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REAL-TIME SINGLE-CAMERA VEHICLE TO VEHICLE DISTANCE MEASUREMENT FOR AUTONOMOUS VEHICLE

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Abstract. *Measuring the distance between vehicles is essential for autonomous vehicle operation to avoid collisions. This paper discusses the use of a single camera as a sensor to measure the distance from vehicles in fronts such as cars and motorbikes. The image of the vehicle in front that was captured by the camera is then carried out by feature extraction using Convolutional Neural Network (CNN) deep learning. The extraction results will be marked in the form of a box to measure the distance using triangle similarity and pixel comparison. This process can produce distance measurements both at night and during the day and when it rains with an accuracy of up to 94%. With this method, the use of several sensors such as lidar and radar in autonomous car control can be reduced and can be integrated into one camera.*

Keywords: Autonomous vehicle, CNN, Deep learning, Distance measurement, Single-camera

1. **Introduction.** Maintaining a safe distance from the vehicle in front is very important when driving. A driver must always be aware of the position and distance of the vehicle in front. If it is too close, the driver must reduce the speed so that a safe distance with the vehicle in front is fulfilled. In autonomous vehicles, measuring vehicle to vehicle distance is very important as a benchmark for autonomous vehicles to regulate their speed [1,2].

There are basically three main sensors on the autonomous car. The three main sensors are camera, radar, and lidar [3]. The use of single-camera as a single sensor is increasingly being used in autonomous car research but only to control steering angle and detect obstacles as well as traffic signs and road markings. In those research studies, a single-camera was not used to measure vehicle to vehicle distance. For instance, Bojarski et al. [4] proposed camera as a single sensor only to predict the steering angle. Manivannan and Ramakanth [5] proposed single-camera as a single sensor only to control autonomous car through detecting the lane marking. Several previous studies have used lidar to measure the vehicle to vehicle distance in front such as Ponnaganti et al. [6], Domínguez et al. [7], and Du et al. [8]. However, the lidar and radar used to measure the distance between vehicles in autonomous cars have several drawbacks. Apart from the high price, the radar cannot differentiate between multiple objects and lidar accuracy is highly affected by dust, fog, and rain [9]. Stereo cameras are also used to measure vehicle to vehicle distances but require inter-camera calibration and accuracy is highly dependent on position and angle calibration of both cameras. For instance, Zaarane et al. [10] and Ashoori and Mahlouji [11] used stereo camera for vehicle to vehicle distance measurement. Chen and Chen [12] and Phelawan et al. [13] proposed estimation for distance measurement using a single-camera based on license plate detection but both experiments were for cars only

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and Chen and Chen [12] in their estimation required a fixed license plate size. Dirgantara et al. [14] also proposed measurement of object distance by monocular camera but the experiment only for the car and based on car classification using CNN.

Not only cars, measuring the distance between the vehicle and motorbike in front is equally important for collision avoidance. In this paper, we will discuss the use of a single camera to measure the distance between vehicles and other vehicles such as motorbikes and cars based on CNN classification, so that the weaknesses that exist in radar, lidar, and stereo camera can be eliminated and the possibility of a collision with the motorbike or car in front can be avoided. This method is quite simple to implement and produces high accuracy.

In the next chapter, the methods used and the results of the experiments carried out will be discussed. The experimental results of this method are very promising with an accuracy of 94% which was tried during the day, night, and on rainy days.

2. **Proposed Method.** The image from the camera is pre-processed first, and detection and classification of objects are carried out using CNN deep learning to identify cars or motorbikes. After the object is recognized as a car or motorbike, the distance measurement is carried out. The results of distance measurement are a recommendation for the autonomous vehicle to adjust their speed. The whole process is depicted in Figure 1.

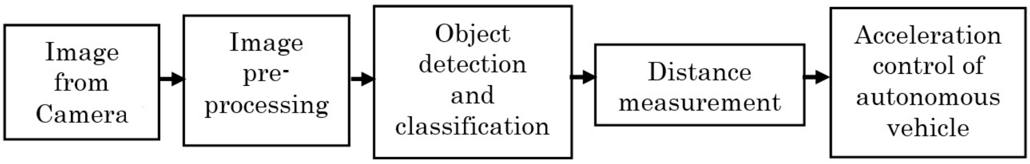


Figure 1. Vehicle to vehicle measurement process for autonomous vehicle

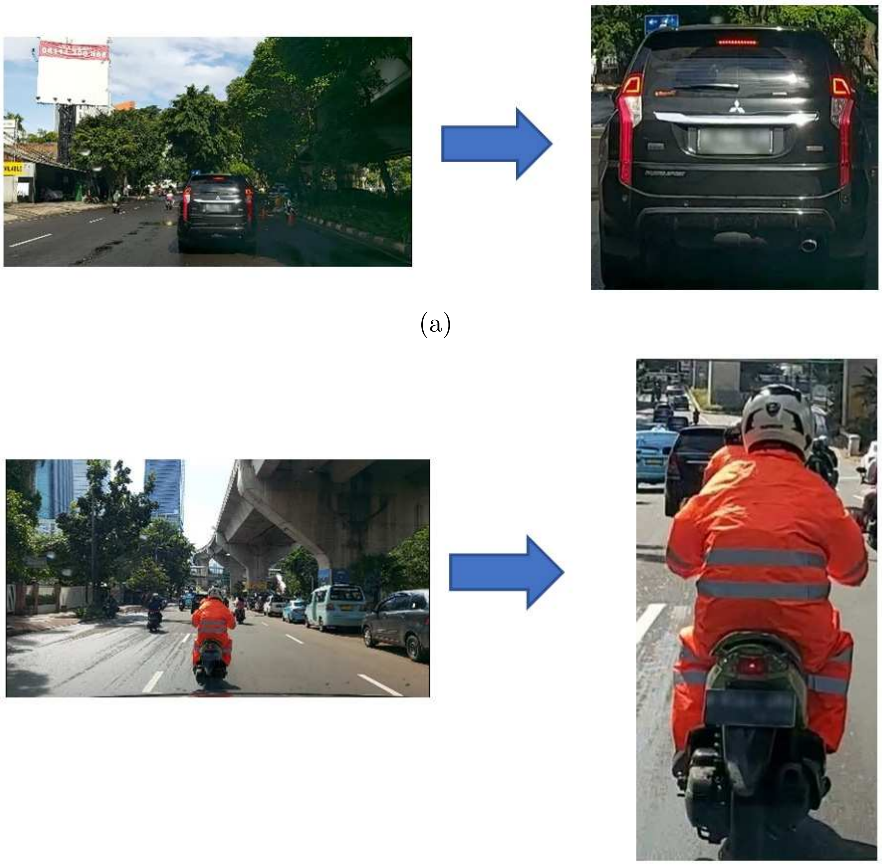
The image pre-processing steps (Figure 2) is used to remove unnecessary parts such as the sky, roads, and trees through the cropping process and also to produce several image combinations through the augmentation and image color conversion process. Several image combinations are needed to recognize objects when it is raining or foggy by creating a blur effect and at night by making a dark effect on the image.

Figure 2. Image pre-processing steps

By doing the cropping process (Figure 3), the image will be simpler and the classification process is more focused on the desired object. Augmentation (Figure 4) is used to add several combinations to the image dataset to produce a generalization for an object to be classified [15]. The addition of dark and blur effect (Figure 5) will increase the combination of the dataset for object classification during night, rainy or foggy weather.

After the image pre-processing is complete, the next step is to classify cars and motorbikes using CNN deep learning [16,17] (Figure 6). The car and motorbike image features from the camera will be extracted by a convolution process into numbers in the form of an array. The dimension of this array will be reduced by max polling through the down sampling process without losing important information by finding the maximum value of the array. The reduced array will be converted into a one-dimensional array by flatten process. After that, deep learning will be classified to determine the image of a camera in the form of a car or motorbike or not both.

Now we have images of cars and motorbikes that have been classified by CNN (Figure 7). The final step is to calculate the distance to the car or motorbike.



(a)

(b)

FIGURE 3. (a) Car cropping process; (b) motorbike cropping process

(a) (b)

FIGURE 4. (a) Horizontal flip car augmentation process; (b) horizontal flip motorbike augmentation process

Triangle similarity and pixel ratio are used to measure the distance of an object using a single camera. The focal length of the camera can be determined by Equation (1) [18].

$$F = (P \times D)/W \tag{1}$$

where P is the apparent width in pixel, D is the distance between the object and the camera, and W is the known width of the object. For example, the width of the car is 1.8 m and the distance between the car and the camera is 2 m and the resulting apparent width is 250 pixels, so the focal length is 277.78. Based on the same focal length for a car, if the distance is getting further away, then the calculation of the car's distance is

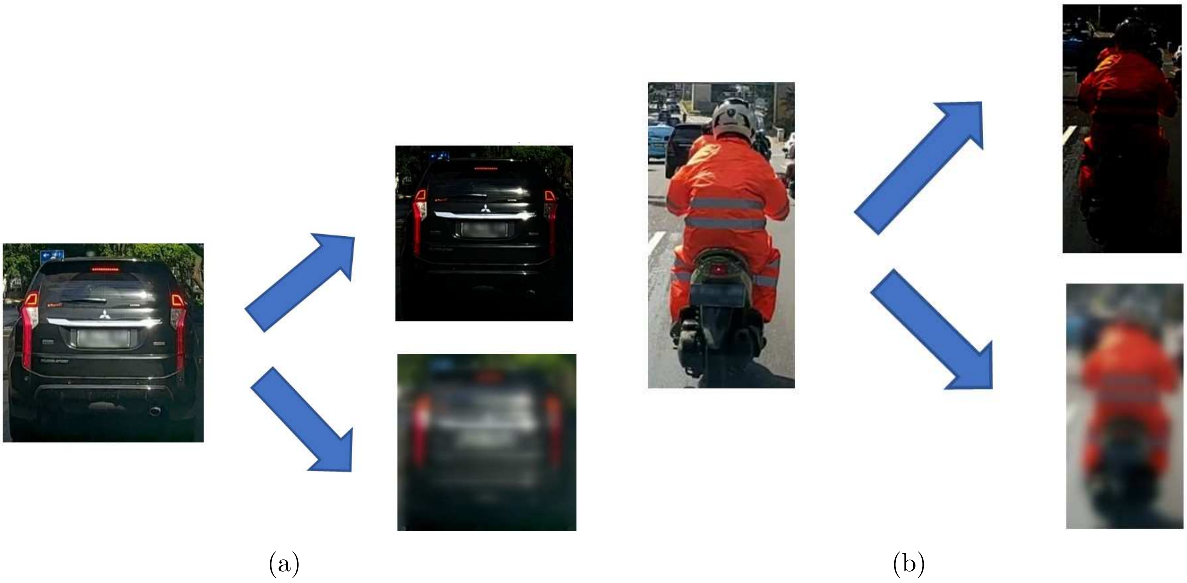


FIGURE 5. (a) Car dark and blur process; (b) motorbike dark and blur process

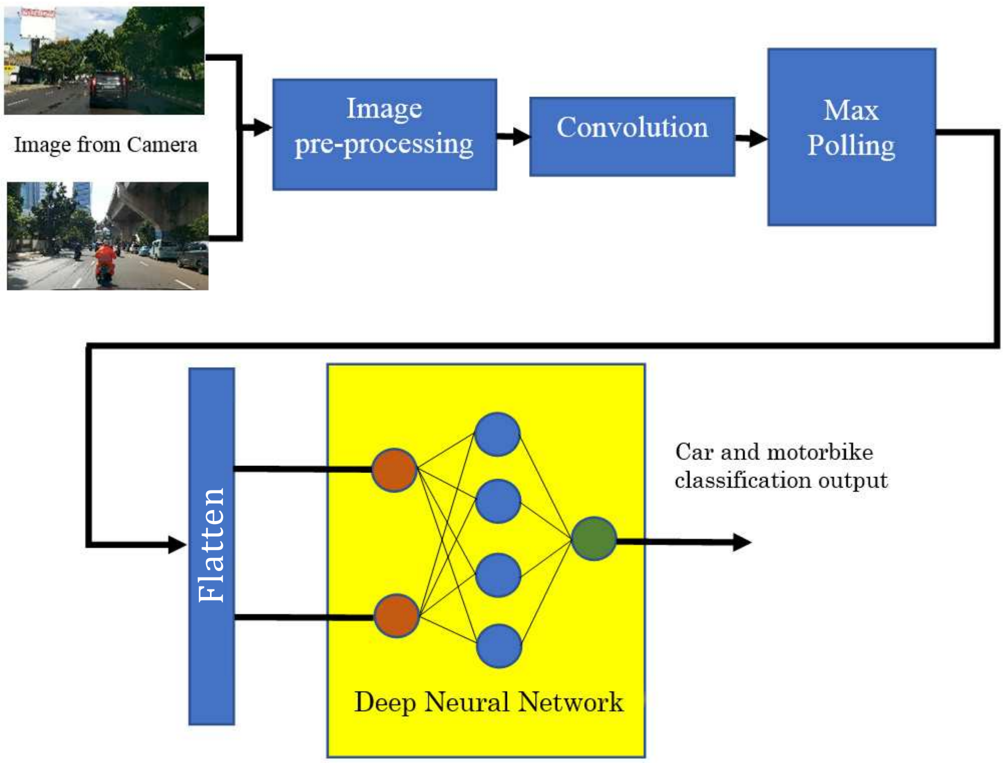


FIGURE 6. CNN deep learning car and motorbike classification process

shown by Equation (2).

$$D' = (W \times F)/P \tag{2}$$

With the further away the car to be measured, the apparent width P is getting smaller. For example, with an apparent width 100 pixels, the distance between the camera and the car is $(1.8 \times 277.78)/100 = 5$ m. The same calculation can be done for a motorbike using the standard width measurement of a motorbike.

After the vehicle distance measurement results are obtained, the next step is to make acceleration control system based on the recommendations from the distance measurement results (Figure 8). In general, with simple calculations, the safe distance between vehicles

(a) (b)

Figure 7. Car (a) and motorbike (b) classified by CNN

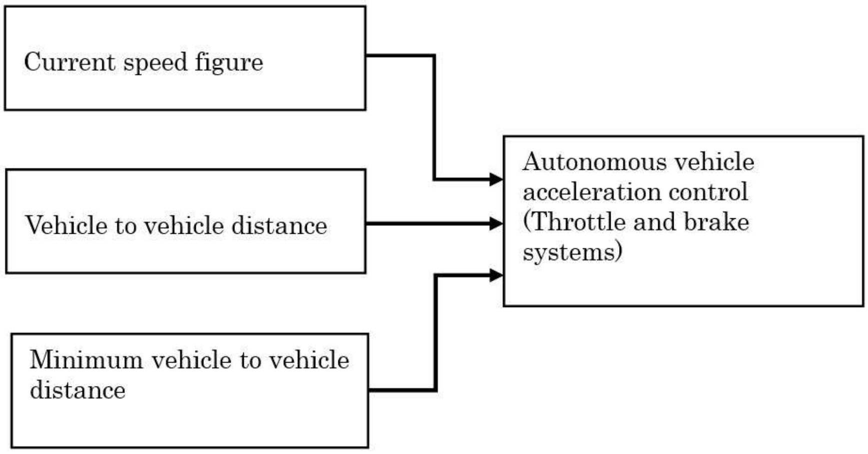


Figure 8. Autonomous vehicle acceleration control

can be determined from half the speed figure [19,20]. For example, if the vehicle speed is 100 km/h, then the safe distance from the vehicle in front is at least 50 m. Likewise, if the vehicle speed is 80 km/h, the safe distance from the vehicle in front is at least 40 m. To anticipate vehicles stopping in front, if the distance between vehicles is at least 10 m, the autonomous vehicle must reduce its speed until it stops at a minimum position of 2 m with the vehicle in front of it.

The following is the pseudocode of an autonomous vehicle accelerator controller.

Algorithm 1. Autonomous vehicle accelerator controller

If *the distance less than half of speed figure* **then**
    Reduce the speed gradually
else
    Keep running
end if
If *the distance less than 10 m* **then**
    Reduce the speed gradually until stop at the 2 m distance
else
    Keep running
end if

3. **Experiment and Results.** The primary dataset of cars and motorbikes from the rear view taken in Jakarta city is used for training in the CNN deep learning system. The dataset contains 2,500 cars and motorbikes where 80% of the dataset is used for training

and 20% for testing. The training process uses an NVIDIA GeForce 740M GPU that runs on a laptop with an i5-4200U CPU and 12GB of memory. The CNN model used is ResNet50 [21].

Reading the apparent width of the result of CNN deep learning classification automatically can be done using the simple Python programming. Two types of distance measurements were made for the classification results of motorbikes and cars. To measure the car distance, the W value is set to 1.8 and to measure the motorbike distance, the W value is set to 0.7. Experiments were carried out during the day, at night, and when it rained. The complete experimental results can be seen in Table 1.

Table 1. Vehicle to vehicle distance measurement experiment result

Condition	Car		Motorbike	
	Measurement (meter)	Actual (meter)	Measurement (meter)	Actual (meter)
Daytime	5.2	5.5	5.1	5.3
	4.4	4.3	4.6	4.5
	3.5	3.6	3.2	3.1
Night	5.5	5.3	5.3	5.4
	4.1	4.3	4.3	4.4
	3.4	3.3	3.5	3.6
Rainy day	5.0	5.3	5.5	5.3
	4.2	4.4	4.7	4.5
	3.1	3.2	3.7	3.6

Based on Table 1, the accuracy generated by this method is 94% where the experiment was carried out 3 times for each condition. Distance measurement and speed figure can be displayed on the live camera view as shown in Figure 9.

(a) (b)

Figure 9. Live camera display of car (a) and motorbike (b) classified by CNN and distance measurement

4. **Conclusion and Future Experiment.** Vehicle to vehicle distance measurement using single-camera can be implemented to maintain the distance between vehicles in an autonomous car by utilizing the existing camera. With this method, the use of radar and lidar to measure the distance between vehicles can be replaced with a single camera.

Further experiments can be carried out to measure distances for larger vehicles such as buses and trucks or to measure distances for pedestrians through classification process and adjustment of W values.

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