Predicting motorcycle riding behavior using vehicle density variation

Takamasa Koshizen, Fumiaki Sato, Ryoka Oishi, and Kazuhiko Yamakawa

Abstract—**Recently, motorcycle accidents are increasing in developing countries. One of the main reasons for this is the increase in traffic volume due to an increased number of four-wheeled vehicles. This brings about a heterogeneous (mixed) traffic flow consisting of two-wheeled vehicles and four-wheeled vehicles, which can result in the occurrence of sideswipe collisions. We carried out a survey of two-wheeled vehicle driving in heterogeneous traffic flow by considering vehicle density, acceleration, and pore (lateral gap), among other factors. Based on the results of this survey, we aim to predict motorcycle riding that carries high risk of collision, and to prevent such accidents from occurring. In this paper, we describe a novel algorithm which is capable of predicting two-wheel driving using vehicle detection and pore consideration. The performance of the proposed algorithm is verified and its associated issues are described. In addition, an example of this prediction algorithm is preliminarily implemented as a smartphone application.**

I. Introduction

Motorcycle accidents in emerging countries are on the rise [1]. It has been shown that damaged road surfaces are a large contributing factor to poor motorcycle safety [2]. Furthermore, an investigative report found that driving mistakes by motorcycle riders can cause accidents [3]. Heterogeneous traffic flow in emerging countries is identified as a 'complex' traffic flow in which two-wheeled vehicles and four-wheeled vehicles are mixed [4]. In addition to an increase in the number of motorcycles, the number of four-wheeled vehicles is also increasing, which can create dense traffic flows. As a result, two-wheeled vehicle drivers are often forced to aim at lateral gaps between four-wheeled vehicles, which increases the probability of sideswipe collisions occurring. Note that sideswipe collisions are often referred to as "blind spot accidents". That is, it is caused by human error due to dense or complex traffic flow. In order to simulate the heterogeneous traffic flow, Nair et al. [5] applied fluid dynamic theory to represent the lateral gap (called a "pore") between four-wheeled vehicles. Two-wheeled vehicles are assumed to traverse a series of such pores as they travel. It should be noted that there exists a "critical" pore size, which is taken into account when determining the minimum traversable pore size, and which is used in order to recognize risky motorcycle riders who attempt to traverse a smaller pore size. Further, fixed-point camera observation of pores was carried out on general roads in Vietnam [6] through which the authors found a theoretical correlation between pore size and the velocity-density of the vehicles. Recently, Gashaw et al. [7] considered the pore size distribution as an exponential function that increases or decreases depending on vehicle density. In addition, Nguyen et al. [8] showed that vehicle density is relevant to the occurrence of sideswipe collisions.

In this paper, we propose a new algorithm to predict the traversal of two-wheeled vehicles by ways of computing vehicle density variation. In the end, our aim is to build a novel smartphone application of information transmission to avoid sideswipe collisions with four-wheel vehicles and two-wheel vehicles. As far as we know, there is no research that predicts that a two-wheeled vehicle will run at high risk as it accelerates toward the pore between the four-wheeled vehicles.

First, the analysis between pore size and vehicle density in Jakarta, Indonesia will be described. The parameters required for motorcycle riding prediction is also extracted by statistical analysis. Based on the analysis, we provide new algorithm for motorcycle riding behavior prediction. We then introduce a case where this prediction algorithm is adopted to a smartphone application. Finally, a summary, including future remarks, will be given.

II. Traffic Flow Survey

To begin with, heterogeneous traffic flow is defined. We then describe the results of traffic flow surveys in Jakarta.

A. Heterogeneous (Mixed) traffic flow

Heterogeneous traffic flow is characterized as a mixed traffic flow that consists of two-wheeled and four-wheeled vehicles. It can be measured by the presence and position of vehicles of various sizes. Moreover, microscopic and macroscopic traffic variables have also been considered. Heterogeneous traffic flow is clearly different from the presence of lane discipline, which results in vehicular movement that is influenced by the vehicles in front as well as on the sides. This causes an increase in sideswipe collision accidents due to high vehicle density.

B. Motorcycle riding

In Indonesia, where growth in vehicle ownership has been remarkable in recent years, sideswipe collision accidents in which two-wheeled vehicles become sandwiched between four-wheeled vehicles continue to increase [9]. Therefore, we analyzed heterogeneous traffic flow, especially the behavior of two-wheeled vehicles and the relationship with the group of vehicles involving four-wheel vehicles, on high-density general roads in Jakarta. Figure 1 shows a histogram depicting the number of vehicles (including two-wheeled and four-wheeled vehicles) within 30 meters. Note that vehicle

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density is distinct from traffic density by fixed-point observations and is based on vehicle observations. If the number of four-wheeled vehicles exceeds 3 per 30 meters, vehicle density can be considered to be relatively high.

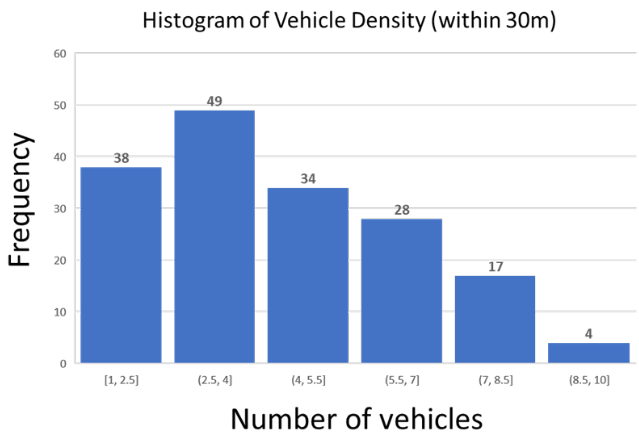

Figure 1. Vehicle density within a 30-meter interval (mean 4.5 vehicles)

Figure 2 provides the relationship between pore size and vehicle density. It is apparent that there exists a negative correlation, with vehicle density decreasing as pore size increases. With regards to the pore size, the result shows that the minimum is 1 meter and the maximum is 7 meters, which agrees with the findings of [7].

Figure 3 shows a survey of motorcycle riding on Jakarta general roads using video analysis. The results are summarized in consideration of the possible acceleration of motorcycle riding and its causes, derived from Figures 1 and 2. It shows an increasing tendency of sideswipe collisions between two-wheeled vehicles and four-wheeled vehicles due to acceleration in high vehicle density traffic where there are 3 or more vehicles within an interval of 30 meters. The vehicle density calculation weights motorcycles by 0.5 and trucks and buses by 1.5, compared to 1.0 for an ordinary vehicle. It is also apparent that there are many sudden course changes that are made to avoid sideswipe collisions. In other words, the reason for the sudden change in course due to motorcycles is to find pore space between vehicles. Frequent acceleration driving and course changes in relatively dense traffic flows is related to motorcycle driving aiming at pores as illustrated in the following figure 4.

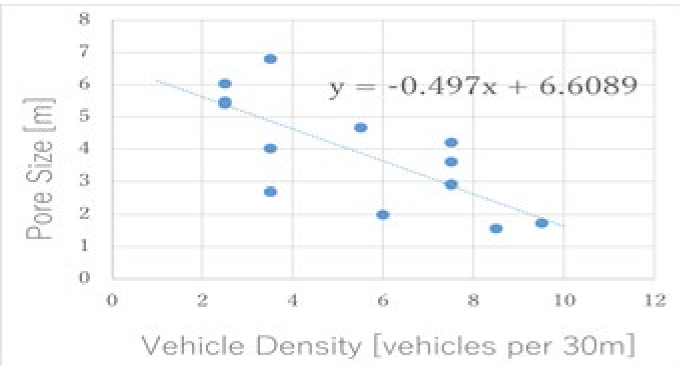

Figure 2. Relationship between pore size and vehicle density

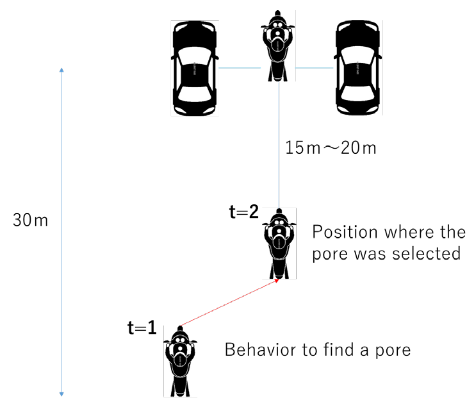

Figure 4. Two-wheeled vehicle driving pattern for the pore.

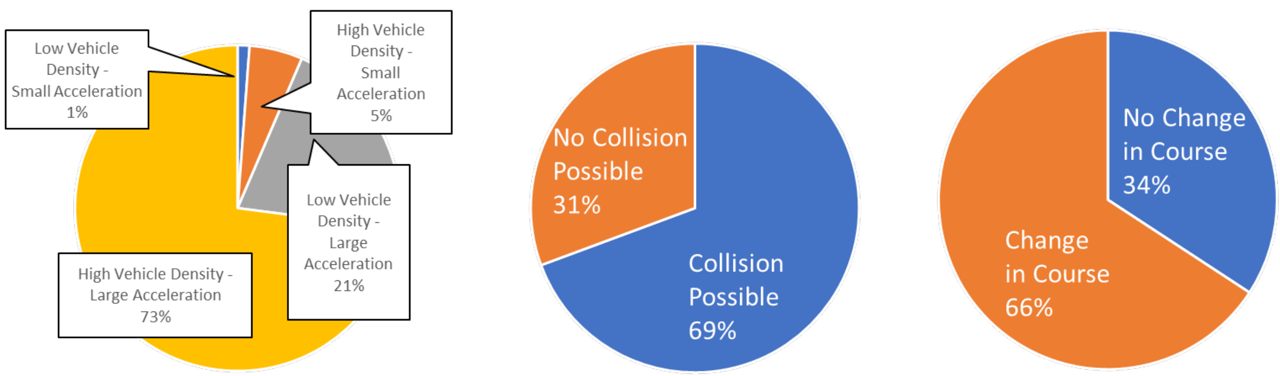

Figure 3. Survey of motorcycle riding on Jakarta

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Figure 4. shows a driving pattern until the two-wheeled vehicle passes through the pore in front. In principle, two-wheeled vehicles take exploratory action to find pores. In our study, many exploratory behaviors involve course changes (i.e., zigzag driving). After finding a pore through it (t=1), the two-wheeled vehicle drives almost linearly (t=2). At this time, acceleration is somewhat accompanied. This is a precautionary behavior to go through before the pore changes. The two-wheeled vehicle driving prediction described in the next section is to predict whether the two-wheeled vehicles taking the behavior at t=2 is acceleration or not.

III. MOTORCYCLE RIDING PREDICTION

In this study, two-wheeled vehicles and four-wheeled vehicles are detected from front camera images acquired by a smartphone, and their positions on the road are estimated. Then, the driving of the two-wheeled vehicle is predicted by measuring the change in vehicle density and the relative speeds of the surrounding vehicles. As a method of recognizing an image and detecting a vehicle, object detection is performed using deep learning. Furthermore, the position of the vehicle on the road is calculated by using the projective transformation from the two-dimensional image.

A. Estimating the position of the vehicle on the road

Cars, buses, trucks, and motorcycles are detected from front camera images taken on a smartphone, using an object detection algorithm based on deep learning (YOLO-v3[10]). An example of detection from an image is shown in Figure 5. From the position information of the rear wheels of the vehicle on the screen, the position on the road is estimated using the perspective projection model. At this time, it is assumed that the detected vehicle exists on the same plane (road).

Figures 6 and 7 show the relationship between the position on the screen taken by the smartphone and the distance on the road. It is assumed that the virtual camera is located at a distance G behind the screen position and at a height H. It is also assumed that the distance between the screen and vehicle A, reflected at the lower end of the screen, is D, and can be measured in advance. Then, it is assumed that the length X from the vanishing point on the screen to the bottom of the screen is also predetermined. Also, let Y be the distance from the position of the rear wheel of the vehicle in front to the vanishing point that is to be calculated. X and Y in Figure 6 and 7 represent the same environment.

Now, in Figure 7, from the similarity between the triangle CBB' and CQR,

$$H : DB = Y : G \quad (1)$$

Also, here, the distance G between the virtual camera and the screen is based on the similarity between the triangle CAA' and CPR.

$$H : D + G = X : G \quad (2)$$

Therefore, G is as follows.

$$G = DX / (H-X) \quad (3)$$

Therefore, the distance D_B is as follows.

$$D_B = D \cdot X / Y \cdot H / (H-X) \quad (4)$$

Figure 5. Detection example of four-wheeled vehicles and two-wheeled vehicles from smartphone images

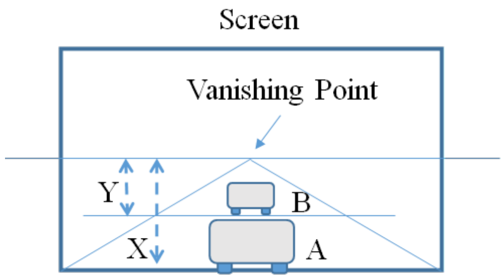

Figure 6. Smartphone screen example

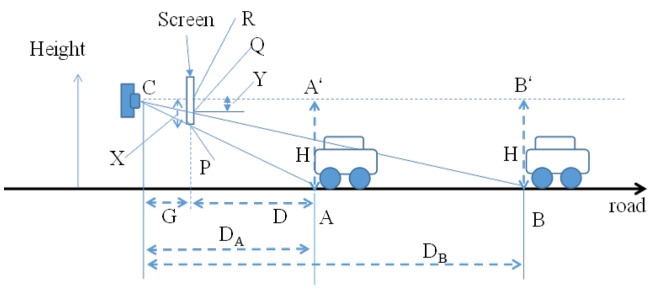

Figure 7. Relationship between the position of the vehicle on the road and the position on the screen

The amount of displacement of the vehicle B from the center to the left and right is based on the similarity of the triangles VSS' and VTT' in Figure 8.

$$Wa = Wb \cdot X / Y \quad (5)$$

Here, when Wsc is the length of the lower end of the screen and W is the width on the road reflected in the actual lower end of the screen, the actual length of Wa' is calculated by Wa as follows.

$$Wa' = W \cdot Wa/Wsc \qquad (6)$$

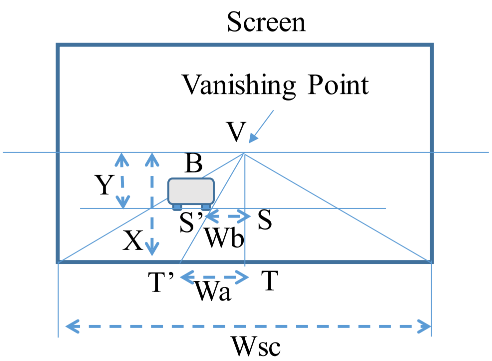

Figure 8. Calculation of left and right displacement of vehicle B

B. Vehicle density calculation and prediction of the trend

The driver of the motorcycle predicts the change in vehicle density on the road and determines the driving route. In order to predict the driving of the driver, the density of vehicles on the road is calculated from the bird's-eye view based on the kernel density estimation method, and the trend is predicted.

The formula for estimating kernel density is shown below. Here, there are n vehicles on the road, and the coordinates of the i-th vehicle c_i are (x_i, y_i).

$$\hat{p}(x,y) = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{h^2}K\left(\frac{x-x_i}{h}\right) * K\left(\frac{y-y_i}{h}\right) \qquad (7)$$

The following Gaussian kernel is used as the kernel function.

$$\mathrm{K(t)} = \frac{1}{\sqrt{2\pi}}\exp\left(-\frac{t^2}{2}\right) \qquad (8)$$

After calculating the vehicle density with the kernel density estimation function, the position of the peak vehicle density in front of the motorcycle is determined (Figure 9). The *peak* we mean is the maximum for the vehicle density *p* that can be multiple. From the record of the peak position for a certain period of time, the trend of the peak position (whether the peak position is approaching or moving away) is calculated. This is calculated by regression analysis of the peak position over time (Figure 10). From the trend of the peak position, the change of the vehicle density in front of the motorcycle is predicted.

In the trend A in the Figure 10, the slope of the regression line is positive, indicating that the peak position is moving away. If the peak position is far away, it means that there is space in front of the motorcycle, which increases the possibility that the motorcycle will accelerate. On the contrary, in trend B, the slope of the regression line is negative, which indicates that the peak position is approaching. This represents an increase in the density of vehicles in front of the motorcycle and promotes deceleration of the motorcycle.

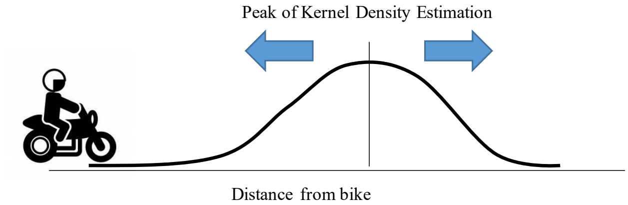

Figure 9. Calculation of the position of the peak vehicle density.

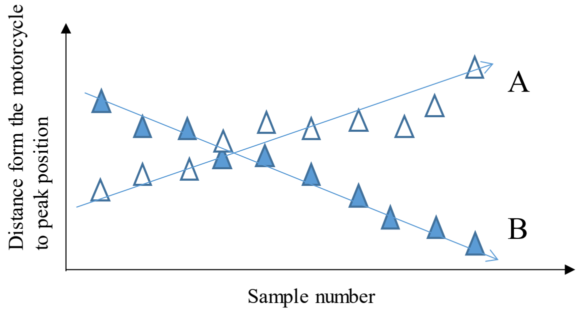

Figure 10. Calculation of the trend of the peak position.

Here, the time width for calculating the trend is important. If the time width is short, the trend that reflects the latest situation can be calculated, but it is easily affected by noise and short-term changes in peak values. On the other hand, when the time width is long, it is not easily affected by noise and a long-term trend can be calculated, but it cannot follow the change of the trend.

By using this position estimation method and vehicle density calculation method, a bird's-eye view as shown in Figure 11 can be constructed from the position on the screen of the vehicle detected in Figure 5.

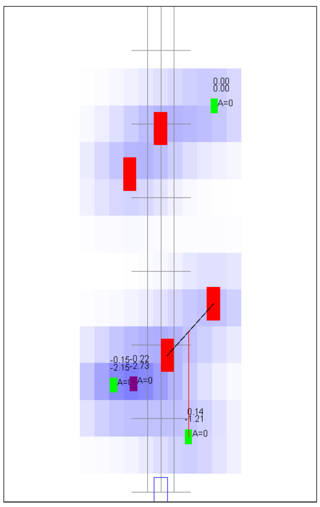

Figure 11. Bird's-eye view generated based on the vehicle detection information in the image of Figure 4.

Here, the red rectangle represents a four-wheeled vehicle. The small rectangle represents the motorcycle. Motorcycles are usually green, but vehicles with higher relative speeds are purple. For motorcycles with a pore in front, the distance to the pore is calculated. The shadow density in the figure represents the magnitude of the vehicle density calculated by the kernel density estimation.

After calculating the vehicle density and the positional relationship between the pore and the motorcycle, the acceleration of the motorcycle is predicted. If a situation is predicted to accelerate towards a pore, our application will alert the surrounding vehicles to make them aware of the motorcycle. The situation in which it is judged that the risk is high and an alert is necessary is when the motorcycle accelerates at a position where the distance from the pore is 15 m to 20 m as shown in Figure 4. If it is closer than this, the alert notification will be too late and the motorcycle will pass through. Also, if it is too early, it will take too long from the alert notification until the motorcycle approaches.

C. Prediction algorithm

By estimating the position on the road from the front image, it becomes possible to track the vehicle, and it then becomes possible to measure the relative speed of the vehicle (with the camera-equipped vehicle), the distance between vehicles, and the change in vehicle density. In this study, we evaluated the density, relative speed, and the change in density of the vehicles in front as factors that determine the acceleration of two-wheeled vehicles.

As a result of analyzing a video filmed on a general road, it was found that the following conditions affect the acceleration of motorcycles:

Acceleration factors:

(1) There is no vehicle in front of the two-wheeled vehicle.

(2) The relative speed of the vehicle in front of the two-wheeled vehicle is increasing (vehicle density decreases, the density peak moves forward).

(3) The relative speed of the two-wheeled vehicle itself is also high and moving towards the pore shown in Figure 4.

Deceleration factors:

(1) There is a vehicle in front of the two-wheeled vehicle, and the vehicle is decelerating.

(2) The relative speed of the two-wheeled vehicle itself is about the same.

(3) The density of vehicles in front is increasing.

A two-wheeled vehicle slows down when the vehicle in front slows down or when the two-wheeled vehicle approaches the vehicle in front, but accelerates when the vehicle in front speeds up, or the two-wheeled vehicle travels towards the pore in front shown in Figure 4 and there is no vehicle in front of the two-wheeled vehicle. From these characteristics, the acceleration tendency of the two-wheeled vehicle can be estimated.

The flow of the motorcycle acceleration prediction algorithm after 1 second is shown in Figure 12.

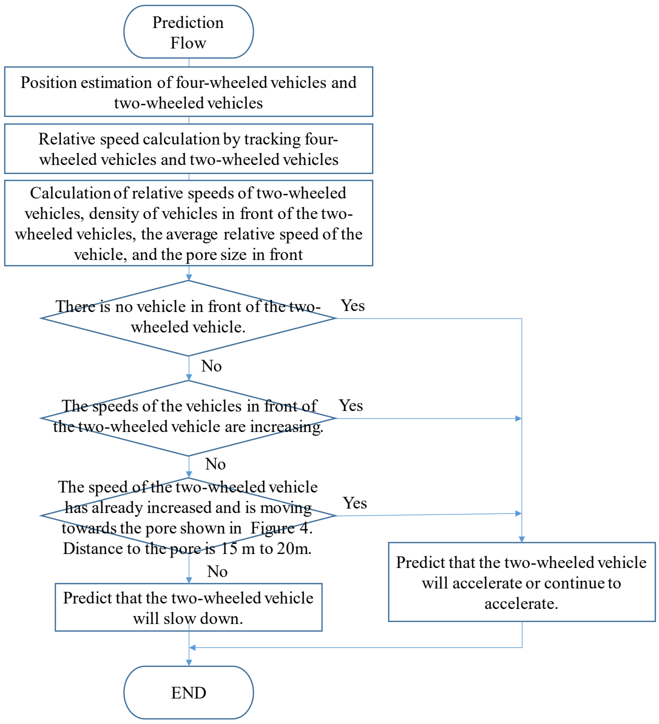

Figure 12. Two-wheeled vehicle driving prediction algorithm.

After predicting the riding of the motorcycle, risk judgment is performed. The criterion for high risk is the situation where the position is t = 2 shown in Figure 4, the distance from the pore is 20 m or less, and the relative speed increases by 10 m / sec. When this happens, the application alerts nearby vehicles that a high-risk motorcycle is approaching.

D. Evaluations

Based on this algorithm, the six video images shown in Figure 13 were processed to evaluate their accuracy. The evaluation method estimated the acceleration/deceleration in the speed of the two-wheeled vehicle, 1 second after the specific time when the image was processed, and then evaluated the accuracy. The results are shown in Table I.

The comparative method only used the trend in the vehicle density in front. When the density of the vehicles in front is decreasing, motorcycles often increase their speed, and in the opposite case, their speed often decreases, which is an important factor for predicting the speed of motorcycles. In this case, a stable trend can be calculated when the time width for measuring the trend is large, but there is a problem in that the influence of the past remains. On the other hand, if the time width is short, the trend is likely to change, but there is an advantage in that the trend that more reflects the current situation can be calculated.

Figure 13. Images from the videos used for evaluation.

TABLE I. PREDICTION ACCURACY

CASE	Proposed method	Trend in density (1 second)	Trend of density (5 seconds)
case 01	81%	53%	38%
case 02	71%	43%	14%
case 03	80%	60%	56%
case 04	63%	36%	36%
case 05	88%	56%	56%
case 06	71%	62%	57%

The proposed method is an improvement of the method that uses the trend in vehicle density. In particular, the proposed method uses the average relative speed of the vehicle in front and the relative speed of the two-wheeled vehicle. The average relative speed of the vehicle in front has the same effect as the trend in vehicle density. In addition, the relative speed of the two-wheeled vehicle is considered to reflect the driving motivation of the two-wheeled vehicle, and is considered to be a more direct estimate.

In cases 01, 02, 03, 05, and 06, the proposed method was able to estimate acceleration and deceleration with about 70% to 80% accuracy. However, for cases 04, the accuracy was less than 70%. Case 04 is a video in which a vehicle makes a large turn because of the curvature of the road, and it was difficult in such cases to estimate the position of the vehicle.

E. Implementation on smartphone

Currently, a part of the proposed algorithm is implemented on a smartphone and its effectiveness is being evaluated. In the smartphone implementation, the future speed of the two-wheeled vehicle is estimated, and the pore between the vehicles in front, through which the two-wheeled vehicle may travel, is also measured from the bird's-eye view. Figure 12 shows an execution screen in the application that is under trial production.

In this system, MobileNet-v3[11] is used as the object detection algorithm. MobileNet has a smaller model size than YOLO-v3, so it has a high frame rate but low detection accuracy.

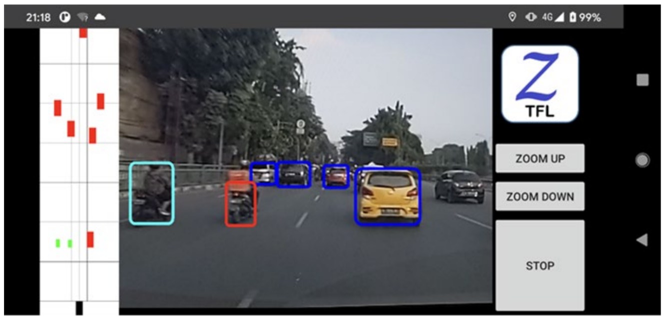

Figure 14. Application on smartphone under trial production.

The positioning accuracy of the prototype application was evaluated. Positioning is used to create a bird's-eye view of the vehicle in front and is required to calculate the size of the pore and the distance to the pore. Positioning was performed 100 times at positions 5 m to 8 m away from the smartphone, and the positioning error was measured. Figures 15 to 18 show the positioning results at the positions of 5 m to 15 m. Furthermore, Figure 19 shows the error rate for the measured value with respect to the distance. From the measurement results, it can be seen that positioning is possible with an average error rate of about 5.8% at 15 m.

In this accuracy evaluation, the measurement is performed without using the screen enlargement (zoom) function, but it is also possible to detect a distant vehicle by using the zoom. On the application screen of Figure 14, the bird's-eye view is displayed on the left side, and the horizontal line represents 10 m. In this example, it is shown that a vehicle in front of about 40 m to 50 m can also be detected.

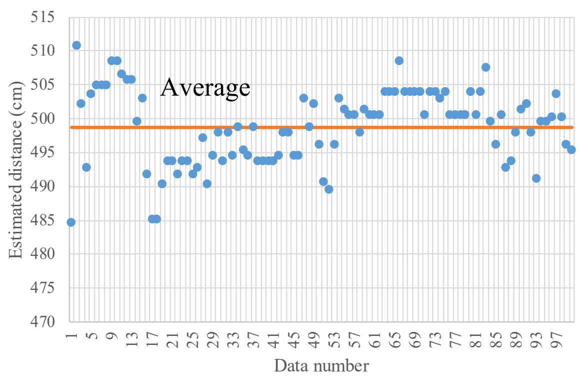

Figure 15. Distance estimation results (5 m).

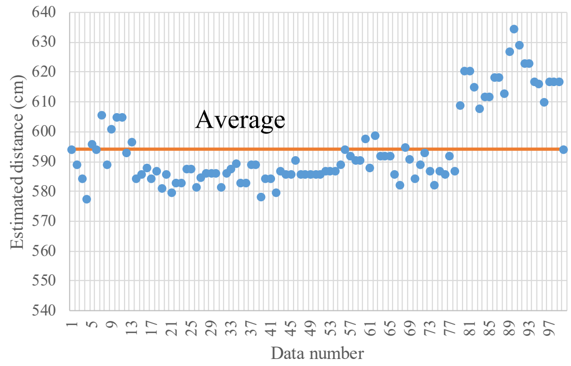

Figure 16. Distance estimation results (6 m).

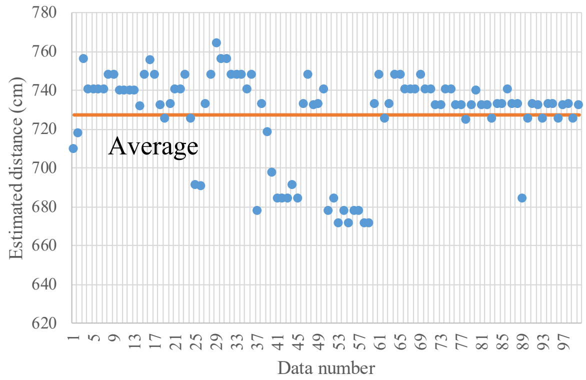

Figure 17. Distance estimation results (7 m).

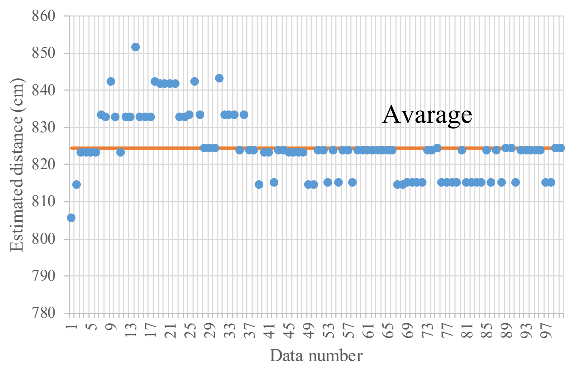

Figure 18. Distance estimation results (8 m).

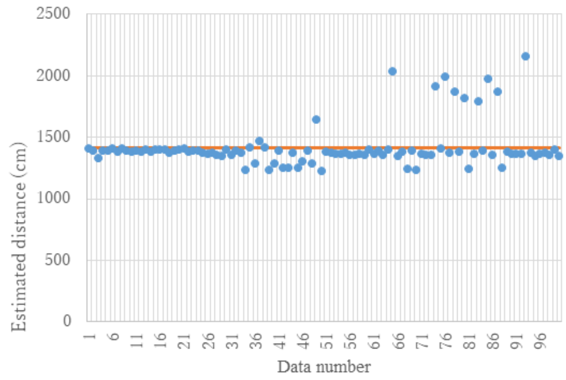

Figure 18. Distance estimation results (15 m).

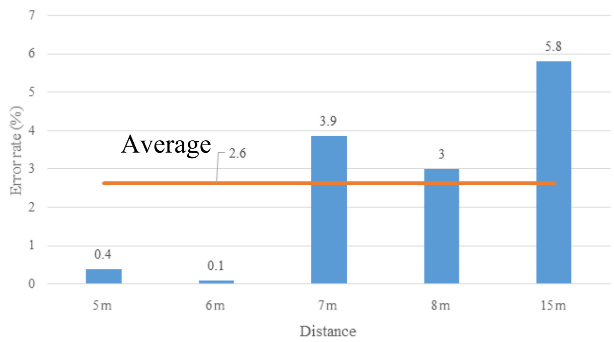

Figure 19. Distance estimation error rate.

IV. Conclusion

This paper describes a motorcycle riding prediction algorithm that evaluates the risks of sideswipe collisions to motorcycles. By detecting vehicles from smartphone images, estimating vehicle density through the generation of a bird's-eye view, and estimating speed using vehicle tracking, accuracy of up to 80% was obtained by the proposed method. However, the accuracy depends on the observation of vehicle density variation in terms of the vehicles that are in front of the two-wheeled vehicle. It is also a question of how long the traffic flow ahead can be captured. In order to address this question, deep learning techniques are used to emulate human perception.

This prediction algorithm is especially effective when the front four-wheeled vehicle makes a lane change without noticing the rear motorcycle. The characteristic of lane changes is that the frequency of occurrence increases as the traffic density increases. Therefore, the aim is to reduce sideswipe collusion accidents by identifying two-wheeled vehicles with a high acceleration risk and making them recognized by the four-wheeled vehicles in front.

As far as we know, there is no research that predicts that a two-wheeled vehicle will run at high risk as it accelerates toward the pore between the four-wheeled vehicles. Jakarta drivers have commented that applications that give such appropriate alerts are useful. In future work, we will seek to address cases in which traffic flow conditions resulted in the proposed method obtaining low accuracy, especially vehicle detection failure that can occur due to overlapping vehicles on the screen and to handling problem in vehicle. For stable tracking of objects, we might consider methods using particle filters. In practice, vehicles in the oncoming lane can be erroneously detected in the calculation of vehicle density. Further, we consider filtering using the directional movement of the vehicle and filtering by detecting lanes using deep learning. In the end, we plan an effective information transmission to surrounding vehicles will be built when a motorcycle at high risk of a collision is predicted.

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