hence, these studies suggest that the traffic congestion affects detectability of VRUs.

This study analyses the change in detectability of VRUs with increasing crash risk when drivers turn right and left at intersections. We utilise the detectability index d' as the dependent variable, while the independent variable is the time *t* until the driver's vehicle reaches the closest point of approach to VRUs. In order to reveal these relationships, we consider two moderators, DCPA and traffic congestion. Our study formulates a classification of functions that predict detectability during right and left turns. Understanding this function is crucial for the development of ADAS.

2 TYPOLOGIES OF DETECTTABILITY TYPES

In this study, d' is viewed as a function of the time *t* taken to reach the closest point of approach. Correspondingly, we hypothetically classify four patterns for this function.

Gradual Increasing Pattern

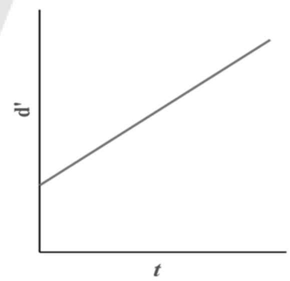

Figure 1: Gradual Increasing Pattern.

Figure 1 indicates the Gradual Increasing Pattern. As the collision risk increases, d' increases gradually. This suggests that detectability increases as the driver approaches the VRUs. Since such an increase in detectability is expected to contribute to avoidance of traffic accidents and risk reduction, this pattern is judged to be relatively safe.

Immediate Increasing Pattern

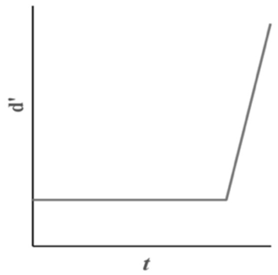

Figure 2: Immediate Increasing Pattern.

Figure 2 indicates the Immediate Increasing Pattern. d' maintains at a low level and increases immediately just before approaching VRUs. This pattern indicates that the driver has not detected the VRUs immediately before. It is considered a dangerous pattern.

High Detectability Pattern

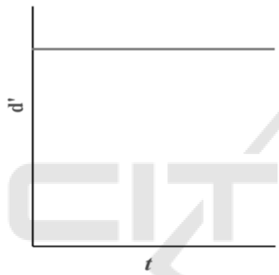

Figure 3: High Detectability Pattern.

Figure 3 indicates the High Detectability Pattern. The driver maintains a consistently high d' regardless of *t*. This suggests that the driver maintains persistently high detectability. Therefore, in such situations, this pattern is judged to be relatively safe.

Low Detectability Pattern

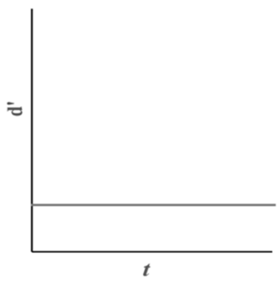

Figure 4: Low Detectability Pattern.

Figure 4 indicates the Low Detectability Pattern. The driver maintains a consistently low d' regardless of *t*. This suggests that the driver does not detect the VRUs. Such a pattern is judged to be the most dangerous because it is difficult to avoid accidents. And this pattern may pose a significant risk to other traffic participants.

3 EXPERIMENT

This study used driving videos to examine how detectability of VRUs changes with increasing collision risk.

3.1 Participants

A cloud service enrolled 320 participants (166 males, 153 females and 1 other), with a mean age of 41.9 years (*SD* = 8.71). 287 participants held a valid driver's licence, and the average duration since the licence was obtained was 18.1 years. fees were provided to each participant.

3.2 Driving Video

The driving videos were produced using the Unity software for 3D graphics by the following five factors: evaluation targets, time to the closest point (*t*), DCPA, traffic condition, and presence/absence of the target.

To calculate the necessary false alarm rate for d' calculation, additional videos were produced without the evaluation target in each condition. As a result, a total of 320 (10 x 4 x 2 x 2 x 2) operational videos were prepared.

Evaluation Targets

Ten evaluation targets were adopted (see Figure 6). When turning left, the evaluation targets included pedestrians in opposite direction, pedestrians in same direction, motorbikes in same direction, bicycles in same direction and bicycle in left direction. When turning right, the evaluation targets included pedestrians in opposite direction, pedestrians in same direction, motorbikes in opposite direction, bicycles in opposite directions, and bicycles in right direction.

Speeds for pedestrians, bicycles, and motorbikes were set to 3.6 km/h, 10.8 km/h, and 32.4 km/h, respectively.

Figure 5: An example screenshot of observing phase. Text information was displayed at the bottom of the screen during the video playback, signalling whether the turn was right or left.

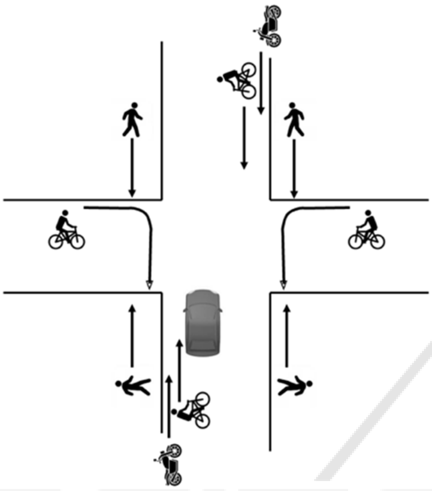

Figure 6: 10 types of evaluation targets.

Time to Closest Point (*t*)
The time *t* was selected as an independent variable to be 0s, 3s, 6s, and 9s before reaching the closest point of approach.

DCPA
DCPA is the distance to evaluation targets when drivers reached the closest point of approach. It served as the first moderator with conditions set at 1 m and 5 m.

Traffic Congestion
Traffic congestion, as the second moderator, was established in two conditions, quiet condition, and crowded condition. This was achieved by manipulating the number of traffic participants.

3.3 Procedures

The study comprised of two phases, the observing phase, and the test phase. During the observing phase, participants were instructed to watch a video from the perspective of an actual driver. The video stopped at seconds before reaching the closest point of approach. For instance, if *t* is 3 seconds, the video paused when there were 3 seconds remaining until the closest point of approach. Figure 5 shows an example screenshot of observing phase.

Subsequently, the test phase began. Participants rated the detectability against the evaluation target as it appeared in driving video. The evaluation target image was positioned on the right side of the display screen. On the left-hand side of the screen, an aerial view displayed the positions of the participant's vehicle and the evaluation target at the time of video cessation. The blue rectangle denoted the participant's vehicle, while the red circle marked the location of the evaluation target. Figure 7 shows an example screenshot of test phase. Participants were presented with the question, "When the video stopped, was the target shown on the right-hand side of the screen at the point indicated by the red circle?" To respond, participants used a slider bar. This rating scale presented 'definitely not' on the left end and 'definitely was' on the right end. Participants moved the slider to indicate their level of confidence in their perception.

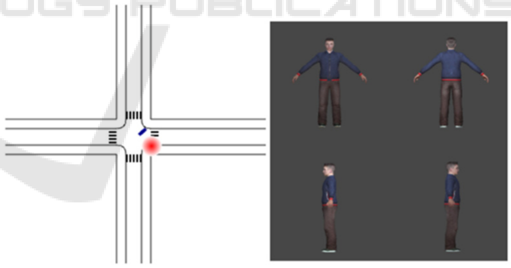

Figure 7: An example screenshot of test phase.

At the outset of the study, the participants were randomly allocated into four distinct groups. Each group was shown 80 videos from the total of 320. The rationale behind dividing the participants into four groups was to ensure that any of them rated only one target, for instance, a motorbike approaching from the opposite direction while turning right. Each of the four groups received a video displaying a single evaluation target approaching the closest point of approach at one of four time-intervals, 0s, 3s, 6s or 9s.

Before the main task, participants performed four practice trials. During the main task, 80 stimuli were presented in a randomised order. A rest was set following every 20 trials. Upon completion of the main task, participants were asked to provide demographic variables. The study parameters encompassed age, gender, driving history, and the duration since the individual acquired their driving license.

4 RESULTS

The results of the analysis, with the time *t* to the closest point of approach as the independent variable and d' as the dependent variable, are shown in the figure (see Figure 8-17). Note that the moderator is shown as a legend.

Gradual Increasing Pattern included motorbikes in opposite direction when drivers turn left, pedestrians in opposite direction when drivers turn right and left, bicycles in opposite direction when drivers turn right and bicycles in right and left directions when drivers turn right and left. And High Detectability Pattern included bicycles in same direction when drivers turn left. These patterns suggest that as the collision risk increases, the detectability of the evaluated target also increases, indicating a safer situation.

Low Detectability Pattern included pedestrians in same direction in the DCPA 5m condition when drivers turn right and left. And Immediate Increasing Pattern included pedestrians in same direction in the DCPA 1m condition when drivers turn right and left, and motorbikes in same direction when drivers turn left. These patterns suggest a hazardous situation where there is low detectability over an extended period, despite increased collision risk.

As mentioned before, when assessing pedestrians in same direction, DCPA significantly adjusted the patterns as a moderator, there was the Low Detectability Pattern in DCPA 5m condition, and the Immediate increasing Pattern in DCPA 1 m condition. Both patterns have maintained low detectability over the long term and are thereby dangerous.

On the contrary, none of the assessment targets were significantly affected by traffic congestion as a moderator.

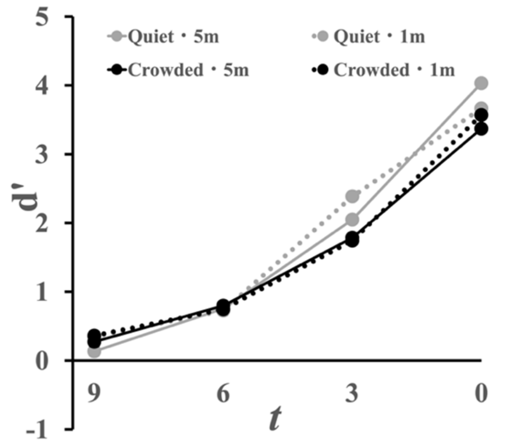

Figure 8: Patterns of motorbikes in opposite direction when drivers turn right.

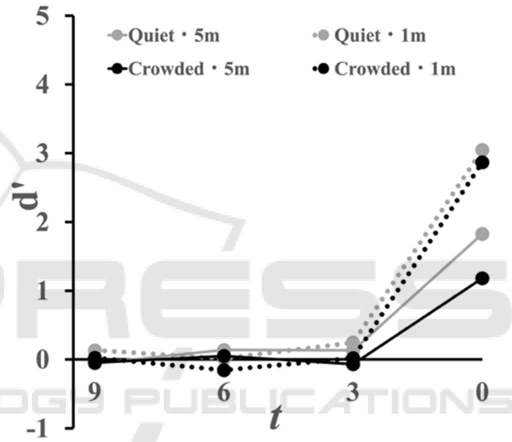

Figure 9: Patterns of motorbikes in same direction when drivers turn left.

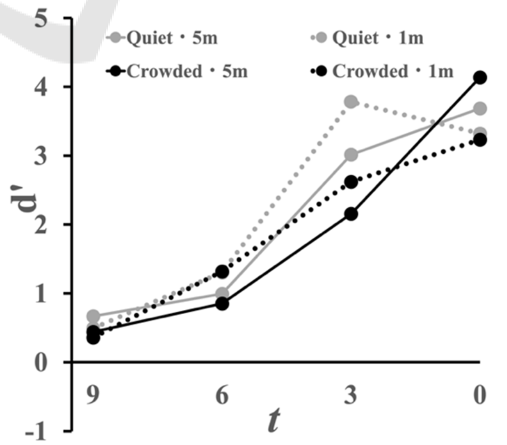

Figure 10: Patterns of bicycles in opposite direction when drivers turn right.

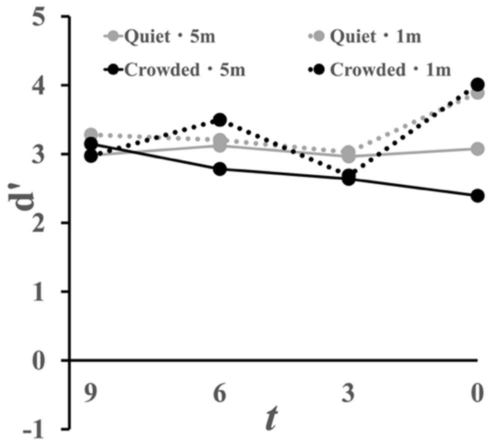

Figure 11: Patterns of bicycles in same direction when drivers turn left.

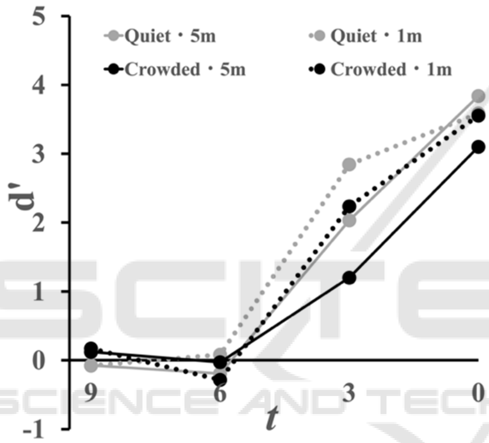

Figure 12: Patterns of bicycles in right direction when drivers turn right.

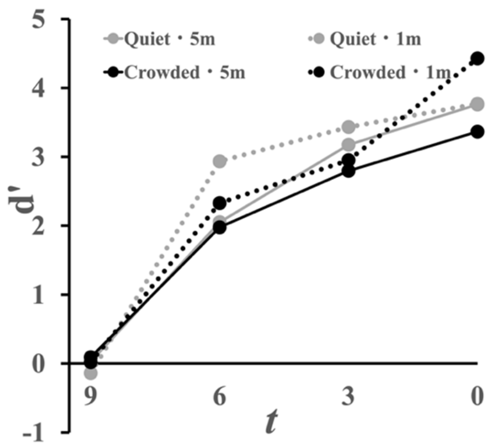

Figure 13: Patterns of bicycles in left direction when drivers turn left.

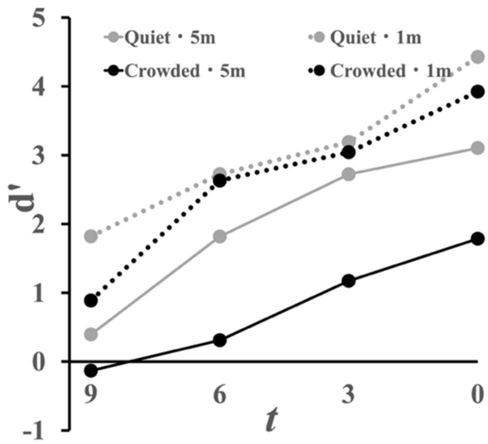

Figure 14: Patterns of pedestrians in opposite direction when drivers turn right.

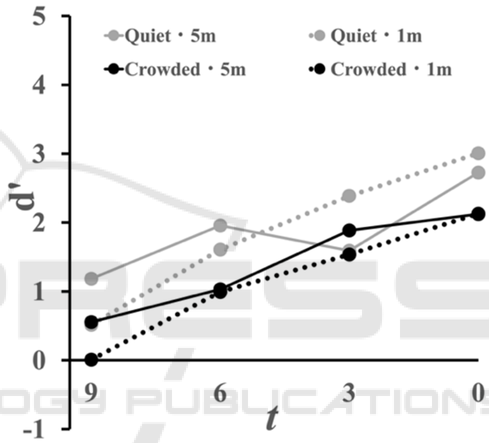

Figure 15: Patterns of pedestrians in opposite direction when drivers turn left.

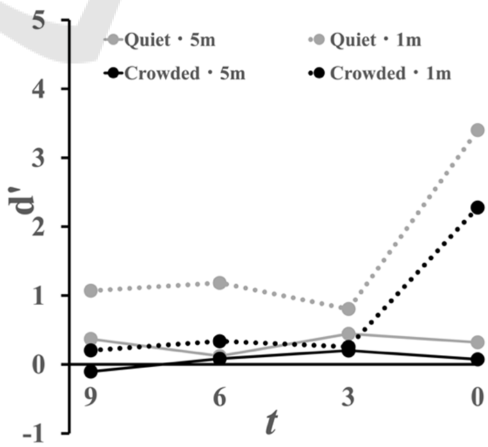

Figure 16: Patterns of pedestrians in same direction when drivers turn right.

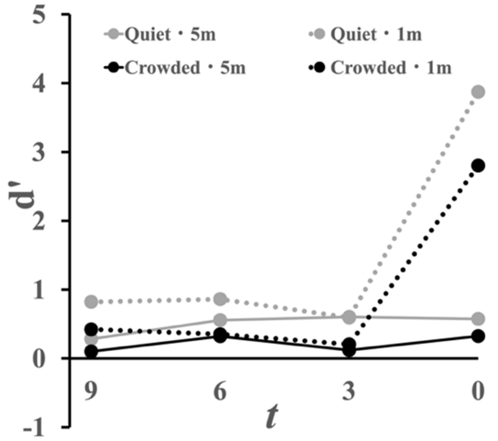

Figure 17: Patterns of pedestrians in same direction when drivers turn left.

5 DISCUSSION AND CONCLUSIONS

In this study, the detectability index d' is considered as a function of the time *t*, and two dangerous patterns are defined: the first is the Immediate Increase Pattern. The second is the Low Detectability Pattern. In these patterns, d' remains low regardless of *t*.

Consistently, the Immediate Increasing Pattern was shown for the motorbikes in same direction when turning left.

For the pedestrians in same direction, the effect of the time *t* was adjusted by DCPA. For the pedestrians in same direction, the pattern was the Immediate Increasing Pattern when the DCPA was 1m. And when the DCPA was 5m, the pattern was the Low detectability pattern. In any case, these patterns indicate a dangerous situation. The Low Detectability Pattern when DCPA was 5m is particularly dangerous.

As described above, the detectability of VRUs in same direction decreased, whether they were turning left or right. These VRUs approach driver from behind. They had a shorter time in the driver's field of view than the VRUs approaching from the front. So, they were therefore considered more difficult to detect.

Low visibility is also considered a reason for lack of detectability. Low visibility is one of the most important factors in accidents (Yousif et al., 2020). In the present experiment, the motorbikes and pedestrian in same direction were only visible in the side and rear-view mirrors for a long time. So, the drivers maintained a low detectability of such VRUs.

For the pedestrians in same direction, with a DCPA of 5 m, the pedestrian was only visible in the side and rear-view mirrors until the video stopped. With a DCPA of 1 m, the pedestrian appeared next to the car at the end of the video, which means that visibility was higher and therefore detectability was higher.

It is interesting to note that even in same direction, the detectability was higher for bicycle. The bicycle in same direction is always in the driver's front left field of view. Driver passes the bicycle once and the bicycle approaches again from behind. The long time spent parallel to the bicycles is thought to be one of the reasons for the high detectability. In addition, the driver's experience with bicycles may also play a role in the detectability of bicycles. A study by Kaya et al. (2021) showed that drivers with more experience with bicycles may have greater visual attention related to the detection of bicycles while driving. The penetration rate of bicycles in Japan is about 0.5 per person, a relatively high proportion, so the detectability of bicycles while driving is likely to be higher.

The VRUs in opposite direction, and those in the left and right direction, both showed the Gradual Increase Pattern, indicating that the participants in this experiment performed adequate detection.

In addition, the traffic congestion was manipulated in this experiment, but the results showed no effect of adjusting the traffic congestion in any of the situations.

ADAS notifies the driver of warnings in hazardous situations. This notification must be made at the required time. Notification of such warnings in relation to objects for which adequate attention has been paid may encourage an inappropriate allocation of cognitive resources to the driver.

Particularly in recent years, there has been a proliferation of devices installed in cars, and it has been suggested that the excessive information displayed by these devices puts pressure on the driver's cognitive resources. For example, early warnings may be perceived by drivers as annoying warnings (Lee et al., 2002), and it has been suggested that warnings that prompt a quick response in emergency situations may also be perceived as unpleasant by drivers (Naujoks et al., 2016).

To address these issues, this study is expected to provide important guidance for the design of ADAS.

Finally, the limitations of the present study and future challenges are discussed. In this experiment, the situation of bicycles in opposite direction when turning left and motorbikes in same direction when turning right was not included. This is because such traffic is illegal under Japanese traffic law. In the same way, there are many violations of the law in the real scene. Discussion on the detectability of VRUs that violate the law is an issue for the future.

Furthermore, in this study, experiments were conducted by using driving videos and having the participants observe them. In future research, it will be necessary to follow up this experiment by conducting experiments in more realistic experimental environments such as VR and driving simulation.

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