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AUTOMATIC VEHICLE COUNTER SYSTEM BASED BLOB DETECTION FOR HIGHWAY SURVEILLANCE

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Abstract—*The number of vehicles that increase every year has a major impact on the occurrence of congestion and accidents and causes a significant increase in the volume of vehicles, especially on the highway. With this increase, many officers find it difficult to be able to anticipate or supervise vehicles directly. The research that we made, entitled Automatic Vehicle Counter System Based on Blob Detection for Highway Surveillance Using OpenCV, is a solution to this problem because by utilizing image transformation it makes it easier for the system to be able to detect vehicles and identify the number of vehicles entering the lane. The results obtained show an accuracy value of 97.11% based on testing with 10 video samples, with a total of 1329 vehicles detected out of a total of 1362, meaning that the total error is only 3.02%.*

Keywords: *Vehicle counter, Blob Detection, OpenCV, Morphological Operation.*

Intisari—*Jumlah kendaraan yang meningkat setiap tahunnya berdampak besar terhadap terjadinya kemacetan dan kecelakaan serta menyebabkan peningkatan volume kendaraan yang signifikan terutama di jalan raya. Dengan peningkatan tersebut, banyak petugas yang kesulitan untuk dapat mengantisipasi atau mengawasi kendaraan secara langsung. Penelitian yang kami buat dengan judul Sistem Pengihitung Kendaraan Otomatis Berbasis Deteksi Blob Untuk Pengawasan Jalan Raya Menggunakan OpenCV merupakan solusi dari permasalahan tersebut karena dengan memanfaatkan transformasi citra memudahkan sistem untuk dapat mendeteksi kendaraan dan mengidentifikasi jumlah kendaraan. kendaraan yang memasuki jalur. Hasil yang diperoleh menunjukkan nilai akurasi sebesar 97,11% berdasarkan pengujian dengan 10 sampel video, dengan jumlah kendaraan yang terdeteksi sebanyak 1329 dari total 1362, artinya total error hanya 3,02%.*

Kata Kunci: *Vehicle counter, Blob Detection, OpenCV, Morphological Operation.*

INTRODUCTION

The significant increase in the purchase of motorized vehicles from year to year, especially private vehicles, has a high impact on the emergence of traffic congestion, particularly in Indonesia. The purchase of private vehicles has increased by 4.12% annually, while commercial and public transport vehicles have increased by an average of 4.69% [1], and this trend continues to rise each year. The consequence of this is the increasing volume of vehicles on the roads, leading to severe congestion in both urban areas and highways where congestion should not occur. In Indonesia, specifically on Java Island, the length of the highway is approximately 526.65 km [1], yet traffic congestion is still frequently encountered. This is especially evident during holidays and festive seasons. Although not all traffic congestion is directly related to the roads, factors such as accidents, traffic violations, pedestrians crossing illegally, illegal parking, and others contribute significantly to traffic congestion.

Therefore, there is a need for intensive monitoring and enforcement of the violations that occur. Currently, monitoring of vehicles on the highway, especially on toll roads, is still carried out manually by field officers and the limited use of

CCTV means that little effort has been made to overcome this problem.,

vehicle images to make it easier to classify and calculate objects from two different directions. The

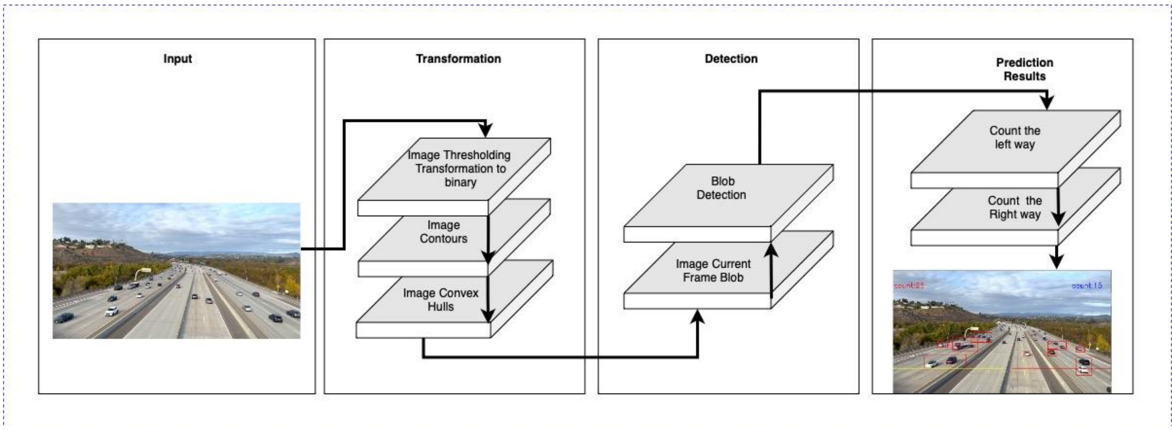

Figure 1. Block Diagram Detection System

CCTV means that little effort has been made to overcome this problem. Manual monitoring often encounters difficulties in estimating the number of vehicles passing through the road, especially during holidays. Therefore, the development of object detection technology and digital image processing is proposed to help monitor and estimate the flow of vehicles on the highway. With this technology, officers are expected to be able to know the number of vehicles passing through the road so that they can predict the buildup of traffic that will occur so that officers can conduct traffic engineering before congestion occurs. This paper is structured as follows: Part II Related Work, Part III Proposed Method, Part IV Experimental Results, Part V Conclusions.

MATERIALS AND METHODS

Several studies have implemented the object detection feature to be able to count the number of vehicles on the freeway, including using a detection technique utilizing the KNN (K-nearest neighbour) algorithm. In a study conducted by Salma Bouaich and her colleagues, they succeeded in detecting and counting the number of vehicles using a method based on real-time object detection with an accuracy of 96% [2]. In addition, research conducted by Prashant Kumar succeeded in detecting computer vision-based vehicles and utilizing morphological operations with an accuracy of 96.85% for the 7 sample videos tested [3][4].

There is a similar study using a different method, as was done by Ravula and friends. In their research, they used morphological operations and utilized the Kalman filter as a basis for transforming research conducted by them used six video samples with an accuracy above 90% for each video tested [5]. In this research, we build on and develop previous research conducted by Salma and friends with different methods. In this research, we use the blob detection method using a morphological algorithm as a basis for object detection and feature extraction from the images obtained. The video samples used will be transformed into binary form. This transformation process aims to be more easily detected by the counter that has been designed by changing the information value to binary, namely 0 and 1. Then the vehicle that is successfully classified will be given a bounding box as a guide so that it can be detected by the counter, which is in the form of a horizontal line that will be applied in each vehicle lane. Later, if the bounding box hits and passes the counter, it will be considered a vehicle and counted into the calculation results. The error threshold that we set in this study is 50%; if the information from the vehicle exceeds this limit, it will be counted, but if it is below the set threshold, it fails to be detected. The purpose of this research is to detect and calculate the number of vehicles passing through the road automatically based on video.

The proposed system is intended to be able to identify vehicles that are running; besides, the system created can detect and simultaneously count the number of vehicles passing through the road from two different lanes. Vehicles that can be detected by the system when the transformation process results show that a portion of the vehicle exceeds a predetermined threshold of 50%, with this threshold value anticipating failures in vehicle detection and calculation.

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Figure 1 shows a block diagram of the system design in this study. The proposed system is able to identify vehicles and count the number of vehicles passing through the road. Initially, video samples were taken with a time frame of each video of 20 seconds and different shooting locations. After that, the results of the video will be transformed by utilizing morphological operations, which aim to change the color values in it to binary. This transformation process will make it easier for the system to be able to select and detect the information you want to retrieve, in this case, cars. The method used to detect this vehicle is blob detection [6][7].

This method has the advantage of recognizing the information entered into the Bounding Box and can identify vehicles based on a predetermined number of thresholds. If a vehicle that has been recognized by the bounding box enters the counter area at more than 50% of the predetermined threshold amount, it will be considered as having provided information about the vehicle, or "positive," but if the recognized value is less than 50% of the predetermined limit, the system will fail to detect the vehicle, and the result will be "negative." This study utilizes aerial video taken using a camera from above the highway. The video quality used in this study is 1280 x 720.

All experiment are carried out on a windows 10 workstation with amd ryzen 5 3600 6-core processor, 32GB of RAM and single NVIDIA Geforce GTX 1060 with 6GB of memory running under Visual Studio 2015 with the 30fps.

A. Input & Image Thresholding

Input

This section will describe the approach used during the test to detect the vehicle from the video frame, as shown in Figure 2. We took ten 20-second video samples from the source youtube and ChangeDetection.net dataset (CDnet 2014) dataset as test samples for testing; The videos we use are road videos taken from the air in various places with different traffic situations.

Figure 2. One of the videos used for the detection

Table 1. Initial Data Sample

Sample Video	Number Of Vehicles		Total Vehicles	Time (s)
	Left Side	Right Side		
Test 1	85	75	160	20
Test 2	50	60	110	20
Test 3	60	40	100	20
Test 4	50	25	75	20
Test 5	75	40	115	20
Test 6	75	83	158	20
Test 7	130	169	299	20
Test 8	70	90	160	20
Test 9	55	63	118	20
Test 10	36	31	67	20

From the initial sample data obtained in Table 1, there are ten samples from different test locations which we named Test because the source dataset we took only met the requirements. as well as measuring in terms of computer computing capabilities used. The initial data contains information on the number of vehicles traveling from the two sides. The purpose of this initial data collection will later be compared with the resulting data as a parameter determining system accuracy.

Image Thresholding

After obtaining the initial data, the next step is to transform the video into binary form. Because binary images only have two possibilities, namely black for 1 and white for 0, it's easier to detect using morphological and bounding box operations.

After that, a thresholding process is carried out, namely filtering incoming information based on predetermined standards so that the video can be easily detected. The thresholding process used is bi-level thresholding, namely, an intensity value that is smaller than the threshold value will be used as the first area, and a value greater than or equal to the set threshold value will be the second area. In this case, one of these areas is located in the background; this process is also known as intensity thresholding. mathematically written in the following equation (1).

$$b(x,y) = f(x) = \begin{cases} 0, & if\ (x,y) \geq T \\ 1, & if\ (x,y) < T \end{cases} \quad \text{.........} (1)$$

Where b binary images, f (x,y) Binary image after thresholding, T threshold, 1 and 0 represents the binary in the image.

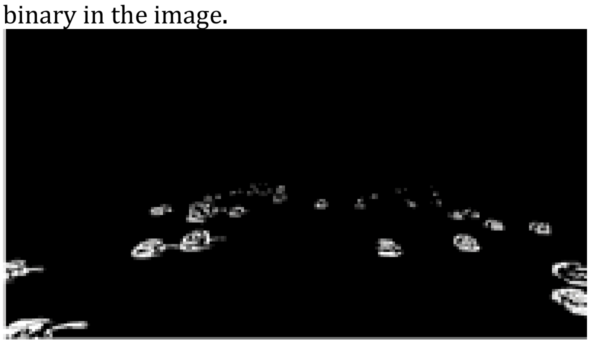

Figure 3. Binary Transformation

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B. *Image Contours*

After the transformation process to binary is carried out, as shown in Figure 3, it can be seen that the results of the transformation carried out succeeded in separating the color channel between the desired information and not the desired information; in this case, the desired information is the vehicle. The next step is the contour image process. This contour process is a process in which the curve connects all continuous points (along the boundary) that have the same color or intensity. Broadly speaking, at this stage, identification of the structural lines of objects in the video will be carried out, which aims to help identify the shape of the vehicle and facilitate the detection process [8][10].

Active Contours Models

The contour model used in this study is the active contour model, also known as the snake contour. This contour model is used in image analysis because of its flexibility and efficiency [7][8]. This method is generally interactive and can only detect contours where the initials or inputs are. It can be expressed mathematically in the following equation (2):

$$E_{images} = \omega_{line}E_{line} + \omega_{edge}E_{edge} + \omega_{term}E_{term} \quad \text{........} \; (2)$$

where ω_{edge},ω_{term}, A higher weight indicates that the features that stand out will have a greater contribution to the style of the image. The results of the image contour can be seen in Figure 4 below:

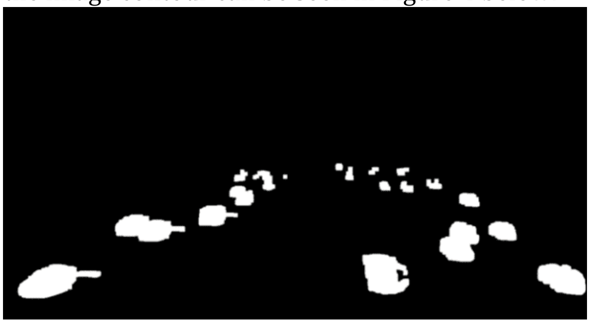

Figure 4. Image Contour

C. *Morphological & Image Convex Hulls*

Morphological

The next step is image segmentation processing using morphological operations on the image to produce smooth edge angles. This morphological operation uses a structuring element in the form of a bounding box with a dynamic diameter according to the size of the vehicle [11][12]. This operation involves two dilation and erosion operators as part of the image smoothing that is entered into equation (3). The dilation operation is performed to get the effect of widening the size of the image segment by adding a layer of pixels around the image, while the erosion operation is performed to trim the surface of the image to make it smoother and easier to detect. The following is an illustration of the detection process in binary images before the vehicle is calculated using the blob method in Figure 5.

$$\textit{Dilation} \quad : A \oplus B = \left\{ z \middle| \left[\left(\hat{B} \right)_z \cap A \right] \subseteq A \right\}$$

$$\textit{Erosion} \quad : A \ominus B = \{ z | (B)_z \subseteq A \} \qquad (3)$$

Where A is binary image, B is structure element, $\subseteq$ is subset , $\cap$ is intersection, B̂ is reflection and $(B)_z$ translation set.

Figure 5. Detection Area

In Figure 5, it can be seen that there are two bounding boxes in the middle of the test area. The function of these two boxes is as a detection limit that is used to be able to identify moving objects in them. The yellow box illustrates the vehicle detection process on the left, while the red box illustrates the detection process on the opposite lane on the right [13]. When viewed in terms of morphological operations on binary images, the resulting image will be as shown in Figure 6.

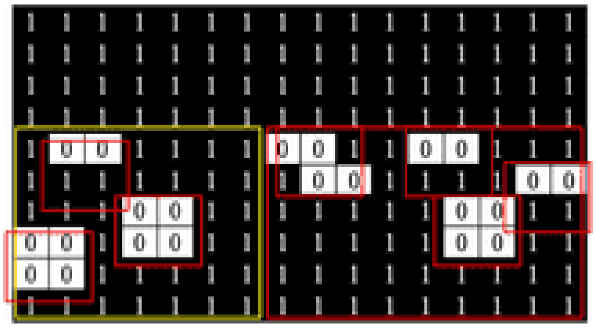

Figure 6. Illustration Detection Area

In Figure 6, it can be seen that the illustration in the detection system will identify pixels that have a value according to a predetermined threshold [14]. Pixels with a value of 0 have a white color, which means the information sought is there, while black pixels, or 1, will be ignored. The pixel value containing the information will be in a bounding box

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as a sign that the information has been successfully detected.

Image Convex Hulls

In this section, the image that has been obtained from the shape of the contour will be changed into the shape of convex hulls. The goal is that the value of the information obtained will be more focused, easier to detect, and minimize detection failure [15][16][17][18]. In addition, at this stage, a subset of the set of points in the binary plane must be found in order to be converted into a convex polygon shape. A polygon is said to be convex if the neighbouring pixel points are connected to each other and no pixels intersect the line that is the outer boundary of the polygon.

Figure 7. (a) Treshold (b) Contours (c) Convex Hull

Figure 7 shows a comparison between the results of the thresholding, contouring, and convex processes. It can be seen that the results of the transformation using a convex hull with a brute force approach $O(n2)$ transform the initial image into a polygon by combining the pixel points based on the selected $X - axis$ coordinates so that the resulting information becomes one indivisible piece of information, as shown in figure 8.

Figure 8. Convex Hull

RESULTS AND DISCUSSION

A. *Blob Detection OpenCV*

The last stage is detecting vehicles using OpenCV blob detection. Blob detection is a group of connected pixels in the resulting convex hull image that share common information, such as grayscale values. In Figure 8, the white connected area is a blob, and blob detection aims to identify and mark this region. We use OpenCV as a method to detect and filter blobs based on desired characteristics.

B. *Prediction Results*

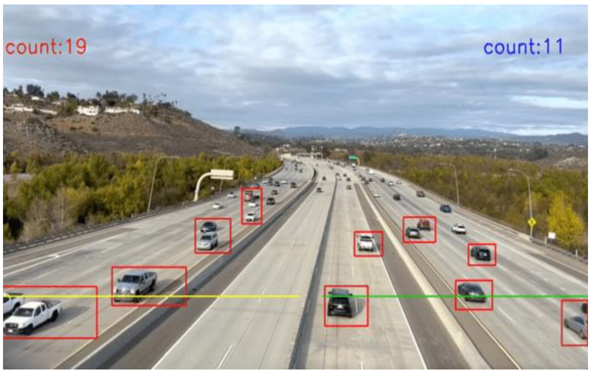

Figure 9. Detection Result Test 1

From the results of the detection of vehicles on the freeway in Figure 9, it shows that the system has successfully detected vehicles and counted the number of vehicles from both directions with an accuracy of 97.11%. These results were obtained after carrying out 10 sample tests with several different test videos, and the total number of vehicles that were successfully detected with this approach was 1329 out of a total of 1362, meaning that the total error rate was only 3.02%.

When compared with the results of previous researchers [2] Of course, the results obtained by previous researchers reached above 90%, which is a very good accuracy value, but when compared with the method, the number of test samples obtained, and the detection time in our study, the performance has been better. This can be seen in table 2, with the accuracy level of each test sample having a value above 90%, with the highest accuracy being in testing close to 100%, and the comparison value between previous researchers in table 3. Factors that influence vehicle detection include the camera angle used in taking pictures, vehicle speed, vehicle size, and the threshold obtained from each vehicle that passes through the bounding box.

Table 2. Experiment Result

No	Sample Video	Time (s)	Number Of Vehicles		Error (%)	Ground Truth	Accuracy (%)
			Left Side	Right Side			
1	Test1	20	85	73	1,27	158	99%
2	Test2	20	49	58	2,80	107	97%
3	Test3	20	58	37	5,26	95	95%
4	Test4	20	50	24	1,35	74	99%
5	Test5	20	73	38	3,60	111	97%
6	Test6	20	73	80	3,27	153	97%
7	Test7	20	130	165	1,36	295	99%
8	Test8	20	69	90	0,63	159	99%

No	Sample Video	Time (s)	Number Of Vehicles		Error (%)	Ground Truth	Accuracy (%)
			Left Side	Right Side			
9	Test9	20	55	60	2,61	115	97%
10	Test10	20	34	28	8,06	62	93%
Total Accuracy							97,11 %

Table 3. Comparison Data

No	Comparison	Number Of Videos Sample	Total Detection	Error (%)	Accuracy (%)
1	Prashant[2]	7	1313	3.15 %	96,85%
2	Our methods	10	1329	3,02	97,11%

Table 3 shows a comparison of the results of the tests carried out by Prashant and friends and the method we used. From the comparative data obtained, a clear difference is seen in the number of test videos and the level of accuracy obtained; the amount of accuracy obtained with our approach has an advantage, although not much compared to the previous one, and the error obtained is at 3%. The results achieved have an advantage with an accuracy value of 97.11% compared to before.

CONCLUSION

This research develops a vehicle counting and road monitoring system using the OpenCV-based blob detection method. By utilizing detection using this approach, passing vehicles can be detected and an estimate of the number of vehicles passing through the road can be calculated. By transforming video images into binary form, it can make it easier for the system to detect the presence of vehicles and count them. The results of the identification were carried out using 10 video samples with a total of 1362 vehicles, of which 1329 were successfully identified with an average total accuracy of 97.11%, which is better when compared to previous studies. This system can help highway officers find information on passing vehicles and calculate the volume of vehicles entering and leaving the city from day to day. In addition, this system can predict the buildup of vehicle flows by calculating the number of vehicles that pass through both road flows, of course, with an estimate of the number of passing vehicles, it can facilitate the work of highway officers to carry out traffic engineering before congestion occurs, in this research we did not test until the process Traffic engineering is ongoing, but the vehicle information obtained will really help officers estimate the number of passing vehicles so that there is an estimate of when officers are needed on the road. The system we create can adjust to changes in information that are different for each test sample used. However, due to limited datasets and video samples, we cannot test it in more detail, such as monitoring vehicles from one road gate to another. We realize that the research we are conducting still has many shortcomings, which, of course, can still be improved upon and further developed in further research. Of course, using a better approach such as YOLO as a method for better detection and the application of deep learning will be very beneficial [19][20][21]. Useful for increasing the accuracy and detail of the detection obtained..

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