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A HYBRID FUZZY MORPHOLOGY AND CONNECTED COMPONENTS LABELING METHODS FOR VEHICLE DETECTION AND COUNTING SYSTEM

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Abstract- A hybrid fuzzy morphology and connected components labeling method is proposed for detecting and counting the number of vehicles in an image taken from a traffic monitoring camera. A fuzzy morphology approach in image segmentation method is used in the system to achieve faster computation time compared to the supervised learning. The connected components labeling method is combined with a fuzzy morphology method to determine the region and number of objects in an image. The processing phases in the proposed system are image preprocessing, image segmentation, and vehicle detection and counting the number of vehicles. Images are captured from the traffic monitoring cameras installed in highways. Results from testing phase using thirty images with varying brightness, contrast, and quality taken from different cameras during daylight showed that the accuracy of the system in counting the number of vehicles is 78.21%.

Index terms: connected component labeling; fuzzy morphology; image segmentation; vehicle detection.

I. INTRODUCTION

Recently, many big cities in Indonesia are facing traffic jam problem, resulting in costly travel expenses, energy waste, and pollution. Building new roads can alleviate the situation, however it takes long time and big funding. In many cases, building new roads is difficult because the unavailability of open space for the new roads. One of the feasible ways to solve the traffic jam problem is to employ traffic management system that monitors the roads in the city according to vehicles densities and controls the traffic based on the information gathered. A vehicle detection system for monitoring the density of vehicles in the roads which uses images taken from the traffic monitoring camera is preferred as it can monitor vehicles densities in real time. This research aims to develop the vehicle detection and counting system using image processing approach. This vehicle detection and counting system is a part of the traffic management systems as a whole real time system. The input image is captured from the highway traffic monitoring camera that is taken during the specific time intervals.

There has been several previous researches on vehicle detection. The number of vehicle prediction using edge detection approach (Sobel operator) and Neural Network method was proposed by [1]. The car detection from the high resolution aerial images using multi feature (shape, texture, and color) was proposed by [2], in which Support Vector Machine (SVM) method for car recognition was used. The researchers in [3] developed a real system for detecting the type of vehicle using three steps: vehicle moving detection, vehicle image processing, and vehicle type recognition. The researchers in [4] developed the vehicle detection, tracking, and classification using the supervised learning method from the CCTV installed on highways. The vehicle detection from aerial image on the highway based on morphology method was proposed by [5], Geographic Information System (GIS) for the moving object detection on highways was used and morphological operator for detecting the location of vehicle was applied. The researchers in [6] proposed vehicle image classification using width and high dimension features and applying SVM method for vehicle classification. Vision based intelligent traffic management system was proposed by [7] for estimating the traffic density in real time. The differential morphology profile (DMP) is proposed by [8] to detect the vehicle automatically from the highway traffic image. The fusion approach of features and classifiers are studied by [9] to detect the vehicle from a video captured in a traffic scene. The literature [10] proposes the 2D deep belief network (2D-DBN) to detect vehicles that are applied on daylight highway, raining day highway, daylight urban, and night highway with road lamp situations. The vehicle detection of thermal images using under various environments is proposed by [11]. The vehicle detection using computer vision approach from captured image is applied for toll collection system. Most of the vehicle detection researches use the supervised learning method for vehicle classification. The researches that did not use the supervised learning method for the vehicle detection are presented in literature [7, 8]. The literature [7] used dynamic background subtraction and morphological operations for vehicle detection and the region of interest based method for vehicle calculation instead. The literature [8] uses differential morphology closing profile to extract the candidate vehicle object from background.

Most of the previous works used the supervised method for vehicle detection that it has proven obtains the good accuracy. However, most of the supervised method requires many parameters that should tuned for different dataset. In addition, the supervised method takes more computational time. Furthermore, training process is not required compared to supervised learning method. In this paper we propose a vehicle detection and counting system using hybrid fuzzy morphology and connected components labeling method to decrease the computational time. The fuzzy morphology is used for image processing (i.e., image segmentation). This is an extension of binary morphology for the gray level images. The connected components labeling is used to define the number and region of objects so that the region resulted from the labeling can be detected as a vehicle or not, based on the size of the region. The system presented here is a part of the traffic management system as the whole real time systems. The input image is captured from the traffic monitoring camera and taken during specific interval time. The output of proposed system is a number of vehicles detected automatically by the system. The thirty images with varying brightness, contrast and quality, taken from different cameras during daylight are used to evaluate the performance of the proposed system.

The paper is organized as follows. The vehicle detection and counting system is introduced in Section 2. Experiments on image segmentation and vehicle detection are shown in Section 3. Finally, the conclusion is presented in Section 4.

II. THE VEHICLE DETECTION AND COUNTING SYSTEM

The vehicle detection and counting system is required to estimate the density of vehicle in a road. By using a camera, images can be taken to monitor the density of vehicles in the road. The vehicle detection and counting system of our research consists of three stages: image preprocessing, image segmentation, and vehicle detection and counting. The result of proposed system is the number of vehicles. The architecture is shown in Figure 1.

Figure 1. The Architecture of the Vehicle Detection and Counting System

2.1. Image Preprocessing

Different monitoring cameras produce different quality and size images, depending on the brand of the camera, the position it is mounted on the location, the size of the road being monitored, etc. Some images from the cameras have relatively good quality and size, easing the process of identification. Some images have low quality that it is difficult to distinguish between foreground and background. To produce an image with good quality, improvement of image quality using image preprocessing is required. In this research, image preprocessing performed by filtering process to remove noise and reduce the blur effect caused by the low quality of an image.

2.2. Image Segmentation

The general method for object detection in an image is image segmentation, that is, a process to divide a digital image into segments (pixels sets) and to differentiate the area of background and the objects. Image segmentation is used to simplify or change the representation of an image into something more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries in an image. Mathematical morphology has been successfully applied to many problems of image processing, e.g., segmentation, thinning or object recognition. Thereafter, mathematical morphology has been extended to gray level images. There are some reports on different approaches that extend mathematical morphology to gray-level images. One of such approaches uses the fuzzy logic approach for the design of morphological operators, such as proposed by Deng and Heijmans [15], which extend the binary morphological operators to gray-level images. Some literatures has been used a linguistic approach based on fuzzy for developing the models. The literature [16] designed a meaningful linguistic labels (granules) model. The level of information granules are fuzzy sets and by modifying and distributing them along the variables of interest can affect the depth of modeling. In addition, the linguistic granules contain some mechanism to deal the noisy data. Granules are formed based on finer granules due to their distinguishability, similarity, and functionality [16]. Granulation is an operation to construct or decompose granules in granular computing field for solving the problem. The literature [16] predicts that the granular computing may lead to new computational paradigms. There are some application using granular computing approaches and built the fuzzy set. The literature [17] analyzed the stability of the fuzzy control system using the circle criterion.

We use fuzzy morphology approach proposed by Deng and Heijmans [15] for image segmentation. The fuzzy morphology for medical image segmentation has been applied by [19, 20, 21]. The fuzzy morphology adopts the fuzzy logic approach to gray-scale morphology and combines it with the concepts of adjunctions. They use notions from fuzzy logic to extend binary morphology to gray-level images. The fuzzy erosion of an image *f* can be defined by a structuring element *B*, in a point *x*, as shown in Eq (1).

$$\varepsilon^F(f,B)(x) \coloneqq \inf_{y\in f}\{I(B(y)), f(y)\} \qquad (1)$$

Then, the fuzzy dilation of an image *f* can be defined by structuring element *B*, in a point *x* as shown in Eq (2).

$$\delta^F(f,B)(x) \coloneqq \sup_{y\in f}\{I(B(y)), f(y)\} \qquad (2)$$

Following the steps of morphological theory, fuzzy opening is expressed as in Eq (3), and fuzzy closing is expressed as shown in Eq (4).

$$\gamma^F(f,B)(x) \coloneqq \delta^F(\varepsilon^F(f,B),B) \qquad (3)$$

$$\Phi F(f,B)(x) \coloneqq \varepsilon F(\delta F f,B,B) \qquad (4)$$

In our research, the fuzzy dilation and fuzzy erosion operators are used to process the images. The step process of image segmentation phase of the proposed method is shown in Figure 2.

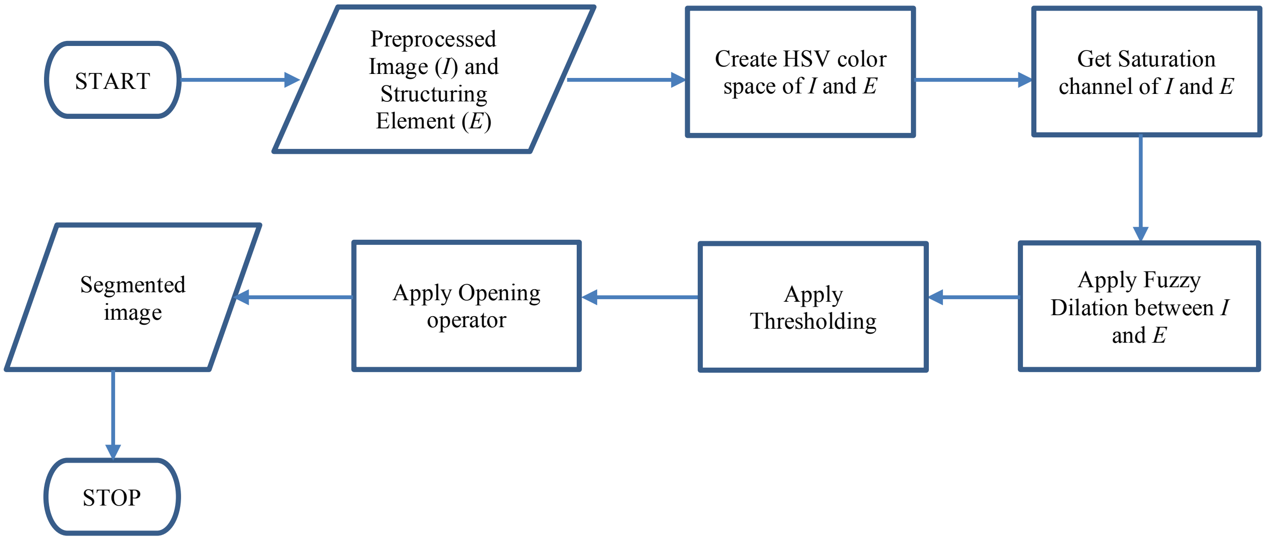
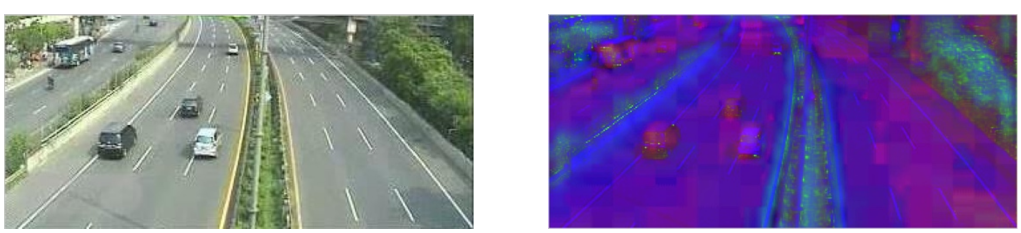


Figure 2. The Step Process of Image Segmentation Phase of the Proposed Method

The first process of image segmentation is providing an input image and structuring image into elements of 9×9 pixels each. In the second process, a HSV (Hue Saturation Value) color model is created using the input image and structuring element image. The third process is applying the fuzzy dilation on the saturation channel of HSV color model of the input image by the saturation channel of structuring element. We use the HSV color model because the HSV color model can represent the natural of visual color on images [22]. The saturation channel for next processing is used because it is easier to differentiate between objects and background by using this channel than other channels of HSV color model. The HSV color representation and saturation channel of HSV of the input image taken from the traffic monitoring camera are shown in Figure 3.



(a) (b)

(c)

Figure 3. The Result of Image Segmentation (a) Original Image (b) HSV Color Space and (c) Saturation Channel

In the fourth process, thresholding is applied to obtain the region of interest. This process uses the different value of threshold for each image depending on conditions of image brightness and contrast. Thresholding is used to set the number of gray levels in an image and will produce a binary image that has two gray level values, such as black and white depending on whether or not the value of a pixel is greater or smaller than the threshold value T. A pixel will be replaced with white if its gray level value is greater than T, otherwise a pixel will replaced with black.

There are several methods to determine the value of T, however Otsu method is the most widely used method among existing thresholding methods. This method maximizes the capability of a threshold to separate an object from its background by selecting the threshold value that gives the best class division for all pixels in the image based on the normalized histogram where the number of each point at each level divided by the total number of points in the image.

In the fifth process, the opening operator is applied to remove the small objects using the binary mathematical morphology with a size of structuring element 3 x 3 pixels. The result of the image segmentation phase is a segmented image containing the region of interest of objects. To detect whether the region of interest of objects are vehicles or not, the final phase of proposed method is applied.

2.3. Vehicle Detection and Counting

This phase detects whether the objects are vehicle or not, and then counts the number of objects that are vehicle in a segmented image. Then connected components labeling is applied to make label the region of object and count the number of objects in a segmented image. Connected components labeling is a method to cluster pixels into a component based on connectivity of pixels [23]. All connected pixels have similar or same intensity color either gray level or RGB color (color labeling). We use two-pass algorithm for labeling the connected components that is proposed by [24]. This process produces some regions which are separated from one another. The two-pass algorithm [24] is presented as below:

The first pass:

1. For each pixel on the image, iterate by column then by row (*Raster Scanning*)
2. If the current pixel is not the background than:
   a. Get the neighbor pixels of the current pixel
   b. If there are no neighbors, labeling the current pixel uniquely and continue
   c. Else, find the neighbor with the smallest label and assign it to the current pixel
   d. Store the equivalence between neighboring labels

The second pass:

1. For each pixel on the image, iterate by column then by row
2. If the current pixel is not the background than:
   a. Relabel the pixel with the smallest equivalent label

The next process counts the area of all identified objects. If the area of an object falls within the determined thresholds (i.e., complies with vehicle size criteria), the object is marked as vehicle and the number of vehicles counter is increased. Otherwise if the area of an object is less or greater than determined thresholds then the object is not marked as vehicle. In this paper, we determine the vehicle size criteria based on the size of area from data samples calculated manually. The size of vehicle area should satisfy with following criteria as shown in Eq (5).

$$t_1 < area \text{ and } area < t_2 \quad (5)$$

where $t_1 = 120$ and $t_2 = 800$. The values of t_1 and t_2 are obtained from minimum and maximum size of vehicles from 15 sample images. This stage produces the number of vehicles in an image and displays original image where objects which are identified as vehicles marked with red rectangle. The process to detect vehicle and count the number of vehicles is shown in Figure 4.

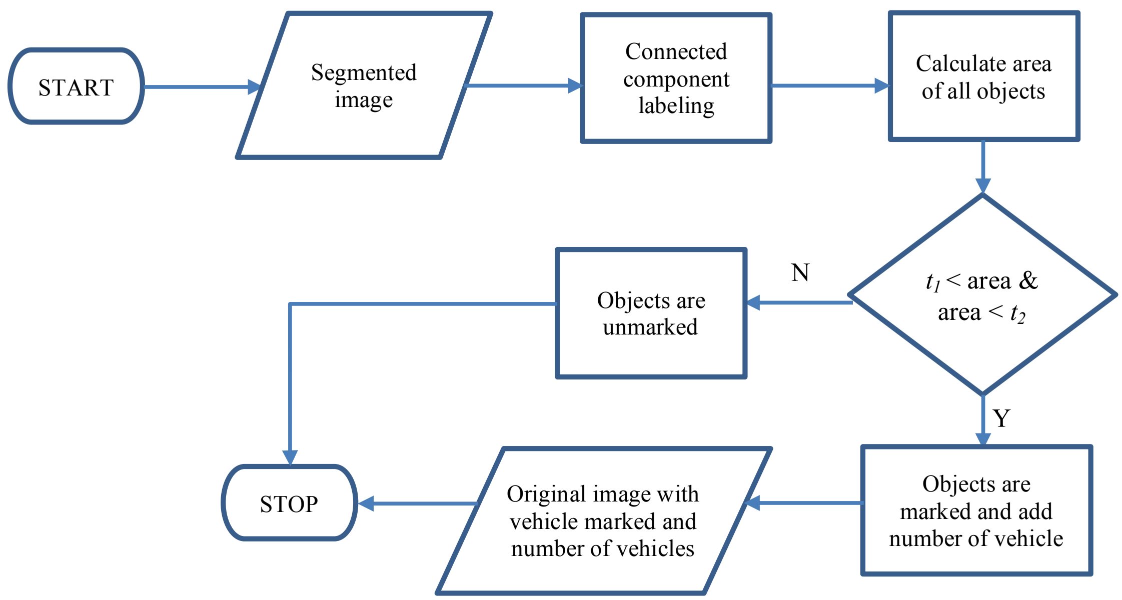
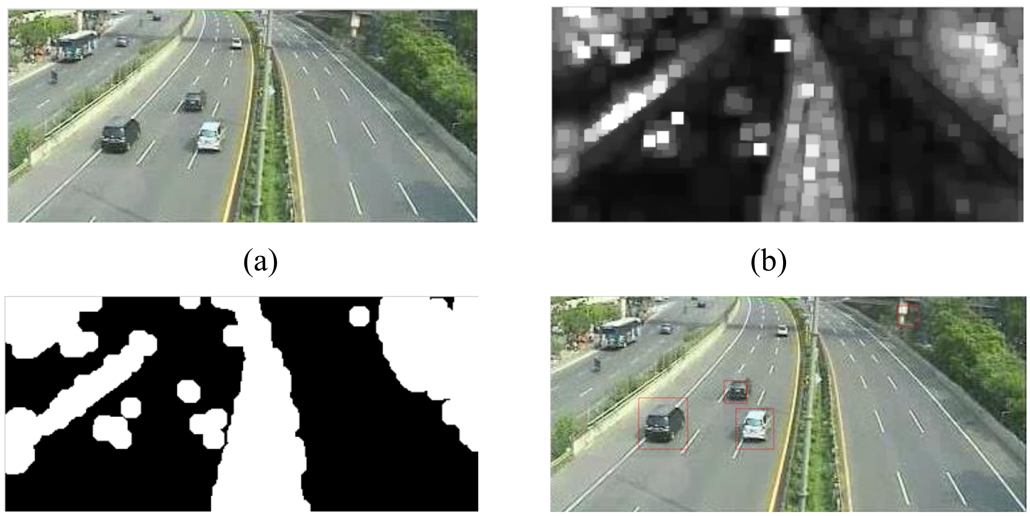


Figure 4. Counting Number of Vehicles Flow Diagram

III. EXPERIMENTAL RESULTS ON VEHICLE DETECTION SYSTEMS

As mentioned earlier, input images are captured by traffic monitoring cameras and taken during the specific interval times. In this experiment, fifteen images with varying brightness, contrast and quality, taken from different cameras during daylight are used to evaluate the performance of the proposed system. The output is the number of vehicles detected by the system. To monitor the accuracy, the original image and the image with marked vehicle objects by red rectangles are displayed.

The experimental result of each phase of the proposed method is visually presented in Figure 5 (a) – (d). Figure 5 (a) is an original image and figure 5 (b) is the result of fuzzy dilation process. The result of image segmentation process is shown in Figure 5 (c), and Figure 5 (d) is the final result of vehicle detection. The fuzzy dilation process is employed on the saturation channel of HSV color model of the input image by the saturation channel of structuring element. The size of structuring element is 9 x 9 and the type of structuring element is rectangle. The next process is applying Otsu method and the binary opening operator that obtain the segmented image. And the final process is counting number of vehicles and marking the vehicle objects with red rectangle.



(a) (b) (c) (d)

Figure 5. The Experimental Result of Each Phase of the Proposed Method: (a) Original Image (b) After Fuzzy Dilation Process (c) Segmented Image and (d) The Result of Vehicle Detection

By manual counting, the accuracy rate can be quantifiably calculated. Here, the result of counting vehicles manually is considered to be the correct result, as presented in Table 1.

Table 1. The Accuracy of the Number of Vehicles Counting

Images	Manual Counting	Proposed Method	Accuracy
Image #1	5	4	80%
Image #2	4	3	75%
Image #3	5	3	60%
Image #4	5	3	60%
Image #5	4	3	75%
Image #6	3	3	100%
Image #7	6	4	67%
Image #8	2	2	100%
Image #9	4	3	75%
Image #10	4	3	75%

Image #11	5	3	60%
Image #12	6	5	83%
Image #13	5	4	80%
Image #14	4	3	75%
Image #15	3	3	100%
Image #16	8	5	63%
Image #17	5	3	60%
Image #18	6	5	83%
Image #19	8	7	88%
Image #20	4	3	75%
Image #21	3	2	67%
Image #22	9	8	89%
Image #23	3	2	67%
Image #24	4	3	75%
Image #25	3	3	100%
Image #26	6	5	83%
Image #27	7	6	86%
Image #28	6	4	67%
Image #29	2	2	100%
Image #30	5	4	80%
		Average of accuracy	**78.21%**

The experimental results of some input images are visually presented in Figure 6. Original images are presented in the left hand side (Figure 6(a), 6(c), 6(e)), and are vehicle detection by proposed method are presented in the right hand side (Figure 6(b), 6(d), 6(f)). The red rectangles on input images indicate the vehicle objects.

(a)

(b)

(c) (d)

(e) (f)

Figure 6. The Experimental Result of Some Input Image: (a, c, e, g) Original Images; (b, d, f, h) The Result of Vehicle Detection

The experimental results show that there are some undetected vehicles because the sizes of vehicles in the image are very small. In order to make those small vehicles identified as vehicle, the lower threshold of the area of an object in vehicle detection phase can be made smaller. However this will result in other small objects along the road identified as vehicles, which is not desired.

IV. CONCLUSIONS

This research aims to develop the vehicle detection and counting system using image processing approach. The input image is captured from the road traffic monitoring camera taken during the specific time intervals. The vehicle detection and counting system using a hybrid fuzzy morphology and connected components labeling method is proposed to decrease the computation time. This method does not require training process as compared with the supervised learning method. The fuzzy morphology is an extension of binary morphology for the gray level images and is usually used for image processing such as image segmentation. The connected components labeling is used to define the number and region of objects so that the region resulted from the labeling can be detected as a vehicle or not, based on the size of the region.

The proposed system consists of three stages that are image preprocessing, image segmentation, and vehicle detection and counting. The output of proposed system is the number of vehicles detected automatically by the system and displaying the original image with marked vehicle objects by red rectangles. From the thirty images used in the experiment, 78.21% accuracy is obtained. The experimental results show that there are some undetected vehicles in some images. Changing the thresholds of the area of an object in vehicle detection phase can make the previously undetected vehicles to be detected as vehicles, however this may result in other small objects along the road identified as vehicles.

Our future works include the detection of vehicles in various lighting or brightness in the image, including those images taken at night. This is required to develop a traffic management system as a whole. The high accuracy results of vehicle detection and counting in various brightness conditions of images are needed to get the best performance for the traffic management system.

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