Real-time Vehicle Color Identification for Surveillance Videos

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***Abstract*— Vehicles are one of the main detection targets of the traffic and security video surveillance system. In this paper, we propose an automatic vehicle color identification method for vehicle classification. The main idea of the proposed scheme is to divide a vehicle into a hierarchical coarse-to-fine structure to extract its wheels, windows, main body, and other auto parts. In the proposed method, the main body alone is used by a support vector machine (SVM) for classification. Experimental results show that the proposed scheme is efficient and effective and the proposed vehicle color identification is suitable for real-time surveillance applications.**

Keywords*— *vehicle color classification; tree structure; support vector machine

I. INTRODUCTION

Video surveillance is a technology that is widely used in our daily lives, especially for the monitoring of public security. In public security, traffic monitoring and vehicle detection are two important issues for the security administration. For example, the police may want to identify a specific vehicle in a surveillance footage to track suspicious criminals. In order to effectively monitor vehicles, an automatic vehicle color classification (VCC) system is required.

For a vehicle color classification system, extracting features from a vehicle is the most critical task. In previous research, color histogram and HSV color space are common features used to VCC. In [1], the authors investigated how the dimensions of a histogram affect the similarity measurement between images. Chapelle et al. [2] showed that image classification can be implemented by SVM for high dimensional features. Sural et al. [3] analyzed the properties of hue, saturation, and intensity and proved that HSV (Hue-Saturation-Value) color space outperforms the RGB color space.

From these previous research results, we recognize that color histogram and HSV color space are two important features in the color classification research area. In this paper, we present a VCC approach with features extracted from the histogram of the HSV color space. The proposed scheme uses a recursive approach to partition a vehicle into a tree structure. Each node in the tree structure represents a part of the vehicle. Our goal is to select the main body of an auto called the representative image of the vehicle from the tree structure, which contains the dominant color of the vehicle. Then, the features of the representative image are extracted from the HSV color space for the input of a SVM classifier. The classifier is used to distinguish four different colors: red, green, blue, and yellow. The rest of this paper is organized as follows. Related works of VCC is discussed in Section II. The propose algorithm is presented in Section III. Experimental results are presented in Section IV. Finally, conclusions are made in Section V.

II. RELATED WORKS

One of the challenges of conventional VCC methods is different shooting angles coming from different surveillance cameras. In [4], the detected vehicle is partitioned horizontally into three layers. Then, the authors set different conditions for different layers in order to remove the non-main body parts of the vehicle. However, the identification accuracy of the VCC of this method depends heavily on the shooting angle. In other words, this method fails in VCC when the shooting angle is not properly set. Therefore, this method is not applicable to a variety of situations. In [5], the authors extract the color histogram in HSI color space as the color feature of a vehicle without removing any non-main body parts. However, the noise greatly affects the accuracy of the VCC. In [6], authors constructed a special and-or graph (AOG) to represent vehicle objects, and detected vehicle objects using a bottom-up inference based on the AOG. The disadvantage of this method is that only front-view and rear-view of the vehicle can be used for detection, so their method cannot be widely used in various shooting angles and situations.

In the following section, we examine the way to both effectively filter out the non-main body parts of the vehicle and design the VCC invariant to shooting angle.

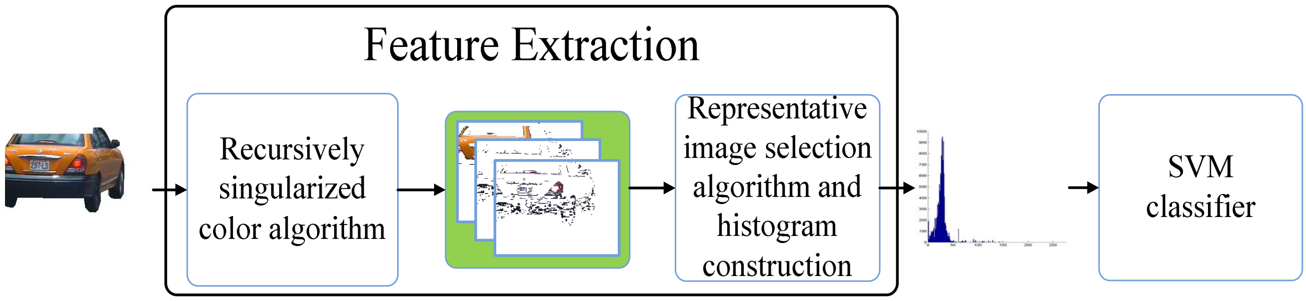

Fig 1. Feature extraction for the SVM classifier.

III. THE PROPOSED VEHICLE COLOR CLASSIFICATION

The proposed scheme is designed for different light conditions and shooting angles. Fig. 1 shows the flowchart of the proposed feature extraction for the SVM classifier. The first step of the feature extraction called "recursively singularize color algorithm" generates a representative image of the vehicle. A representative image contains only the main body of the vehicle and removes all its non-main body parts including wheels, windows, and shadows.

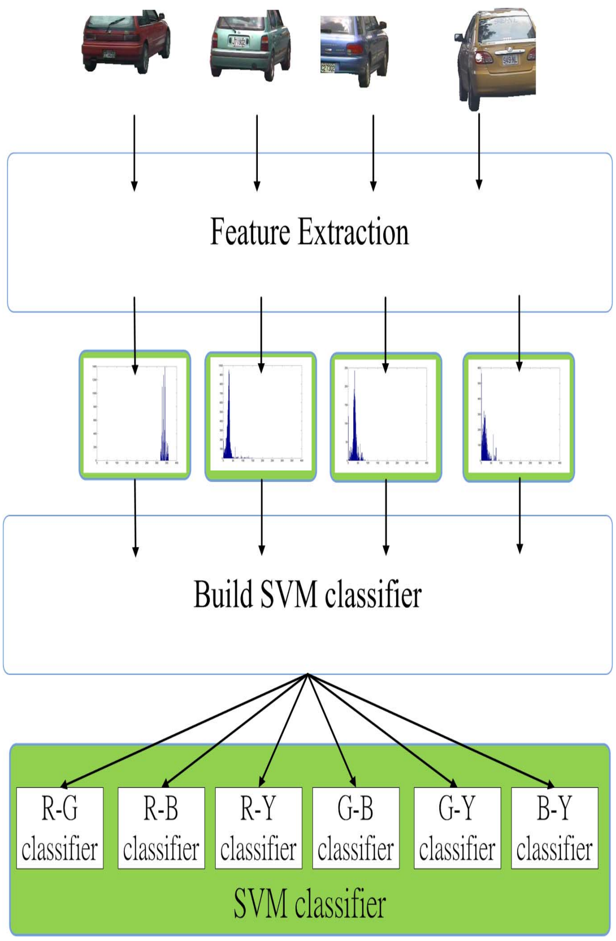

Fig 2. SVM classifier construction.

Then, the representative image generates a hue histogram for the input of the SVM. In the proposed scheme, four vehicle colors are identified by the SVM, which are red, green, blue, and yellow. The traditional SVM is a binary classifier. In order to extend the classifier to handle the four colors, any of the two colors generate a classifier. In this case, six classifiers altogether are generated for the VCC. Fig. 3 shows the SVM classifier construction for the VCC.

A. Recursively singularized color algorithm

A vehicle may contain several different colors, but the main body of the vehicle is what determines the representative color. The proposed strategy uses the color information of the detected vehicle image to decompose this image into several single color subimages. Since the proposed partition process is recursive, *Image_In* is defined as the input of the recursive function, and *Image_H* and *Image_L* are derived from *Image_In*. Initially, the detected vehicle image (*Image_In*) is transformed into the HSV (Hue-Saturation-Value) color space. In the proposed scheme, only the hue channel is used. Then the mean value and the standard deviation of *Image_In* of the hue channel are represented as *Mean_In* and *Std_In*, respectively. Equations (1) and (2) illustrate the calculates of these two parameters, where $P(x_i,y_i)$ is the hue value of the *i-th* pixel in the image and N is the total pixel number of *Image_In*.

$$Mean\_In = \sum_{i=1}^{N} \frac{P(x_i, y_i)}{N}. \tag{1}$$

$$Std\_In = \sum_{i=1}^{N} \frac{\sqrt{\left(P_{(x_i,y_i)} - Mean\_in\right)^2}}{N}. \tag{2}$$

The value of *Mean_In* is used to generate two subimages. If a pixel is greater than *Mean_In*, the pixel is classified into the *Image_H* category; otherwise, *Image_L* is generated for the pixels smaller than or equal to *Mean_In*. Similarly, *Mean_H* and *Std_H* representing the mean and thestandard deviation of the *Image_H* are obtained, and *Mean_L* and *Std_L* are generated for *Image_L*. The process is repeated until all the subimages become single color images. Therefore, a tree structure of a vehicle is generated. The single color criteria of an image are shown in (3) to (5). Equations (3) and (4) represent the color variations of the input image and (5) is used to measure the hue distribution of the input image. If (3) to (5) can be satisfied, the image is regarded as a single color image.

For example, if one of the (3) to (5) cannot be satisfied by *Image_In*, it means that *Image_In* is not pure enough and *Image_H* or *Image_L* may be better representatives for the main body color of the vehicle. In this case, *Image_H* (or *Image_L*) is regarded as another new input image *Image_In'*, and the new image is further partitioned into two parts *Image_H'* or *Image_L'* to evaluate (3) to (5) again.

$$\frac{Std\_In}{Std\_H} > Threshold\_std \quad (3)$$

$$\frac{Std\_In}{Std\_L} > Threshold\_std \quad (4)$$

$$Mean\_H - Mean\_L < threshold\_mean \quad (5)$$

However, during the partition process, some subimages may be too small. If the size of *Image_In* is much smaller than that of the original vehicle, the subimage will be removed. This part will be discussed in the next subsection. The complete algorithm of the proposed partition process is shown in the following.

- **Recursively singularized color algorithm**
- **Input**: A vehicle image.
- **Output**: A tree structure of the vehicle.
- **Step 1:** Calculate the mean (*Mean_In*) of the input image *Image_In*.
- **Step 2:** Set *Mean_In* as the threshold value and divide the input image into two parts, "*image_H*" and "*image_L*"
- **Step 3:** Calculate the mean and the standard deviation of *image_H*, *Mean_H* and *Std_H*, respectively, and *Mean_L* and *Std_L* for *image_L*.
- **Step 4:** If one of the Eqs. (3) to (5) cannot be satisfied, *image_H* (or *image_L*) will be treated as another new input image *Image_In'*. Go to step 1. Otherwise, a hierarchical coarse-to-fine tree structure of the vehicle is generated.

Fig. 3 shows the partition result of the detected vehicle. In this example, Fig. 3(h) is too smaller so it is removed. Figs. 3(f), 3(g), 3(i), 3(j), and 3(j) will not be involved in the further partition process since Figs. 3(c), 3(d), and 3(e) all satisfy (3) to (5). In the next subsection, we describe how one of the Figs. 3(c), 3(d), and 3(e) is selected as the representative color of the detected vehicle.

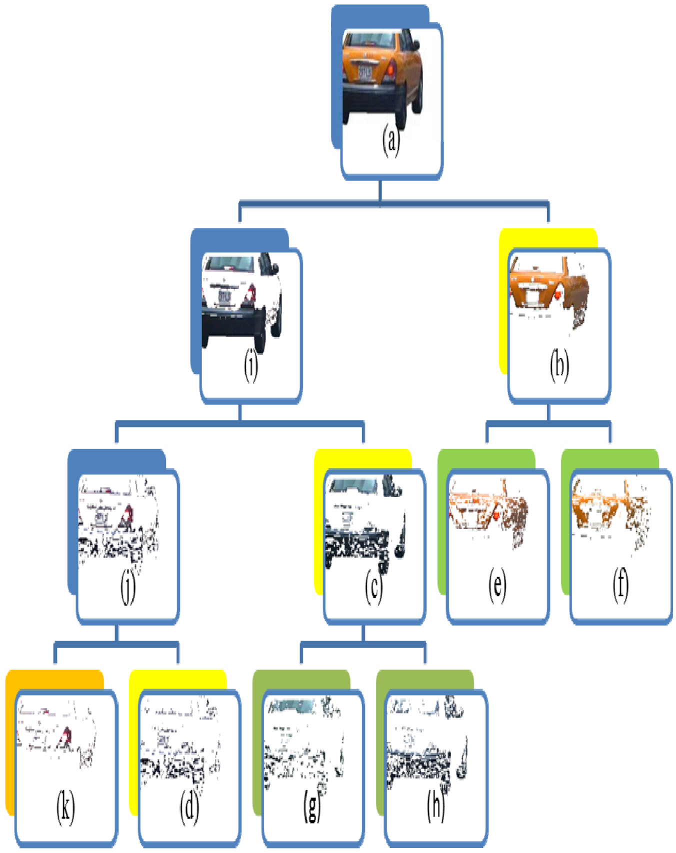

Fig. 3. The generation of the tree structure.

B. *Selection of the representative image*

The representative image contains the major color of the vehicle. Since the main-body of the vehicle, the area that helps determine the color of the vehicle, is always larger than the noise area, the subimages in the tree structure can be removed if their size is too small. In order to filter out the small sub-images, the minimal size of a subimage is set by (6). If the subimage size is smaller than the threshold, the subimage is removed. In (6), the *qualified_subimage*$_i$ means that the subimage has passed the criteria from (3) to (5) and could be the valid candidate for the vehicle's representative image. Therefore, the threshold is set by selecting the maximal size of the valid candidate multiplied by 0.8. In our previous example, Fig. 3(h) is removed because its size is not larger than or equal to the threshold.

$$threshold = 0.8 \times \max(qualified\_subimage_i) \quad (6)$$

After the noise subimages are removed, one of the remaining subimages will be selected as the main body of the vehicle. According to our observation, the main body of the vehicle usually contains more prominent color information than the other parts. In other words, the colors of the non-main body parts of the vehicle are usually close to gray. Therefore, (7) is used to determine whether there exit a dominant color other than gray in the subimage. If a pixel's color is not gray, the differences between its R, G, and B values should be large. Equation (7) shows the channel difference of a pixel.

$$\text{Channel difference} = \max(R,G,B) - \min(R,G,B) \tag{7}$$

In the above formula, the average channel difference of each of the sub-images is calculated. The sub-image that has the greatest channel difference will be selected as the representative image of the vehicle.

C. *Extracting features and building SVM classifier*

This subsection describes how the SVM classifier of four colors classification is built: red, green, blue, and yellow. First, for each color, randomly select *N* vehicle images as the training data. Then, the hue histogram of the representative image is used as the feature of each vehicle. The dimensions of the hue histogram is set to 360. In the training phase, any of the two colors will generate a classifier, so six classifiers will be generated altogether. In the testing phase, the test image will go through each classifier and the final result of the color identification will be decided by the six classifier. Since the sizes of representative images are varied, the normalization process in (8) of the histogram should be completed before training and testing.

$$Normalize\_d(i) = \frac{d(i)}{\sum_{i=1}^{360} d(i)}, \tag{8}$$

where d(*i*) is the original value of *i*- th bin in the histogram.

IV. EXPERIMENTAL RESULTS

The following shows the experimental results of the proposed scheme. Fig 4. shows the results of the selected representative images of the four vehicle colors. Fig. 4(a) is the detected original vehicle images and Fig. 4(b) shows the representative images. The results show that the proposed method can successfully remove the non-main body parts of a vehicle properly.

The number of images used for training and testing are listed in Table 1. In our method, only a small amount of data are used for training.

Table 1. The numbers of images used in the training and testing phases

	Red	Green	Blue	Yellow
Training data	8	8	8	8
Testing data	200	200	200	200

Table 2 lists the accuracy of the classification of the four vehicle colors. The "Original" in the table suggests that the detected vehicle is the input of the SVM directly without the proposed partition process. The results show that the proposed scheme improves classification accuracy, especially for the colors blue and green. In average, the accuracy is improved from 68% to 85.75%.

Table 2. Accuracy of classification

	Red	Green	Blue	Yellow
Original	73%	55.5%	57%	86.5%
Proposed	85%	77.5%	84%	96.5%

V. CONCLUSIONS

In this paper, we propose a VCC method for vehicle color classification. The image of the detected vehicle is first divided into several sub-images through the proposed recursive partition process. Then the selection of the representative image is used to choose the best representative image from the subimages. Finally, the extracted feature, the hue histogram, is used to establish the SVM classifier. The built SVM classifier is responsible for the classification of the four colors (red, green, blue and yellow). Experimental results show that the average accuracy of the proposed method reaches 85.75% and prove that the proposed method is feasible for vehicle color classification.

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Fig 4(a). Detected original vehicle images.

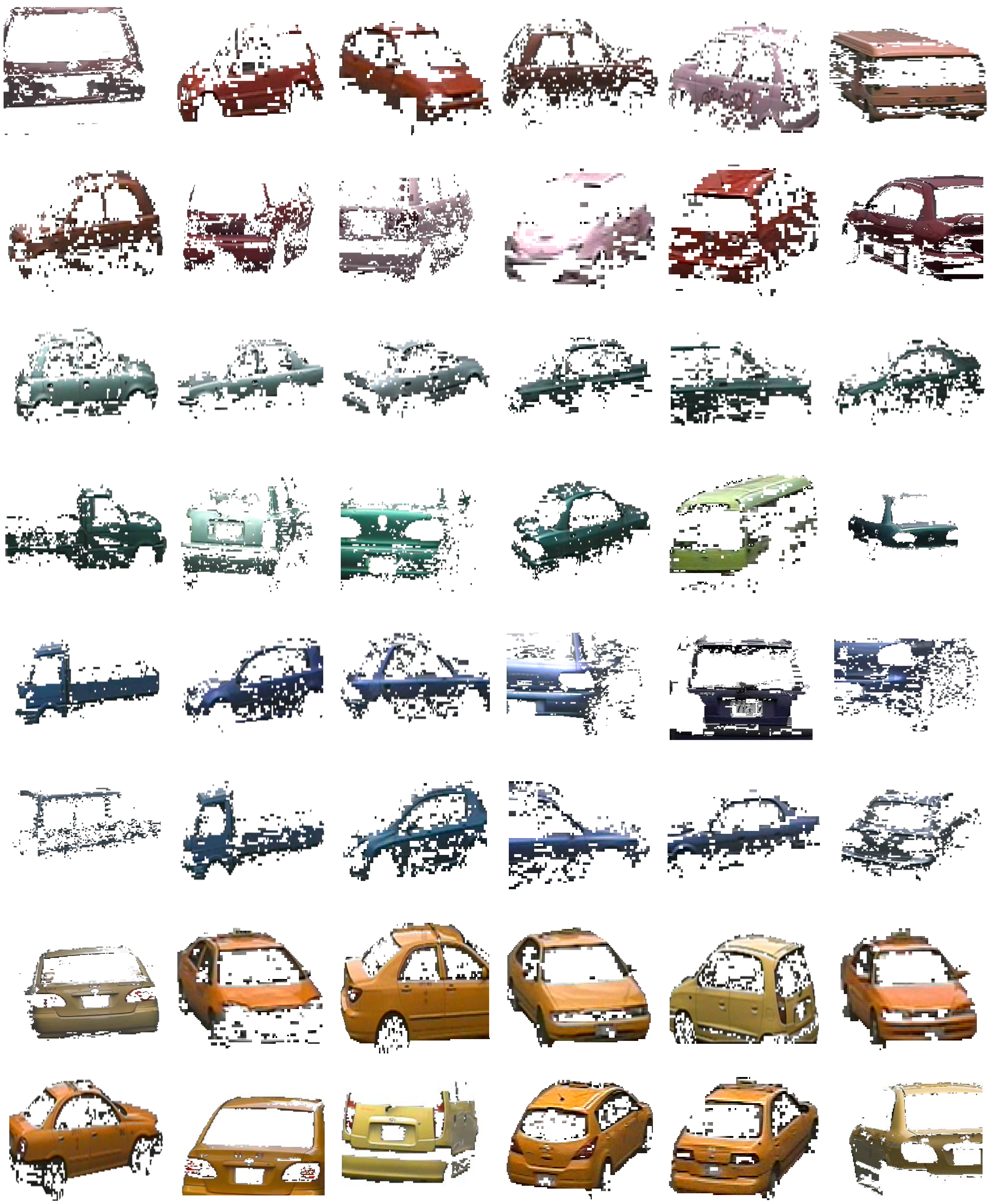

Fig 4(b). Representative images.