COLLISION RISK PREDICTION UTILIZING ROAD SAFETY MIRRORS AT BLIND INTERSECTIONS

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ABSTRACT

Traffic accident number in Japan has been reduced year by year by growing ADAS technologies, revising the traffic rules, improving traffic environment. However, to realize the Vision Zero world which is zero traffic accidents, zero fatal accidents and zero injured seems far away currently. According to the traffic accident statistics data in Japan, more than half of accidents are occurring both in and around intersection areas [1]. The accident number at the intersections without traffic light is bigger than that with traffic light and has been seen at residential areas. To reduce the accident number at the intersection without traffic light, road safety mirrors have been installed in the intersection frequently [2]. In our study, using the front camera, which is one of ADAS sensors, even if it is a scene where the front camera cannot detect the object directly, our purpose is to reduce the collision risk by detecting the approaching vehicle using its image in road safety mirrors.

In this paper, our collision avoidance method which consists of the 3 steps "Road safety mirror detection", "Object detection in the road safety mirror" and "Risk prediction" has been proposed. Especially, in road safety mirror detection, one countermeasure for false positives (FP) has been introduced. Our proposed method has

been verified using front camera as a feasibility study, and the effectiveness of our proposed method has been demonstrated by experimental results on the public road. If the effectiveness of our proposed method is proven, since road safety mirrors will be utilized, which are a legacy infrastructure element, new investment at poor visibility intersection can be reduced which will be one of the merits of the proposed method. Also, the scalability of the system supporting not only Autonomous Driving (AD) systems of level 3 and higher, but also AD level 1 and 2 such as Advanced Driver-Assistance System (ADAS) will be an advantage.

1. SYSTEM OPERATIONAL CONCEPT FOR T-CROSSING WITH ROAD SAFETY MIRROR

Road safety mirrors can be frequently seen at poor visibility intersections in Japan. In other words, road safety mirrors can be seen at intersections which seem to have a high collision risk. This paper is focusing on collision avoidance at road safety mirror equipped intersections which is one of Japan specific environments. And, we have been focusing on the analysis of reflected images of road objects in the road safety mirror. For collision avoidance by using the reflection in the road safety mirror, our proposed method has been expected to support the recognition of road objects out of the direct field-of-view from the front camera at poor visibility intersection.

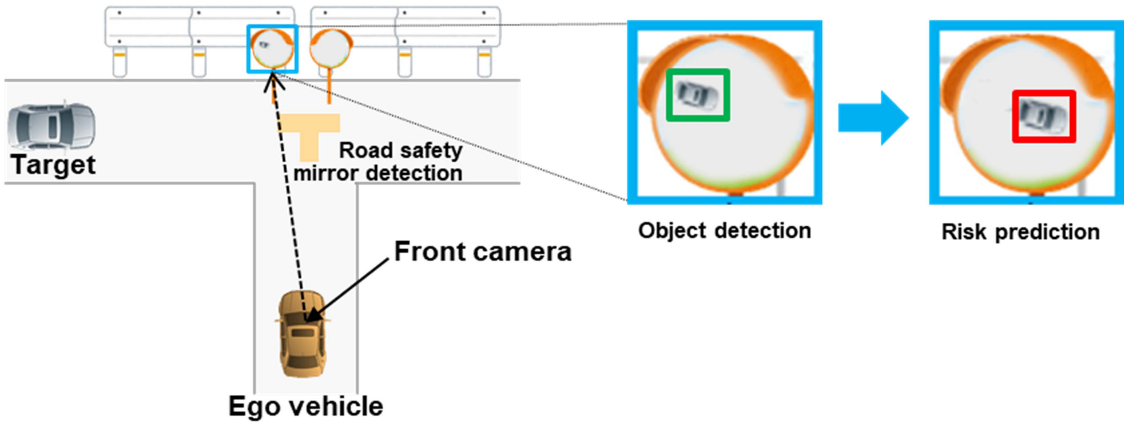


Figure 1. System purpose.

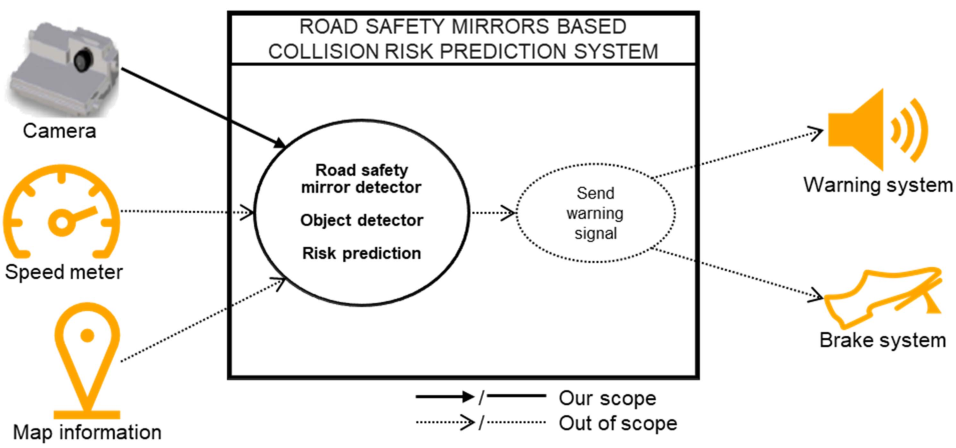


Figure 2. System scope from use-case and actor perspectives.

1.1. System Purpose

The purpose of this system is, for example, to support detection of approaching vehicles, to estimate the risk of collision, and to give the risk information to the driver through a driver warning system. Figure 1 shows the system context which shows a situation for the mitigation of predicted risk using the road safety mirror at a T-crossing. The front camera of the ego vehicle detects the road safety mirror and extracts the piece of the image containing the reflected approaching target vehicle on the road safety mirror. When the target vehicle is approaching, it is estimated that there is a high collision risk, which is the case shown by the red square in right side picture in Figure 1.

1.2. System Context

Figure 2 shows the system scope and interaction between scope of interest and external systems. Our study scope in this paper is the software algorithm including the road safety mirror detector, the object detector within detected road safety mirrors and the risk prediction at the T-crossing if the target object is a passenger vehicle. It means it does not include the interface to the vehicle speed meter, brake system, map information or to a warning system for sending a signal. The calculation of the estimated collision risk is based on image data from the front camera. The system is enabled based on a trigger by a defined threshold of the ego vehicle speed. When it detects a high collision risk target vehicle is approaching, the system sends a warning signal to inform the driver. Additionally, the system can have an interface to the brake system because it can be utilized to give brake assistance for the driver. For the system it is also desirable to have a map information interface because the map is expected reduce FP and false negative (FN) events.

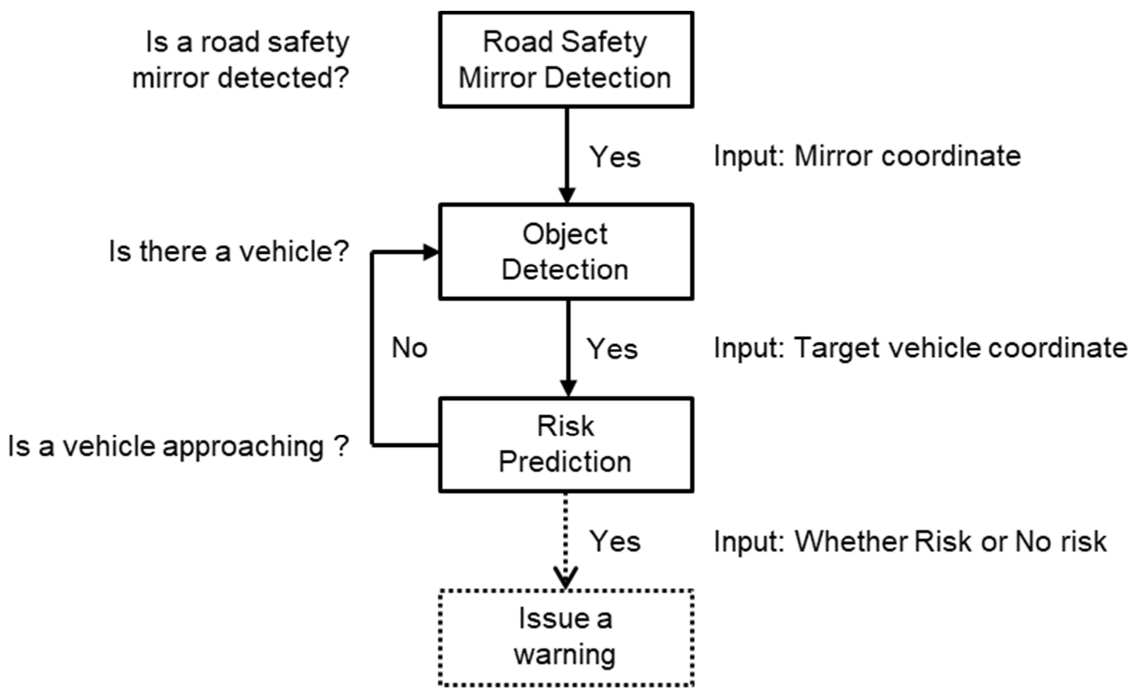


Figure 3. Schematic flow of our system.

2. PROPOSED SYSTEM FUNCTION

Figure 3 shows a schematic flow of our system. When the system detects a road safety mirror, it starts to search for a vehicle on the road safety mirror. At this time, if it detects a target vehicle reflected in the road safety mirror, it is transitioning to risk prediction. Risk prediction is an algorithm that determines whether the target vehicle in the road safety mirror is approaching and, if it is determines that it is approaching, issues a warning to the driver. For the road safety mirror detection, not only a detection approach using YOLOv3 [3] but also FP prevention by applying Deep Autoencoding Gaussian Mixture Model (DAGMM) [4] has been developed. For road object detection in the road safety mirror, Faster-RCNN (F-RCNN) [5] has been selected, and a risk prediction method which applies interpolation by a Kalman filter and object tracking [6] is applied in this paper. Additionally, although it has been not applied in this paper, an enhanced approach for risk prediction [7] has also already been published.

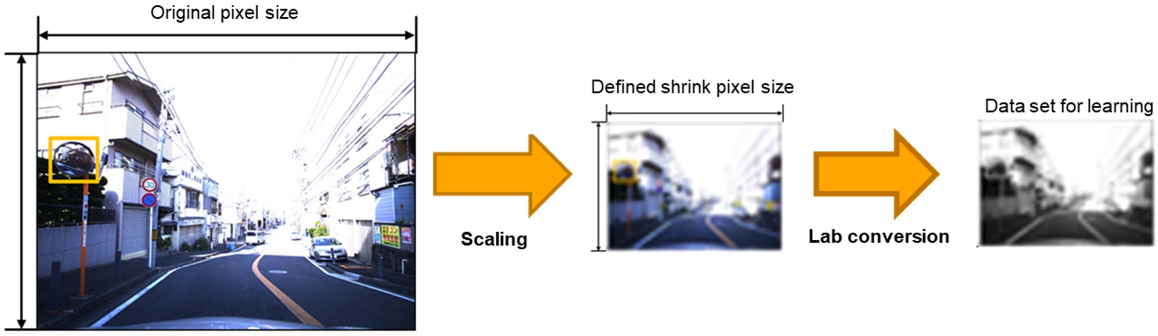


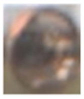
Figure 4. Data set preparation for road safety mirror detection using YOLOv3.

Figure 5. One frame shot of verification result of road safety mirror detection.

2.1 Road Safety Mirror Detection

For road safety mirror detection, YOLOv3, which is one of the well-known deep learning methods, in its latest version as of 2019 has been selected. For learning data, it has been using high resolution pixel image (approximately 12 M pixel) and the Region of Interest (ROI) information of the road safety mirror has been included. The ROI means the area where we are searching a potential target object is a box around the detected road safety mirror like enclosed in the yellow square in Figure 4. The original image will be scaled to a defined reduced size and converted to L*a*b* [8] color space image as shown in the left side picture in Figure 4. Here, RGB means color based on red, green, blue colors. Capital L* of L*a*b* means luminosity and small a*, b* means complementary colors. The L*a*b* color space seems to be closer to human visual. In RGB, it is sometimes hard to distinguish colored areas depending on the brightness situation. On the other hand, in L*a*b* it might be possible to distinguish the color areas like in human vision. Thus, in this paper, the L*a*b* color space is the input for the deep learning method which has been applied.

Table 1.
Verification result of road safety mirror detection

True positive (TP)	False positive (FP)
e.g.,  	e.g.,    
696 detections	35 detections

<u>2.1.1. Public-road-running-test</u> Public road tests have been executed using a low-resolution camera (approximately 0.32 M pixel) which is different from the high-resolution camera used for data collection. As controller, a NVIDIA Jetson Xavier has been used. Nevertheless, the results seem to have very good precision of more than 95% as described in Table 1 and Equation (1). Figure 5 shows the one frame shot of verification results of road safety mirror detection.

$$Precision = \frac{TP}{TP+FP} = \frac{696}{696+35} = 95.2\% \qquad \text{Equation (1)}$$

Although it is not so many issues, we can see some FP in these results. In the next section, the countermeasure to reduce the FP issues is described.

<u>2.1.2. Countermeasure-to-false-positive</u> The countermeasures to FP issues are described in this section. A FP is one of the issues which often limits performance in this perception field. In order to reduce the FP issues, an anomaly detection method has been used. Recently, the Deep Autoencoder Gaussian Mixture Model (DAGMM) has been published (2018). By using a Gaussian Mixture Model, we can find a cluster of features for each object.

However, the mirror image is inconsistent. So, it was hard to define the distribution of the road safety mirrors features in comparison with traffic sign features. Thus, in order to overcome this issue, we have created the opposite idea to a conventional approach. Figure 6 is just an example to explain our approach. If the red points in Figure 6 are assumed to be clusters of traffic signs features, the black points close to these clusters might also be a traffic sign. Our proposed method estimates that the points far away from these clusters might be road safety mirrors. After detecting potential road safety mirrors by the deep learning method YOLOv3, we calculate their distance to these red clusters. If the distance is over the defined threshold, the system regards the detected object is road safety mirror. If the distance is within the defined threshold, the system regards the detected object is not a road safety mirror.

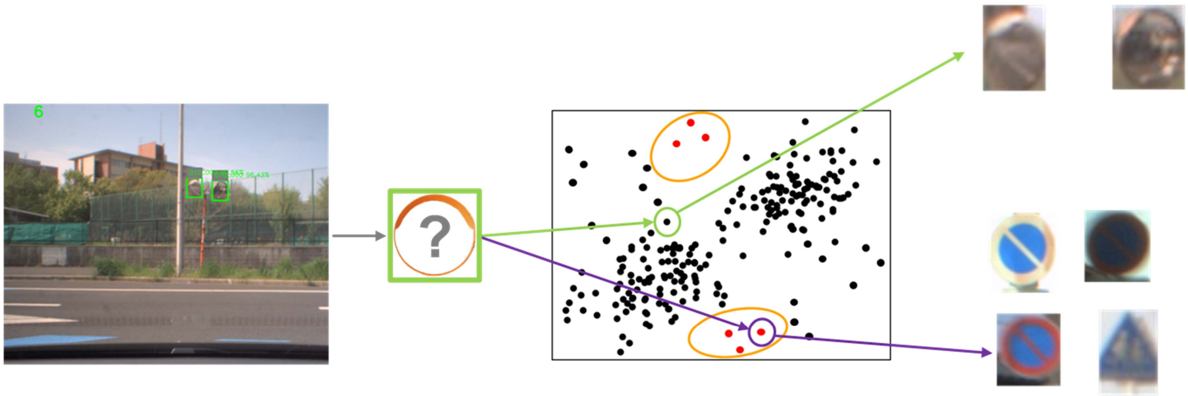
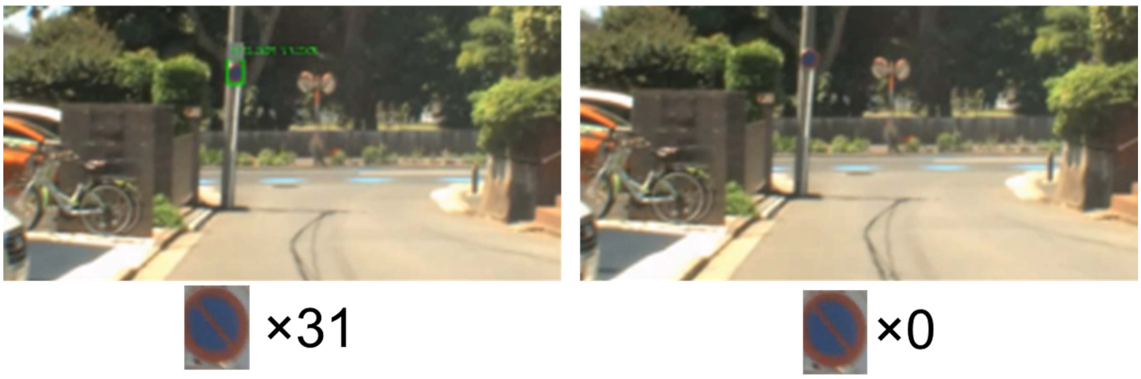


Figure 6. Our proposed approach for detecting the road safety mirror to reduce the false positive



(a) W/o DAGMM (b) With DAGMM

Figure 7. Effectiveness of our proposed approach applying DAGMM

Figure 8. Road safety mirror detection by our proposed approach applying DAGMM

Figure 7 (a) shows the result for a part of a recording without DAGMM. As the result, FP count was 31 in this recording. On the other hand, the right picture in Figure 7 (b) shows the result for the part of the recoding with DAGMM as proposed by our approach. FP was zero counts based on the same recording. The effectiveness by our proposed method was proved by this recording. Furthermore, the road safety mirror detection by our proposed method applying DAGMM has been confirmed after approaching to the T-crossing as shown in Figure 8. As summary in road safety mirror detection, it has been verified that the FP count can be effectively reduced, and road safety mirrors can be detected by using our proposed method.

2.2. Road object Detection in Road Safety Mirror

In order to detect road objects, the deep neural network Faster R-CNN has been used. For the feature extraction in Faster R-CNN, Resnet 50 is used here. It is a deep residual network to handle the problem of vanishing/exploding gradients[9][10][11]. The basic unit is shown in Figure 9, which has better performance in small objects detection [12].

In this paper, we use a pre-trained Faster R-CNN with Resnet 50 model [13] based on the Microsoft Coco dataset [14]. The following 7 classes are targeted for road objects, which are the most-seen objects on roads in Japan:

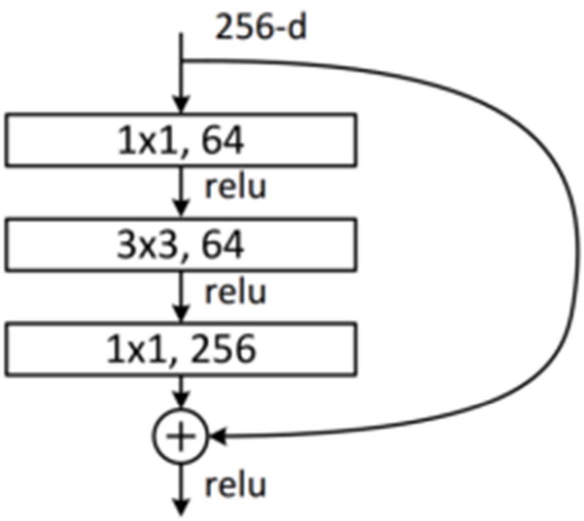


Figure 9. Basic unit of Resnet 50

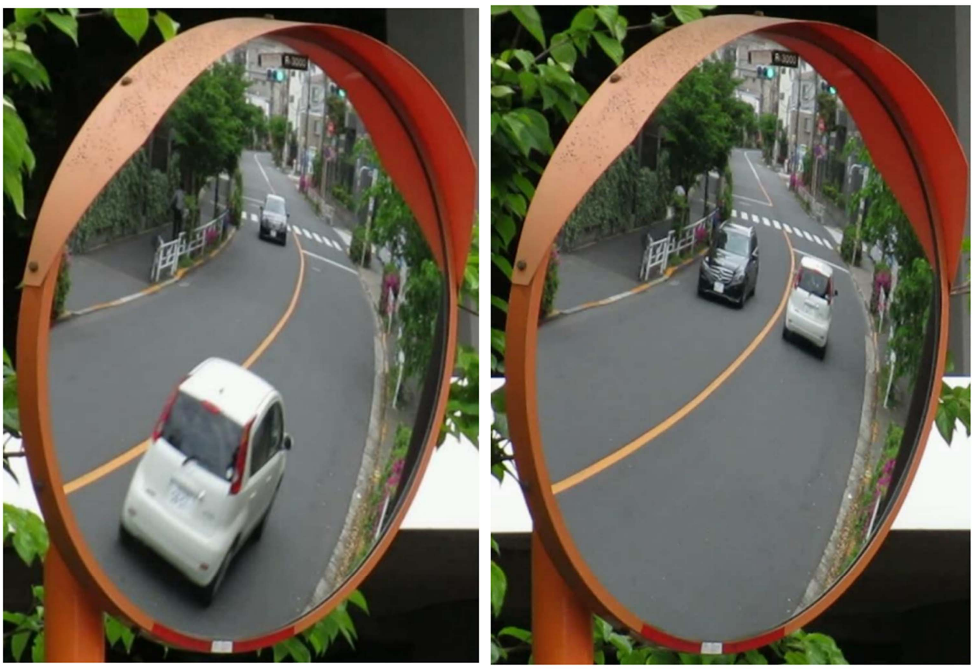


Figure10. Moving objects in road safety mirror

Table 2.

Relationship between local direction and risk level

Local direction of objects	Risk level of objects
Up to down	High
Down to up	Low

(1) Pedestrian (person)

(2) Bicycle

(3) Car

(4) Motorcycle

(5) Bus

(6) Train

(7) Truck

2.3. Risk Prediction

For human drivers, the road safety mirror is a tool to confirm if there is any object like vehicle or pedestrian coming with a possible collision risk. The direction of a moving object in the road safety mirror is a critical factor to decide whether it has potential collision risk for the driver. As shown in Figure 10, while the black vehicle moves from top to bottom in vertical direction in the road safety mirror, it is coming closer to the road safety mirror, which has relatively high collision risk for the ego vehicle. On the contrary, while the white vehicle moves from bottom to top in vertical direction in the road safety mirror, it is going away from the road safety mirror, and the risk to collide with the ego vehicle is relatively low. As a result, by detecting the moving direction of an object in the road safety mirror (called local direction), it can be estimated whether the object is coming near or heading away, which can be used for the classification as a high-risk object or a low-risk object, respectively. The local direction of an object has been calculated from the track of the object obtained in described in Reference [6]. The correspondence relationship between local direction and risk level of objects is described in Table 2.

3. EXPERIMENTAL RESULTS

To verify the effectiveness of our proposed method, public road tests have been executed using a high-resolution camera (approximately 20 M pixel). Although the resolution might be reduced, this high-resolution camera has been selected to verify the feasibility of our proposed method which is object detection in the road safety mirror and the risk prediction in first combined tests on the public road.

Figure 11 shows the experimental result of the road safety mirror detection. Figure 12 shows the experimental result of the object detection in the road safety mirror. Figure 13 shows the experimental result of risk prediction of the target vehicle approaching. It seems that the road safety mirror detection by our proposed method can detect the road safety mirror stably as shown in Figure 11. Also, it seems that the object detection in the road safety mirror by Faster R-CNN which we applied can detect road objects stably as shown in Figure 12. Furthermore, we can see that the risk prediction works as planned as shown in Figure 13.

From the above experimental results for our combined proposed method, our proposed concept for detecting high collision risk of approaching vehicles at T-crossings equipped with a road safety mirror by using only the front camera image have been proven in public road test.

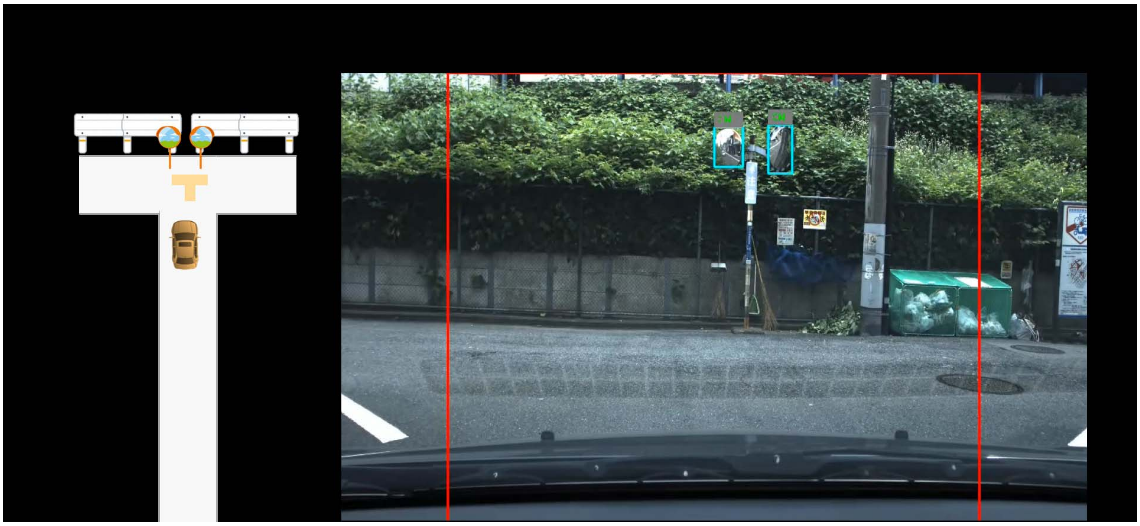


Figure11. Experimental result of road safety mirror detection

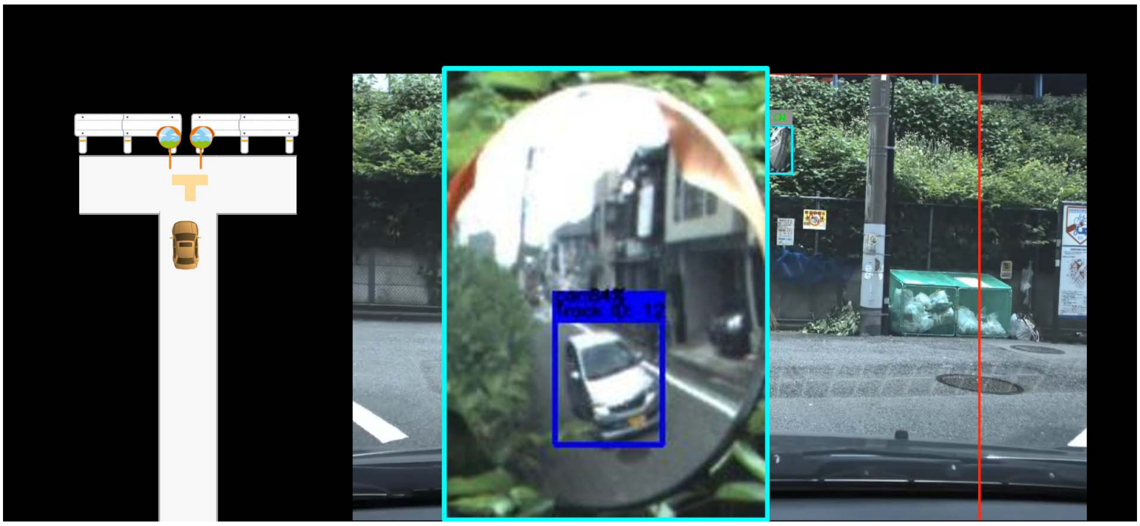


Figure12. Experimental result of object detection in the road safety mirror

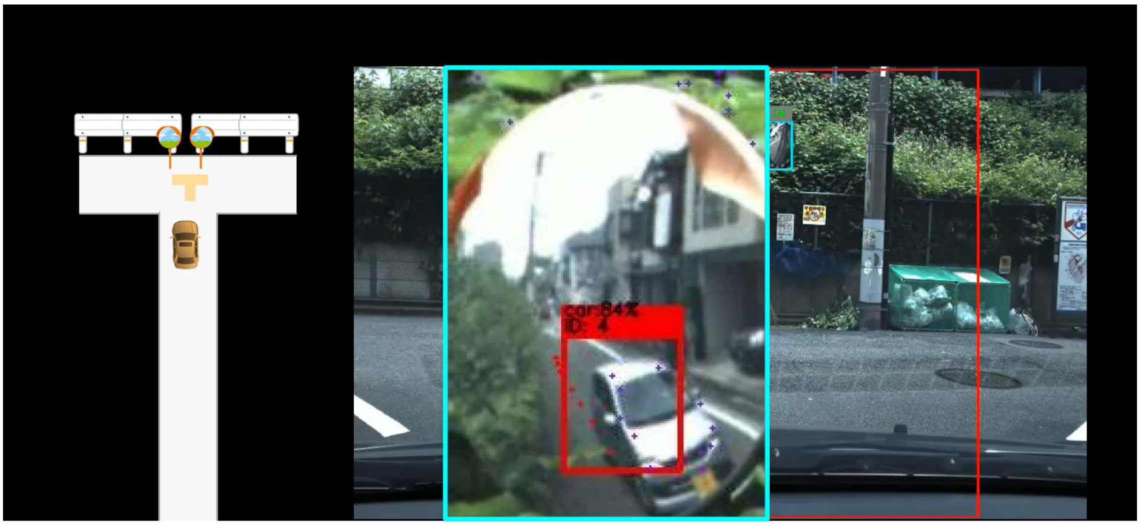


Figure13. Experimental result of risk prediction to the target vehicle approaching

4. CONCLUSIONS

In this paper, we propose a method to reduce the collision risk at crossings by detecting approaching vehicles using their reflection in road safety mirrors, using a 3-Step approach consisting of "Road safety mirror detection", "Object detection in the road safety mirror" and "Risk prediction". Our proposed method has been verified using real world camera data as a feasibility study, and the effectiveness of our proposed method has been demonstrated by experimental results at T-crossing on public roads. Considering these results, it will be expected that our proposed method improves safety while avoiding new investments at poor visibility intersections and can be adapted to any levels of AD/ADAS system. The next steps considered are to improve robustness in different weather and illuminance conditions, to add more classes of target objects and to bring maturity closer to production level.

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