www.bircu-journal.com/index.php/birci
Budapest International Research and Critics Institute-Journal (BIRCI-Journal)
Humanities and Social Sciences
ISSN 2615-3076 Online)
ISSN 2615-1715 (Print)
Budapest Institute

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

Moch Fachri[1], Nur Hikmah[2], Nuke Lu'lu ul Chusna[3]
[1,2,3]*Faculty of Engineering, Universitas Krisnadwipayana, Indonesia*
moch.fachri@unkris.ac.id, nurhikmah@unkris.ac.id, nukelchusna@unkris.ac.id

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 (Region of Interest) pixel area method. 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 capable of regulating traffic flow based on lane density. Adaptive traffic management utilizes a smart traffic light system known as *smart traffic light* in a system called *Intelligent Transportation System* (ITS). *a smart traffic light* is capable of acquiring data from captured digital images. From this data entered, data on vehicle density in a traffic is obtained by recognizing objects on the route. The data entered into the *Intelligent Transportation System* must be as accurate as possible with the actual conditions. Data inaccuracies will result in decisions that are not in accordance with the original conditions. Transportation at this time has become a basic need for community activities, especially the activities of the people of North Sumatra. These activities make transportation an important choice with an increasing number of populations using transportation modes, especially public transportation. (Agussani, 2020)

Some of the vehicle density data methodologies in a 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 not *real*. 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 get *real*. Sensor-based data acquisition uses physical quantities taken by sensors to detect passing vehicles.

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 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. This function is in detecting accidents that occur in traffic and also traffic violations.

The method of detecting vehicles in traffic by engineering digital images from camera captures, one of which is the pixel area. This method processes digital images from *video feed* which is then detected by the segmentation process of the oncoming vehicle object. If the segmentation output is in the ROI (*Region of Interest Has* been reached, *threshold* it will 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%.

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 traffic cameras will match the actual conditions.

II. Research Method

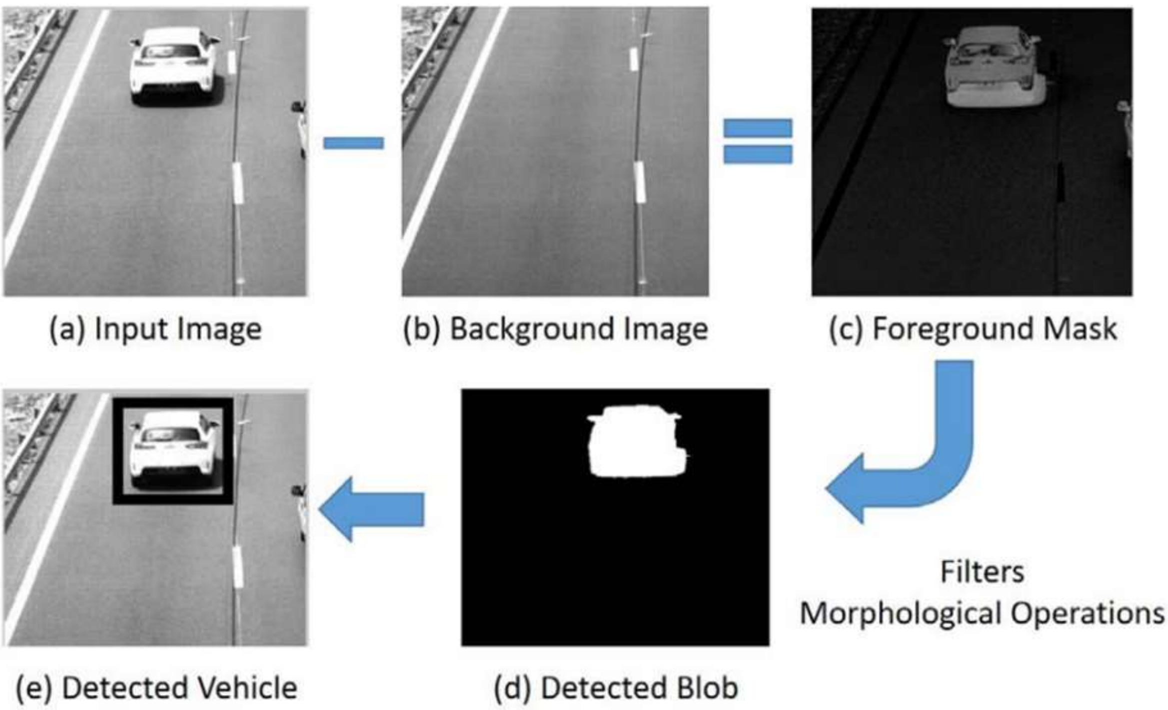

Figure 1. *Traffic image*

Computer vision capability 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 regulation. 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*.

In the case of appearance-based detection, there is a form of knowledge to segment *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 results of both produce *foreground*. The result of segmentation that produces *foreground* 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 of the vehicle object. Machine learning techniques use these representations for training data.

Scale One of the feature-based recognition methods is the *Invariant Feature Transform* (SIFT) method. In this method, the input image will be transformed to a *set* of feature vector values, where the members in *the set* do not vary for the magnitude of image translation, scaling, and rotation. The Key *points in* SIFT are taken from *min-maxing* the differentiation of the *Gaussian* at the spatial scale to *set* the smoothed and resampled image. The low-contrast candidate points along with the edge response points present 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.

Another method is *Speed Up Robust Features* (SURF). The SURF method has the same principles and steps as SIFT. In the SURF method, *the filter* used is square in the *Gaussian smoothing*. In contrast to SIFT which uses *a cascaded filter* to detect invariant characteristic points, the *Gaussian* calculated on a progressively scaled image. Then there is the *Histogram of oriented gradients* (HOG) method. HOG is a form of *feature descriptor* in digital image processing for object detection. 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*. *The Otsu threshold* was originally used as a segmentation method, but the *threshold* has been found to be used in capturing representations of the content of an image, as well as texture recognition. The use of *Otsu threshold* previously mentioned has a fairly good performance with an accuracy of up to 88% for vehicle detection.

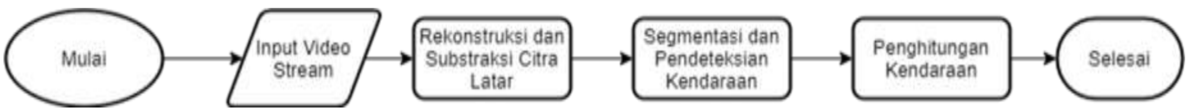

Figure 2. *Research method*

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 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 datasets that are available online. The data is stored in localhost which will later be streamed as video input.

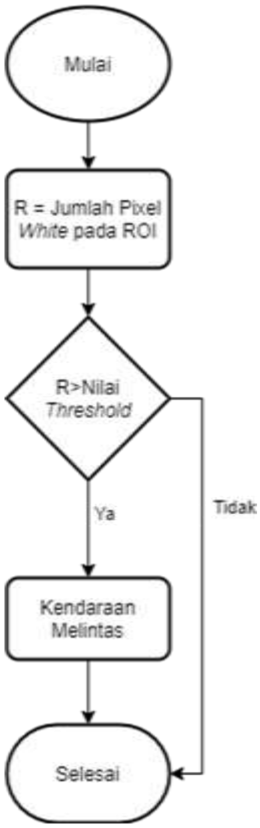

Figure 3. *Flowchart of vehicle detection*

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 stage after the web application receives input data, the data will be continued 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 Open CV. 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 frame from the input video and subtract the background image. Background image subtraction is obtained by the accumulate weighted where the number of pixel weights from the input digital image is calculated and then a running average on the 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.

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 uses Otsu threshold, in this Otsu threshold, the threshold value method is determined automatically. Determination threshold based on the intensity value of the input image histogram.

The image from the segmentation results 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 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 traffic detection results that have 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 calculation results accuracy is obtained from the comparison of the two values.

III. Results and Discussion

Experimentation of the system 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.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 Otsu threshold method. An example of a digital image from the Otsu threshold is shown in Figure 4c. In Figure 4c there is a value of passing vehicle objects that will be hit by threshold. Objects that are hit by threshold cause 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. 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 threshold on the ROI is met. In our tests, the vehicles to be detected are four-wheeled vehicles.

(a)

(b)

(c)

Figure 4. *Footage the frame from the image processed video: (a) Initial image, (b) Image after reconstructed and subtracted, (c) Image after segmented to be recognized as a vehicle object calculated at a certain ROI*

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 occurs 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 true positives in the confusion matrix table in tables 1 to 4. However, in the table it can also be seen that the false positive also increases 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.

Table 1. *Confusion matrix* for single-ROI

		Predicted Result	
		Positive	Negative
Actual Result	True	612	21
	False	113	127

Table 2. *Confusion matrix* for two ROI

		Predicted Result	
		Positive	Negative
Actual Result	True	657	31
	False	68	117

Table 3. *Confusion matrix* for three ROI

		Predicted Result	
		Positive	Negative
Actual Result	True	671	81
	False	54	67

Table 4. *Confusion matrix* for four ROI

		Predicted Result	
		Positive	Negative
Actual Result	True	679	132
	False	46	15

IV. Conclusion

The 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 dataset* 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 ROIs 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.

Acknowledgments

The authors would like to thank RISTEKBRIN for its research grant funding.

References

A. El Bouziady, ROH Thami, M. Ghogho, O. Bourja, S. El Fkihi, "Vehicle speed estimation using extracted SURF features from stereo images," in 2018 International Conference on Intelligent Systems and Computer Vision (ISCV), Fez, Apr. 2018, pp. 1–6, doi:10.109/ISACV.2018.8354040.

AAAR Magableh, MA Almakhadmeh, N. Alshin, and AF Klaib, "Smart Traffic Light Management Systems: A Systematic Literature Review," International Journal of Technology Diffusion, vol. 11, no. 3, pp. 22–47, Jul. 2020, doi: 10.4018/IJTD.2020070102.

Agussani. (2020). Implementation Analysis of Trans Mebidang Program in Transportation Mode Services, North Sumatera (Comperative Study of Medan City). *Budapest International Research and Critics Institute-Journal (BIRCI-Journal).* P. 1167-1174.

AMAM Akbar, A. Kurniawan, A. Zaini, "Traffic IP Camera for Counting Four-Wheel Vehicles Using the Pixel Area Method," in the Digital Library of the Sepuluh Nopember Institute of Technology, Surabaya, Apr. 2016.

C. Vertan, C. Florea, L. Florea, MS Badea, “Reusing the Otsu threshold beyond segmentation,” in 2017 International Symposium on Signals, Circuits and Systems (ISSCS), Iasi, Romania, Jul. 2017, pp. 1–4, doi:10.109/ISSCS.2017.8034908.

D. Pavleski, D. Koltovska Nechoska, “Evaluation of Adaptive and Fixed Time Traffic Signal Strategies: Case study of skopje,” Transport for Today's Society, 2019, doi: 10.20544/TTS2018.P21.

Drive Cam UK, Aug. 04, 2020. https://sites.google.com/site/drivecamuk/.

E. Odat, JS Shamma, C. Claudel, “Vehicle Classification and Speed Estimation Using Combined Passive Infrared/Ultrasonic Sensors,” IEEE Trans. Intell. Transport. Syst., vol. 19, no. 5, pp. 1593–1606, May 2018, doi: 10.1109/TITS.2017.2727224.

M. Al-Smadi, K. Abdulrahim, RA Salam, “Traffic Surveillance: A Review of Vision Based Vehicle Detection, Recognition and Tracking,” vol. 11, no. 1, p. 15, 2016.

M. Liepins, A. Severdaks, “Vehicle detection using non-invasive magnetic wireless sensor network,” in 2013 21st Telecommunications Forum Telfor (TELFOR), Belgrade, Serbia, Nov. 2013, pp. 601–604, doi:10.109/TELFOR.2013.6716302.

MA Manzoor, Y. Morgan, “Vehicle Make and Model classification system using bag of SIFT features,” in 2017 IEEE 7th Annual Computing and Communication Workshop and Conference (CCWC), Las Vegas, NV, USA, Jan. 2017, pp. 1–5, doi:10.109/CCWC.2017.7868475.

Open CV, I., 2017. Open source computer vision library.

P Jing, H Huang, L Chen, “An Adaptive Traffic Signal Control in a Connected Vehicle Environment: A Systematic Review,” Information, vol. 8, no. 3, p. 101, Aug. 2017, doi:10.3390/info8030101.

P. McGowen and M. Sanderson, “Accuracy of Pneumatic Road Tube Counters,” Western District Annual Meeting Institute of Transportation Engineers, Anchorage AK, United States. p. 17. May. 2011

S. Bougharriou, F. Hamdaoui, A. Mtibaa, “Linear SVM classifier based HOG car detection,” in 2017 18th International Conference on Sciences and Techniques of Automatic Control and Computer Engineering (STA), Monastir, Dec. 2017, pp. 241–245, doi:10.109/STA.2017.8314922.

S. Dutt, A. Kalra, “A scalable and robust framework for intelligent real-time video surveillance,” in 2016 International Conference on Advances in Computing, Communications and Informatics (ICACCI), Jaipur, India, Sep. 2016, pp. 212–215, doi:10.109/ICACCI.2016.7732049.

S. Sheik Mohammed Ali, B. George, L. Vanajakshi, J. Venkatraman, “A Multiple Inductive Loop Vehicle Detection System for Heterogeneous and Lane-Less Traffic,” IEEE Trans. instrument. Meas., vol. 61, no. 5, pp. 1353–1360, May 2012, doi: 10.1109/TIM.2011.2175037.

SA Rajab, A. Mayeli, HH Refai, “Vehicle classification and accurate speed calculation using multi-element piezoelectric sensor,” in 2014 IEEE Intelligent Vehicles Symposium Proceedings, MI, USA, June. 2014, pp. 894–899, doi:10.109/IVS.2014.6856432.

Y. Na, Y. Guo, Q. Fu, Y. Yan, “An Acoustic Traffic Monitoring System: Design and Implementation,” in 2015 IEEE 12th Intl Conf on Ubiquitous Intelligence and Computing and 2015 IEEE 12th Intl Conf on Autonomic and Trusted Computing and 2015 IEEE 15th Intl Conf on Scalable Computing and Communications and Its Associated Workshops (UIC-ATC-ScalCom), Beijing, Aug. 2015, pp. 119–126, doi:10.1109/UIC-ATC-ScalCom-CBDCom-IoP.2015.41.

YB Brahme, PS Kulkarni, “An Implementation of Moving Object Detection, Tracking and Counting Objects for Traffic Surveillance System,” in 2011 International Conference on Computational Intelligence and Communication Networks, Gwalior, Oct. 2011, pp. 143–148, doi:10.109/CICN.2011.28.

Z. Yang, LSC Pun-Cheng, “Vehicle detection in intelligent transportation systems and its applications under varying environments: A review,” Image and Vision Computing, vol. 69, pp. 143–154, Jan. 2018, doi:10.1016/j.imavis.2017.09.008.