A Novel Car Body Color Recognition Algorithm Based on Defogging and Weight Block

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Abstract — This paper proposes a car body color recognition method that can be used at highway toll gate and parking entrance to gather and extract the color information of the vehicle. Defogging algorithm, weight block, and HSV color space histogram are adopted to recognize the body color. During the preprocessing stage, color equalization and defogging algorithm are firstly used to avoid the influence of rainy and foggy days. An improved dark channel prior method is presented to reinforce the clarity of atomized images which can make defogging better and faster. Then, the car image is generally divided into twelve blocks and each block has different weight according to its position, which can avoid interference of the background colors. Next, RGB color space of the block is converted into HSV space. Each block image in HSV color space is beneficial to the histogram statistics. Finally, the body color is decided by the sum of weight of each color. Experimental results show that the body color can be recognized fast and accurately from all kinds of complex backgrounds.

Keywords - Car body color recognition, Dark channel prior, Weight block.

I. INTRODUCTION

Since the rapid development of economy and road traffic, the number of cars has increased significantly. Meanwhile, many efforts have been undertaken to reinforce the traffic management. Further improvement capabilities are associated with being free charge and parking management. Considering all these cases the extraction of vehicle body color feature is proposed to achieve car detection combining with other vehicle features, which greatly strengthens the management of the vehicle.

The car recognition approaches have been widely studied for many years. The algorithm of license plate recognition has been relatively well developed. However only relying on license plate recognition cannot meet today's vehicle management. Thereby the recognition of the car body color which can assist license plate recognition to manage vehicles is presented. The car color information can be divided into two categories including license plate and car body. License plate color recognition is to find the target regions of images taking advantage of an algorithm to recognize and locate. The recognition of the body color, in contrast, is very complicated. Generally, it will be affected by the background colors and only identifies single-colored cars or the main color of the car. So far, in the existing literatures, most of the algorithms are to convert RGB color space into other color space and to use some algorithms to recognize the vehicle color. M. Merler presented a method that calculates the Euclidean distance of RGB color space to recognize the vehicle color [1]. G. Li et al. proposed a car body color recognition approach using HSI (Hue, Saturation, Intensity) color space combining with color difference formula of unified standard [2], but the result is erroneous for the image lack of sunlight using this method. Yang Feng introduced an approach based on support vector machine to recognize car body color [3]. The recognition accuracy of this approach is greatly improved comparing with previous algorithms. However, the results of the images under rainy weather and strong light are not accurate. K. He et al proposed a theory based on the dark channel prior [4] that could recover atomized images well. Kong Chao et al. proposed the research and application of vehicles consistency checking based on multi-feature [5]. A car body color recognition approach presented in this paper combines defogging and weight block to identify the car colors. An improved dark channel prior principle is adopted as the preprocessing step to increase the recognition accuracy. And the image is divided into several weighted blocks to avoid interference of the background colors. Then weight block and color histogram in HSV space are combined. The color is identified by using H and V values, which can accurately identify the car body color. The rest of this paper is organized as follows. In Section II, the overall scheme of the car body color recognition algorithm is briefly introduced. In Section III, color equalization and defogging based on dark channel prior theory are used as the preprocessing step. In Section IV, weight block and HSV color space are applied to the car body color recognition. In Section V, experimental results are demonstrated to show the effectiveness of the proposed method. Finally, the paper is concluded in Section VI.

II. OVERALL SCHEME

In recent years many kinds of recognition methods have emerged including calculating the Euclidean distance of the RGB space and support vector machine-based. The latter can be much more efficient than the former. Subsequently, in this paper a method of histogram statistics combining with weight block is put forward to recognize the car body color,
which can not only improve the accuracy rate but also apply to the complex weather conditions.

The overall flowchart of car body color recognition method is shown in Fig. 1. Firstly, preprocessing is necessary to avoid the influence of environment. In the preprocessed step, color equalization is used to reduce light and defogging is used to recover the image from atomized image. Preprocessing reinforces anti-interference capability of the approach, but it does not eliminate the influence of background color. So weight block plays an important role in eliminating the background color. Then the image is separated into several blocks according to their positions. Each block is set to a weight depending on its location and is converted into HSV space to compute the color histogram and determine the main color. Then the main colors of sub-blocks are stored into an array and the weight values of color appearing in the image are counted. The color whose weight value is the largest is regarded as the main color of body. Finally, classify the colors and output the car body color.

Figure 1. Overall Flowchart.

III. PREPROCESSING

The information of the captured image is possibly declined due to the influence of weather conditions. The images collected in rainy days or foggy days have blooming phenomenon, which will decrease the car body recognition accuracy. Therefore, the preprocessing is necessary to recognize the car body color accurately.

A. Color Equalization

The car color information will decline affected by weather, which will lead to the confusion of car body color. Color histogram equalization [6] is presented to solve this problem. Color histogram equalization of colored image has similar theory as gray image. The only difference is that gray image is single channel, whereas colored image is RGB three-channel. So, firstly, colored image can be separated into three single-channel images, and then each channel is made histogram equalization separately. Then three independent channels equalized are combined into one. By this time histogram equalization of the colored image has been achieved to equalize the pictures that are too dark or too bright, as shown in Fig. 2 and Fig.3.

B. Defogging

It is difficult to identify the original color of the car when subjecting to foggy weather. Color histogram equalization can only improve the quality of the pictures, but it does not have effect for atomized images. In a non-fog color picture, there is always a channel whose pixel values are low even close to zero. While in the foggy weather, the pixel values are higher significantly. In other words the images atomized seriously are interfered in this location. So the fog density can be calculated beginning with this position to recover the original color of image.

Figure 2. Picture Renderings before Equalization.

Figure 3. Picture Renderings after Equalization.

Among the image $J$, the dark channel is defined as follows:

$$J^\text{dark}(x) = \min_{y \in \Omega}(\min_{c \in \mathcal{C}}(J^c(y)))$$

(1)

Where $\mathcal{J}$ is representative for a color channel of image $J$ and $\Omega(x)$ represents rectangular area regarding $x$ as the center. An atomized image will be affected by light and scattering and so on, so it can be expressed by the following model:

$$I(x) = J(x) + A(1-t(x))$$

(2)

Where $I(x)$ represents atomized picture, $J(x)$ represents the original image, $A$ represents light intensity and $t(x)$ called
transmission ratio represents the scattering parts due to the effect of the fog and light. Indeed defogging is the process that atomized image $I(x)$ known is made use to seek original vehicle image $J(x)$. First the transmission ratio is estimated. The light intensity $A$ of a region is assumed and the transmission ratio is a constant. Under these conditions transmission ratio is expressed as:

$$t(x) = I - \min_{y \in [0,\max]}(\min_{x \in \Omega} \left( \frac{I^*(y)}{A} \right))$$

(3)

The image obtained is a non-fog image using the above $t(x)$, but in fact there will be some granule that will generate scattering and refraction. In order to make the picture look true, an adjustment factor $\omega$ is joined to (3) ($0 < \omega < 1$), then $t(x)$ is expressed as:

$$t(x) = I - \omega \min_{y \in [0,\max]}(\min_{x \in \Omega} \left( \frac{I^*(y)}{A} \right))$$

(4)

Then the overall atmospheric light intensity of the image atomized should be estimated. When estimating the transmission rate, the value of the dark channel is approximate to the fog intensity. Likewise, the atmospheric light intensity can be estimated using the same method. First 0.1 percent of the maximum value of the dark channel pixel is found whose effect is the largest by fog and transmission ratio is the least. Then the position of the pixel can be found in the atomized image and the maximum of brightness is regarded as atmospheric light value among these points. So far atmospheric light intensity and the transmission ratio have been known, next the original image $J(x)$ can be got according to the model (2).

$$J(x) = \frac{I(x) - A}{\max(t(x), t_0)} + A$$

(5)

As described above, the image is assumed to be non-sky and non-fog image. However, it does not give clear explanation for those images containing the sky, white building, strong light and other bright regions of large area. The pixel values of dark channel are very low, even close to zero. The values of RGB three channels are all close to 255 in these bright areas. The approach based on the dark channel principle does not apply to these images. In order to solve this problem, an improved dark channel principle [7-9] is proposed to expand its scope of application.

When there is a few of points of high pixel values and low pixel values appearing in images, the image will take place the color deviation. The transmission ratio obtained is wrong using the above method. For these areas that dark channel principle is not applied to, the actual transmission ratio is defined as:

$$t(x) = \frac{I - \min_z(\min_{y \in \Omega} \left( \frac{I^*(y)}{A} \right))}{I - \min_z(\min_{y \in \Omega} \left( \frac{I^*(y)}{A} \right))}$$

(6)

Aiming at the case that RGB values are all close to 255, parameter tolerance which represents the distance between the light intensity value $A$ and pixel values $x$ in the image is introduced, $J(x)$ is expressed as:

$$J(x) = \frac{I(x) - A}{\min(max(\frac{K}{I(x) - A})*\max(t(x), t_0), 1)} + A$$

(7)

IV. COLOR RECOGNITION

In this work, the relative position between the camera and the vehicle is stationary and the car has the largest portion of each collected picture. Weight block is proposed to avoid the interference of background colors. The image is segmented into twelve blocks according their positions. Each block is converted into HSV space from RGB space to calculate color histogram. Finally the weight of each color is calculated to decide the body color. Fig. 4. shows the body color recognition flowchart.

A. Weight Block

The car accounts for the center and the most of the captured image, so it can be considered that the most color of the image is the car body color. But a few colors will appear in background resulting in color recognition interference. Weight block can be used to reduce the influence of background color. Since the car information concentrates on the center of the image, the weight in the center should be larger than the weight in the edge. Therefore, the image is segmented into twelve blocks according to their positions, and then the main color is calculated in each block. Fig. 5. shows the image partition of the whole image. $N1$ to $N12$ represent each sub-image. In order to avoid the influence of other colors, each sub-image is set to a weight according to its position. The weight from $N1$ to $N4$ is set to 0.05 as the block in the edge may contain background information. The weight from $N5$ to $N8$ is set to 0.08 because these parts may include either car body or car window. The weight from $N9$ to $N12$ is set to 0.12 since most of these areas are the car body. The sum of weights $N1$ to $N12$ is equal to 1.
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Figure 5. Weight Blocks of an Image

In order to make the process more clearly, the picture shown in Fig. 6 is set as an example. The car image is divided into twelve blocks according to the weights. The color recognized includes green, black, and white. The weight of each color is calculated as follows.

\[ N_{\text{green}} = N1 + N2 = 0.1 \]  
\[ N_{\text{black}} = N3 + N5 + N6 + N7 + N8 = 0.37 \]  
\[ N_{\text{white}} = N4 + N9 + N10 + N11 + N12 = 0.53 \]  

The results show that the weight of white is the largest, and it can be regarded as the main color, which matches the true color of car body. So the method of weight block can reduce the interference of background.

B. Color Space Transformation

RGB color space based on red, green and blue is the manifestation of color pattern. Each color can be generated by red, green, and blue colors changed in their respective channels or mixed. This kind of color space is easily displayed on the illuminant, such as color display on television. But it is not easy to identify the RGB color by eyes when making the color statistics. So it should be converted into other color spaces. HSV space that can reflect the color characteristics directly adopts a user intuitive color description method where \( H \) denotes the hue, \( S \) denotes the saturation and \( V \) denotes the value. HSV space [10] converted from RGB space seems to be an inverted hexagonal pyramid. \( H \) is only sensitive to color and brightness is determined by \( V \) axis. \( V \) axis \([0, 1]\) shows the different gray levels. Black and the color close to it are described by the position 0, while location 1 describes white and the color close to it.

\[ V = \max(R, G, B) \]  
\[ S = \begin{cases} V - \min(R, G, B) & \text{Others} \\ \frac{V}{R} & V = 0 \end{cases} \]  
\[ H = \begin{cases} 60 \frac{(G - B)}{(S \times V)} & \max(R, G, B) = R \\ 120 + \frac{60(B - R)}{S \times V} & \max(R, G, B) = G \\ 240 + \frac{60(R - G)}{S \times V} & \max(R, G, B) = B \end{cases} \]  

Adjust the result \( H \) to ensure that it is a positive value. \( V \) component is divided by 255 to ensure that it is in the range \([0, 1]\). The range of \( S \) is \([0, 1]\). When RGB space is transformed into HSV space, two cases must be considered. Judge whether \( S \) is equal to 0 or not. If it is equal to 0, then \( R = G = B = V \). Otherwise the equation is conveyed as:

\[ f = \frac{H}{60} - h \]  
\[ p = V \times (1 - S) \]  

Figure 6. Image Block Renderings

Figure 7. HSV Space Renderings

RGB color space is converted into HSV space to adapt to compute color histogram. R, G and B values are converted to floating-point format and are scaled to fit the range \([0, 1]\) in 8 or 16 bit pictures. The equation that RGB space is converted into HSV space is defined as:

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\[ q = V \times (1 - f \times S) \]  
(16)

\[ t = V \times (1 - (1 - f) \times S) \]  
(17)

For each color vector \((R, G, B)\) the Equation is different depending on the differences of values of \(h_i\), the Equation is expressed as:

\[
\begin{align*}
R = V, G = t, B = p & \quad hi = 0 \\
R = q, G = V, B = p & \quad hi = 1 \\
R = p, G = V, B = t & \quad hi = 2 \\
R = p, G = q, B = V & \quad hi = 3 \\
R = t, G = p, B = V & \quad hi = 4 \\
R = V, G = p, B = q & \quad hi = 5 
\end{align*}
\]  
(18)

C. Color Decision

As described above, the image is divided into twelve blocks. Then each block is counted color histogram in HSV color space. Color histogram has been used in many image detections [11]. Depending on color characteristic the frequency of color are counted and the most color is regarded as the main color. The color histogram only cares about color space ratio instead of color distribution. So in the image the main color of each block is found and is stored into an array. The color weight is counted according to sub-image weight. The color whose weight is the most can be regarded as car body color.

After finding the car color it needs to be identified. In HSV space \(H\) values can be used as a basis to analyze color and \(V\) values can distinguish different gray level colors. So the color threshold can be set to differentiate the nine colors. Finally HSV color space is converted to RGB space to display car body color.

V. EXPERIMENTAL RESULTS

The image database is made up of 150 single-car images captured in highway toll gate and parking entrance including 95 images under normal light during the day, 40 images in cloudy day, and 15 images captured at night. The image database is also divided into nine categories according to the colors of vehicle, including 53 images in black, 24 images in white, 7 images in red, 10 images in blue, 5 images in green, 6 images in yellow, 6 images in purple, 21 images in silver and 18 images in gray. Table I shows recognition results of various colors. The overall accuracy of the images reaches 83.33%. Among all of the colors the recognition rate of white is the worst due to the influence of light.

<table>
<thead>
<tr>
<th>Kinds of Color</th>
<th>Number of Test Images</th>
<th>Number of Correct Ones</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Black</td>
<td>53</td>
<td>42</td>
<td>79.25%</td>
</tr>
<tr>
<td>White</td>
<td>24</td>
<td>17</td>
<td>70.8%</td>
</tr>
<tr>
<td>Red</td>
<td>7</td>
<td>7</td>
<td>100%</td>
</tr>
</tbody>
</table>

Table II shows the different recognition results from different weather conditions. The results in Table II show that the accuracy rate in cloudy or foggy day is the highest, while in contrast the accuracy rate at night is the worst. The quality of the images at night that are affected by lights or other external factors degrades, which results in the inferior recognition accuracy. For example, the white-car image shown in Table III is detected to be yellow affected by the light of night. The accuracy rate during the day is not high partially because of the strong light. When subjecting to strong light, black is easily identified erroneously. For example, the black-car image shown in Table III is identified incorrectly to the silver under strong lighting conditions.

<table>
<thead>
<tr>
<th>Number of Test Images</th>
<th>Number of Correct Ones</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>During the day</td>
<td>95</td>
<td>78</td>
</tr>
<tr>
<td>Cloudy or foggy day</td>
<td>40</td>
<td>36</td>
</tr>
<tr>
<td>Night</td>
<td>15</td>
<td>11</td>
</tr>
<tr>
<td>Overall</td>
<td>150</td>
<td>125</td>
</tr>
</tbody>
</table>

TABLE IV. THE COMPARISON OF SEVERAL CAR BODY COLOR RECOGNITION ALGORITHMS

<table>
<thead>
<tr>
<th>Algorithms</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>RGB Euclidean Distance Algorithm</td>
<td>61.42%</td>
</tr>
<tr>
<td>SVM-based Algorithm</td>
<td>80.34%</td>
</tr>
<tr>
<td>The Proposed Algorithm</td>
<td>83.33%</td>
</tr>
</tbody>
</table>

TABLE I. RECOGNITION RESULTS OF VARIOUS COLORS

<table>
<thead>
<tr>
<th>Original Color</th>
<th>Recognition Color</th>
<th>Weather Conditions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Black</td>
<td>Silver</td>
<td>Strong light during day time</td>
</tr>
<tr>
<td>White</td>
<td>Yellow</td>
<td>Night</td>
</tr>
</tbody>
</table>

TABLE II. COLOR RECOGNITION RESULTS UNDER DIFFERENT WEATHER CONDITIONS

<table>
<thead>
<tr>
<th>Number of Test Images</th>
<th>Number of Correct Ones</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Blue</td>
<td>10</td>
<td>9</td>
</tr>
<tr>
<td>Green</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>Yellow</td>
<td>6</td>
<td>6</td>
</tr>
<tr>
<td>Purple</td>
<td>6</td>
<td>6</td>
</tr>
<tr>
<td>Silver</td>
<td>21</td>
<td>19</td>
</tr>
<tr>
<td>Gray</td>
<td>18</td>
<td>14</td>
</tr>
<tr>
<td>Overall</td>
<td>150</td>
<td>125</td>
</tr>
</tbody>
</table>
The comparison of several car body color recognition algorithms is shown in Table IV, including RGB Euclidean distance algorithm, SVM-based algorithm, and the proposed algorithm. The proposed method has superior in accuracy rate and reliability comparing with other algorithms. In complicated environment the method is used to recognize the car body color avoiding the influences of bad weather. In addition, weight block is used to reinforce the accuracy rate of the work. Particularly the vehicle images identified are captured under various conditions such as night, rainy days, fogging days and sunny days. Therefore the approach has strong robustness against complex weather conditions and backgrounds.

VI. CONCLUSIONS

This paper proposes a novel car body color recognition algorithm based on defogging and weight block, which can be beneficial to the modern intelligent traffic management. Dark channel prior method is used at the preprocessing stage to weaken the influence of rainy and foggy days. To avoid interference of the background colors, the whole image is divided into several independent sub-images according to their positions, which can increase the accuracy of color recognition. HSV color space is also used for precise color classification. Experimental results show that the proposed method can achieve high color recognition rate under complex weather conditions and backgrounds. In the future work, color inpainting for the strong-light car images would enhance the performance of color recognition system.

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