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Vehicle Counter in Traffic Using Pixel Area Method with Multi-Region of Interest

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Abstract

Traffic density data plays an important role in decision making by the Intelligent Transportation System (ITS). This system uses this data in the process of adaptive traffic management. The inaccuracy of the data provided into the ITS system can result in errors in decision making. This study utilizes digital image engineering technology in the detection of four-wheeled vehicles in traffic traffic for the purpose of acquiring traffic density data. In this study, we propose a multi-ROI (pixel area methodRegion of Interest). This multi-ROI proposal is to be put forward to improve reading accuracy compared to just one ROI. With the use of this multi-ROI, the information obtained from the overall ROI can strengthen the accuracy of the data of vehicles passing in a lane. Our experimental results show that the use of multi-ROI with a certain amount of ROI can produce an accuracy rate of up to 88.66% compared to single-ROI which has an accuracy rate of 84.65%.

Keywords
vehicle detection; pixel area; traffic counter; digital image engineering.

I. Introduction

Traffic regulation using adaptive traffic lights produces a system that is able to regulate traffic flow based on lane density. (P Jing, H Huang, L Chen, 2017). Adaptive traffic management is known as smart traffic light smart traffic light system in a system called Intelligent Transportation System(ITS). (AAAR Magableh,ET AL. 2020) This smart traffic light is capable of acquiring data from captured digital images. From this data entered, data on vehicle density in traffic is obtained by recognizing objects on the path. The data entered into the Intelligent Transportation System must be as accurate as possible with the actual conditions. Data inaccuracies will result in decision making that is not in accordance with the original conditions.

Some of the vehicle density data methodologies in traffic can be done conventionally. This conventional method is by counting by observers who make observations at a certain time. The data obtained are calculated statistically. With this method, there are drawbacks, namely the data that is processed is notdata real-time. (D. Pavleski, D. Kotlovska Nachos, 2019) Sensors are used to obtain this data. Sensors such as pneumatic road tube counting,piezoelectric sensor, inductive loop, magnetic sensor, acoustic detector, passive infrared, and traffic camera are examples sensors that can be used to getdata real-time. Sensor-based data acquisition uses physical quantities taken by sensors to detect passing vehicles. (YB Brahme, PS Kulkarni, 2011)

Camera traffic as a sensor has advantages over other sensors. The traffic camera detects vehicles based on the input image so that the data taken is the result of processing with an

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object recognition process. The other sensors mentioned earlier are unable to verify that the object that triggers the sensor is a vehicle or not. This fact is also a source of data errors caused by objects that are not related to vehicles that can be read by sensors. The existence of a camera for traffic has a wider function than the sensors we mentioned earlier. The function is in detecting accidents that occur in traffic and also traffic violations.

The method of detecting vehicles in traffic with digital image engineering from camera captures, one of which is the pixel area. This method processes digital images from the video feed cameras which is then detected by the segmentation process of the oncoming vehicle object. If the segmentation output is in the ROI (Region of Interest), and the has been reached, its threshold ROIwill be recognized as an object from the detected vehicle. Studies on this method to detect day and night traffic show an accuracy of 88.3%. (AMAM Akbar, et al, 2016)

We propose the use of multi-ROI in the pixel area method. Our proposal is intended to improve the accuracy of the previous method. In our proposal, vehicle detection in a traffic lane is carried out with multiple ROI. With our proposed multi-ROI, it is predicted to increase accuracy. Our prediction is based on the failure of one ROI to detect the vehicle, the other ROI can still detect it. In addition, the presence of multi-ROI can verify the results of readings between ROIs so that readings of one ROI strengthen other ROI readings. With this proposed method, it is hoped that the data acquired from the traffic cameras will be in accordance with the actual conditions.

II. Review of Literature

Computer vision ability in traffic image processing is needed in object recognition. Digital image data acquired by traffic cameras is processed by the recognition method so that objects in traffic can be recognized. The data that is used as a reference by the Intelligent Transportation System (ITS) as the basis for traffic management. This data allows the ITS system to know the state of the regulated traffic environment. There are two ways to detect vehicle objects in a traffic digital image. This method is vehicle detection based on appearance, and based on motion. (M. Al-Smadi, 2016)

In the case of appearance-based detection, there is a form of knowledge to segment the foreground against the background. An example is shown in Figure 1 where in the image there is an input image coming from a traffic camera with a background. The result of both produces foreground. The result of segmentation that produces object foreground this will then be tried to be recognized. The method for recognizing this object is in the form of feature, part, or three-dimensional model-based recognition. Feature-based recognition method, extracting areas of interest. The result of this extraction represents an instance specific to the vehicle object. Machine learning techniques use these representations for training data. (MA Manzoor, 2017)

The concept of human resource development is an attempt to improve technical, theoretical, conceptual, and education and training. The types of development are grouped into informal development and formal development: 1) Informal development, namely employees on their own desires and efforts train and develop themselves by studying literature books that have to do with their work or position. Informal development shows that the employee is eager to advance by improving his work ability. 2) Formal development, where employees are assigned by the company to take part in education and training, both those conducted by the company and those carried out by educational and training institutions. (Setiawan, D and Marfistasari, A. 2021)

One of the feature-based recognition methods is the method Scale Invariant Feature Transform (SIFT)[14]. In this method, the input image will be transformed to a set largeof feature vector values, where the members in the set do not vary for the magnitude of image translation, scaling, and rotation key point(keypoint)is the SIFT taken from the min-maxing differentiation result function Gaussian in scale-space to set the image smoothed and the sampling repeated. Low-contrast candidate points along with edge response points that are along the edges will be removed. The dominant orientation will be the key point locally. This step is intended to ensure a stable key point in the matching and recognition of an object that varies due to different orientations.

III. Research Method

Another method is Speed Up Robust Features (SURF)[15]. The SURF method has the same principles and steps as SIFT. In the SURF method, the filter used is square in the process of Gaussian smoothing. In contrast to SIFT which uses a cascaded filter to detect invariant characteristic points, the differentiation Gaussianis calculated on a progressively scaled image. Then there is the method Histogram of oriented gradients (HOG). HOG is a form of feature descriptor in digital image processing for object detection. (S. Bougharriou) This technique is based on calculating the orientation of the gradient that appears on local parts of an input image.

One other technique is the Otsu threshold. Otsu threshold was initially used as a method of segmentation, however Otsu threshold has been found to be used in making the representation of the content of the image, as well as texture recognition. The use of this Otsu threshold previously mentioned has a fairly good performance with an accuracy of up to 88% for vehicle detection. (C. Vertan, et al. 2017)

This research was conducted using the method as shown in Figure 2. The digital image that became the input was made in the form of a video stream which was obtained via the TCP (Transport Control Protocol Protocol)on the localhost. This design considers further development where by building a TCP/IP-based system, input data can be streamed via an internet connection. The input data to be used in this method can be via livestream from IP-based traffic cameras, as well as video data from existing databases. In this study, the data used are traffic datasets that are available online. The data is stored in localhost which will later be streamed as video input.

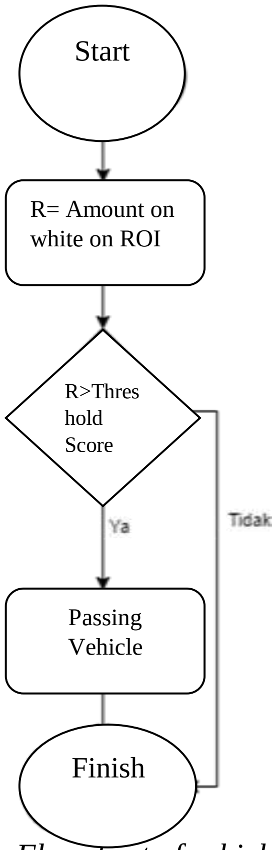


Figure 1. *Flowchart of vehicle detection*

For consideration of system expansibility, this application is made web-based. This is because this application can be utilized in the cloud. This web-based use also makes it easier to input data sent via the TCP/IP protocol. Later this web application itself will be made in a modular manner with a vehicle detection system.

The next step is after the web application has received input data, the data will proceed to the first digital image processing process, namely the reconstruction and subtraction of the background image. Digital image processing is made using an application built using OpenCV [19]. This image processing application is connected to the web application and is placed on the same host. This digital image processing application will reconstruct each piece of the frame from the input video and subtract the background image. Background subtraction image obtained by the method of weighted accumulate where in the sum of weights of pixels of a digital image input is calculated and then do the running average(runningaverage)against that image. Later the background image will be obtained based on the comparison of the average weight value between the input frames. That way, the results of background subtraction from the input video will produce an image with remaining objects other than the background. (OpenCV, I, 2017)

The results of the image after being subtracted will be segmented followed by the detection of passing vehicles. This segmentation is done to divide the objects that exist in the image so that it can be calculated how many objects are in a frame in the image. This segmentation wears Otsu threshold, onmethod, threshold Otsu that the threshold value(threshold)is determined automatically. Determination of the threshold based on the intensity value of the input image histogram.

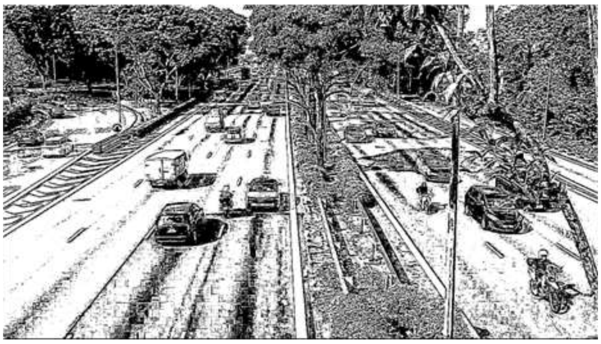
The image from this segmentation will be further processed for vehicle detection. Vehicle detection is a process to determine the presence of passing vehicles. This detection is carried out in an area of the image called the region of interest(ROI). The vehicle detection process can be seen in Figure 3. The first process is to calculate the pixel area on the ROI which is white from the results Otsu threshold. Where the white pixel is the magnitude of an object in the image. Next is checking the number of pixels against the vehicle threshold value. The vehicle threshold value is obtained from the number of pixels in the percentage of the detection area. If this threshold value is exceeded, it indicates a passing vehicle. In the method in this study, vehicle detection in a lane will use multi-ROI. The results of each ROI will be compared to determine the number of vehicles that pass. By using this multi-ROI, vehicle detection accuracy is expected to be more accurate than using a single ROI.

The results of the detection of passing vehicles by the image processing application will be sent to the web application. These results are used for the final process, namely vehicle counting. This web application will record the results of traffic detection that has been carried out on the database. This result is in the form of the number of vehicles detected along with a description of the time when each vehicle was detected. The detection results will be compared with the actual value of the amount of traffic in the dataset. This true value is obtained from processing the dataset tested by an analyst. Performance in the form of the accuracy of the calculation results obtained from the comparison of the two values.

IV. Result and Discussion

The system experiment was carried out with input from the dataset and tested with the number of ROI from one to four ROI. A snapshot of one of the frames taken from the recorded traffic on the dataset can be seen in Figure 4a.The data frame is processed by reconstructing the image from the background. This process is shown in Figure 2, the image will be reconstructed which then produces the output image in Figure 4b. The next process is image segmentation. This segmentation uses the method Otsu threshold. An example of a digital image from the Otsu threshold is shown in Figure 4c. In Figure 4c there is a value of the object of a passing vehicle that will be hit by the threshold lower. Objects that are hit by threshold this lowercause the object to be reconstructed into an object with white pixels. On the other hand, the object that becomes the background image is exposed to the threshold upper. This causes the background image to become a black image. Detection of a passing vehicle object is shown in Figure 3. When a passing vehicle is detected in the ROI, the vehicle will be calculated as a passing vehicle when the value requirements threshold on the ROI are met. In our tests, the vehicles to be detected are four-wheeled vehicles.

(a)



(b)

(c)

Figure 2. *Footage of the frame from the image processed video: (a) Initial image, (b) Image after reconstructed and subtracted, (c) Image after segmentation to be recognized as a vehicle object calculated at a certain ROIFig.*

The test results of our proposed method show the results shown in tables 2 to 4. Table 1 is the result of using single-ROI as a comparison of performance with the multi-ROI method. The single-ROI results show an accuracy of 84.65%. Our proposed multi-ROI method results in increased accuracy at a given amount of ROI. In the use of two ROI there is an increase in accuracy when compared to single-ROI. Testing the use of two ROIs resulted in an accuracy of 88.66%. Meanwhile, in the three ROI tests, the accuracy dropped to 84.54%. The decrease in accuracy occurred again in the use of four ROI, namely with an accuracy result of 79.59%.

The addition of our proposed ROI increases the detection sensitivity. This increased sensitivity makes vehicle detection more accurate. This is shown in the increase in detection true positive in the confusion matrix table in tables 1 to 4. However, in the table it can also be seen that the results of false positives also increase along with the addition of this ROI. The optimal ROI value with the highest accuracy is in the two ROIs for the data we tested.

IV. Conclusion

Test data show that the use of our proposed multi-ROI method has an impact on vehicle detection sensitivity. Using the optimal number of ROIs for detecting vehicles in one lane is at two ROIs for the datasets we tested. However, the data obtained also shows that increasing the amount of ROI does not always increase accuracy. The best accuracy is on a certain amount of ROI where in our case, the best accuracy is on two ROI with an accuracy of 88.66%. The topic of determining the optimal amount of ROI for various cases will be the subject of further study for further research studies.

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