Vehicle Classification Algorithm using Size and Shape

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Abstract: Automatic classification of vehicles into different classes based on their sizes and shapes is very useful for traffic control and toll collection process. Effective intelligent transportation system that incorporates vehicle classification technique is needed in many cities to prevent road accident and traffic congestion caused by illegal movement of vehicles. This work presents method of getting structural information from detected vehicle images and then uses it to classify vehicles into different classes. The technique involves extraction of contour features from vehicle images side view using morphological operations. The extracted features were combined and used to generate feature vector that serve as input data to vehicle classification algorithm based on Euclidean distance measure. Impressive result was achieved from the proposed vehicle classification method.

Index Terms: Vehicle, Shape, Size, Features, Boundary, Classification.

I. INTRODUCTION

Vehicles are mainly used for transportation of people, animals and goods from one place to another. Vehicles of different sizes are made by manufacturers to suit different purposes. There are different classes of vehicles; they include cars, buses, vans, trucks and trailers. Generally vehicles are grouped into different classes based on their sizes; this parameter is normally used to determine toll charges. Applications of image processing are vital components of vehicle image classification or identification system.

Moving or still vehicle images can be clearly captured using camera and they serve as input image to vehicle identification or classification system. Classification output decision depends mainly on type of image processing techniques and pattern classifiers involved. In case of vehicle identification system, image area of interest for processing is vehicle license plate number which is used to establish identification of vehicle owner [1]. Whereas in vehicle classification method the image area of interest is part or whole vehicle image whereby size and shape of the vehicle are measured and subsequently use to determine their classes.

Numerous research works have been done in the area of vehicles classification. Some researchers engaged input devices such magnetic loop sensor, laser sensor to detect vehicles for classification [2][3]. While in [4], [5] and [6] cameras were used to capture moving and stationary vehicles as input images to vehicle classification system. Normally sensor detects present of vehicles at particular position whereas cameras are usually positioned to capture vehicle images for further processing. In many cases the type of image processing techniques involved depends on types of input device, vehicle motion and environmental condition.

Vehicle classification system that classified vehicles into four different classes was proposed in [7], images were captured from vehicle rear-side view. Feature vector was formed from features extracted from tail light and vehicle dimension. Classification of vehicles was done by passing feature vectors to classifier called Hybrid Dynamic Bayesian Network (HDBN). In [8], two-class vehicle classification system was proposed. Key-points features are extracted from edge detected line and pixels of vehicle image. The key-points are detected using Scale Invariant Feature Transforms (SIFT). K-mean clustering method was used to group features for training and matching process. The matching of a query vehicle image with the output from training stage was done using Euclidean distance measure. Also, in [9] vehicle classification system using neural network was developed. Vehicle images are captured from vehicle front view using immovable camera. Six features were extracted from input vehicles after image background had been removed. Extracted features include ratio of distance between the center of object and its lengths main axis, length and width of the labeled objects and the area. The features were combined and used to classify vehicles as heavy vehicle, light vehicle and motorcycle.

Performance of some previous vehicle classification systems was negatively affected by ineffective background remover methods. Also image area of interest captured in previous systems produced inactive features. These features were unable to describe vehicle size and shape needed for effective classification. In this work effective method of classify vehicles into different categories putting into consideration vehicle background is proposed. Structural measurement of vehicle side view is done within uniform background set-up. This is achieved using positioned camera at specific toll collection or monitoring entrance aiming at the side view of targeted vehicle overlapped a uniform background.

This paper is designed into five sections. The topic is introduced in section 1, section2 describes image processing techniques, Section 3 introduces boundary extraction method and feature extraction is done in section 4. Experimental result is given in section 5 and finally, conclusion is drawn in section6.

II. IMAGE PROCESSING

Vehicle of different types are captured for processing using digital camera. Five vehicle images are taken at different time interval from the same vehicle. The images are captured from vehicle side view within uniform background. Figure1 shows sample of input vehicle images that are acquired for this work.

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A. Vehicle Graylevel Images

The vehicle images captured by camera into the system are described by combination of three colors namely Red, Green and Blue (RGB) and each pixel in the image has a particular color that indicate amount of red, green and blue in it. Color attribute cannot be used to classify vehicles into different classes therefore it necessary to convert 24-bit colour vehicle image to 8-bit gray-level image using (1). It means 24 bit per pixel is transformed to 8bit per pixel hence each pixel in a gray-level image has one integer value between 0 to 255. Samples of gray-level vehicle image obtained in this work are shown in figure2.

$$G(i, j) = 0.299 *R + 0.587 *G + 0.114 * B \qquad (1)$$

Figure1. Samples input vehicle image

B. Vehicle Binary Images

In this work, gray-level vehicle images are converted to binary images before features extraction is done. Method of creating binary image from gray level image is called thresholding, it involves locating a particular intensity value called threshold within integer 0 and 255 in a gray-level image and thereafter it sets all intensity values above the threshold to "1" and all other values below it to "0".

Figure2. Samples of gray-level vehicle image

Histogram distribution of a gray-level image is normally used to determine suitable thresholding method. If the histogram distribution plot is bimodal shape, it means there is gap between foreground and background information then global thresholding can be applied. Otsu's method is an improvement on global method. The algorithm applied threshold value that minimizes intra-class variance and also able to maximize inter-class variance [10]. In case of uneven illumination of object, adaptive thresholding is required because a single threshold value may not be suitable for the whole image due to uneven distribution of intensity. Therefore such image needs to be partitioned into non-overlapping sub-images using different threshold values. In this work Otsu's method is used to convert gray-level vehicle images to binary images, samples of vehicle binary image obtained using Otsu's method are shown in figure 3.
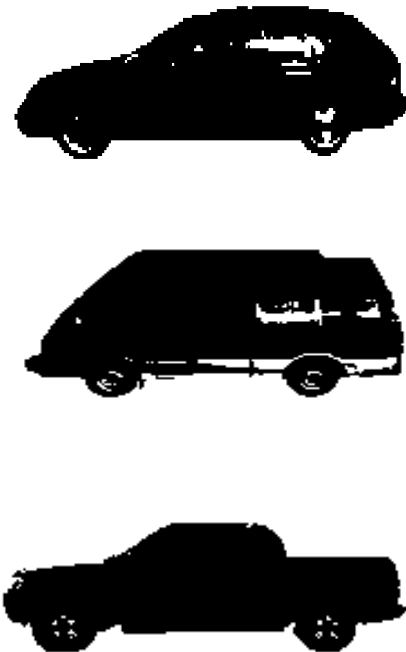

Figure3. Samples of vehicle binary image

III. BOUNDARY EXTRACTION

Vehicle binary images generated in this work are further processed by using morphological operations to reveal image boundary. Morphological operations are methods engage to manipulate image structure to obtain desired image. Morphological operations modify image structure with help of structuring elements. Structuring elements are template of small matrix shape. The shape of a structuring element is determined by the arrangement of 1's and 0's element in a square matrix. Structuring element act on image by moving to all pixels positions and manipulates corresponding neighborhood pixels to give new pixel values. Examples of structuring element shape include disk-shape and 3×3 square as shown in figure 4. Morphological operations include erosion, dilation, closing, opening and boundary extraction.

A. Dilation and Erosion

Dilation make image foreground pixels grow in size and reduces holes within image background while erosion causes image foreground pixels to shrink in size, and enlarge holes within image background. The rate of growing or shrinking depends on type and size of structuring element involved. Dilation of image A by structuring element B; all z in A such that B hits A when origin of B=z is defined as in (2)

$$A \oplus B = \{ z/(\hat{B})_z \cap A \neq \Phi \} \qquad (2)$$

Erosion of image (A) by structuring element (B); all z in A such that B is in A when origin of B=z is defined as in (3)

$$A \ominus B = \{ z/(B)_z \subseteq A \} \qquad (3)$$

0	0	1	1	1	0	0
0	1	1	1	1	1	0
1	1	1	1	1	1	1
1	1	1	1	1	1	1
1	1	1	1	1	1	1
0	1	1	1	1	1	0
0	0	1	1	1	0	0

1	1	1
1	1	1
1	1	1

Figure4. Examples of structuring element

B. Closing and Opening

Closing is a dilation operation followed by erosion operation using the same structuring element thereby preserves background regions that have a similar shape to the structuring element. It can be used to fill gap, connect one object to another. Opening is erosion operation followed by dilation using the same structuring element, it can be used to reduce small objects, smoothing and thinning contours of objects.
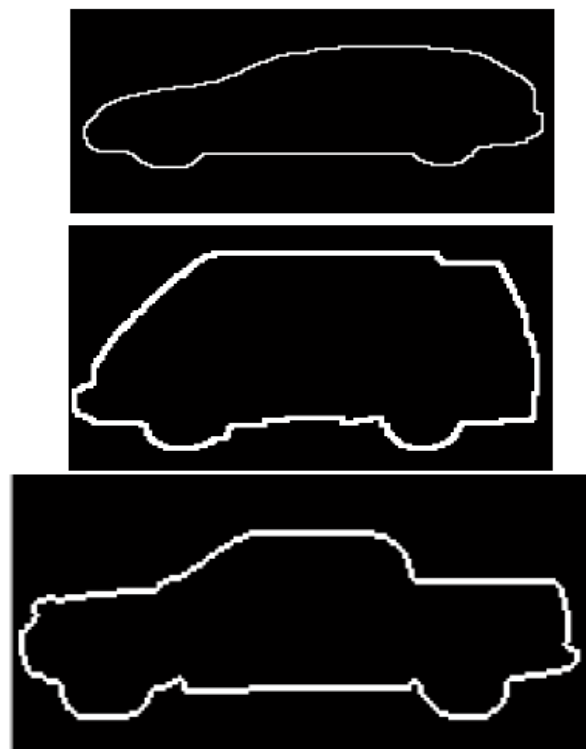

Figure5. Samples of contour vehicle image

Boundary extraction process is used to get contour or border pixels from input binary image. It can be achieved by performing erosion operation on input binary image (A) using structuring element (B) and thereafter subtract the eroded image from the input image (A), this is defined as in (4)

$$\beta(A) = A - (A \ominus B) \qquad (4)$$

Figure 5 shows examples of output boundary image extracted from three different samples of input vechile image.

IV. FEATURE EXTRACTION

Feature vector that can represent vehicle shape and size is extracted from vehicle boundary pixels. The feature called bounding box is extracted from vehicle boundary image to capture the size that is width and height of the bounding box. The shape of the vehicle boundary image is obtained from the extreme points in the region occupied by the boundary image. The following steps are involved in the extraction process:

(i) Calculate rectangle bounding box coordinate that contains vehicle boundary image.

(ii) Derive extreme vectors that contain x and y-coordinates of contour extreme points using the format: [top-left, top-right, right-top, right-bottom, bottom-right, bottom-left, left-bottom, left-top].

(iii) Form 8x2 Matrix from extreme vector.

(iv) Combine bounding box values obtained in step one with Matrix elements obtained in step two, to form 20 dimensional feature vector:

Feature vector = [bounding box, extreme]

V. RESULT AND DISCUSSION

The template vehicle feature is defined based on the three feature vectors from each vehicle. The three vehicle features are given as V_1, V_2, and V_3 the corresponding feature vector element of each is represented as v_1, v_2, v_3....... v_{20}. As given in (5)

$$V_1 = [v_{1,1}, v_{1,2}, v_{1,3}, ..., v_{1,20}]$$
$$V_2 = [v_{2,1}, v_{2,2}, v_{2,3}, ..., v_{2,20}]$$
$$V_3 = [v_{3,1}, v_{3,2}, v_{3,3}, ..., v_{3,20}] \quad (5)$$

The template vehicle feature vector of each of the vehicles is obtained by finding the mean values (v_{mean}) of each corresponding feature vector elements. Therefore the feature model for each of the vehicle is represented by (6).

$$V_f = [v_{mean,1}, v_{mean,2}, ...v_{mean,20}] \quad (6)$$

A. Classification Results

The proposed system is developed to classify vehicles into four different classes based on their size and shape features extracted from vehicle side view. In this work, vehicles are group into four classes, they are: Class 1(Passenger car), Class2 (Van and pick up), Class3 (Bus and lorry) and Class 4 (Trailer).

Euclidean distance measure is engaged to assign incoming vehicle feature vectors into one of the four classes. The class of a query vehicle feature vector is determined based on the lowest distance value obtained between the feature vector and the template feature vectors of all the classes. For instance query vehicle feature vector (p) will be classified to class (w) if the distance (d) between the vehicle feature vector and vehicle template vector of that class (w) is the lowest compared to values obtained from other classes.

The highest similarity score between query feature (T_f) and template feature (V_f) of all vehicle classes depend on the lowest minimum distance (d) obtained using Euclidean distance as in (7). 90% similarity score was obtained when 20 different type of vehicles are classified into four different classes.

$$d = \sqrt{\sum_{f=1}^{20} (V_f - T_f)^2}$$

$$(7)$$

VI. CONCLUSION

Vehicle image classification algorithm is a very useful component of automatic transportation control system. The proposed algorithm will enhance toll collection and traffic control operations in urban cities where different lanes are assigned to vehicles of various sizes for easy flow of traffic. Size and shape features have been extracted from vehicle side view and they are passed to Euclidean distance measure to develop vehicle classification algorithm. The proposed method is tested and has shown to be good enough in classifying vehicles into separate classes

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