Color Classification of Vehicles Based on Two-Layer Salincy, Illumination-Invariant Transformation, and Adaptive KNN

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Abstract: In the process of color classification of vehicles, the accurate segmentation of color regions and the elimination of non-color interference regions remain to be dealt with. Therefore, a vehicle color algorithm based on two-layer saliency map, illumination invariant transformation, and adaptive KNN is proposed in this paper. A two-layer saliency map is used to remove interference regions independent of the color of vehicles. The graph is transformed and finally classified based on the adaptive k nearest neighbor algorithm. The experimental results demonstrate that the method can accurately extract the body of the vehicles to a certain extent, and preprocessed with illumination invariance transformation, colors of vehicles can be accurately classified even in dark and reflective environments. The further work of this study is to extract slightly deeper features and directly obtain the preliminary saliency graph based on the decoder processing.

Key words: Color classification of vehicles, two-layer saliency, illumination-invariant transformation, adaptive KNN.

1. Introduction

With the increasing number of vehicles in the urban road, the traffic environment becomes more and more complex, and when the license plate target is small, it is likely to be obstructed by the interference of dust and so on, and it is arduous to identify accurately. It will be a great help to make up for this deficiency by accurately identifying the color of the vehicles. It can not only improve the safety and reliability of the intelligent transportation system but also help the security department to locate and locate the vehicles quickly. As a result, criminal activities are effectively combated.

Previously, in the field of vehicle color recognition at home and abroad, the general practice is to locate the vehicles in video or image first, and then make use of the more obvious features in the vehicles on this basis. The location of modules such as light, bumper, license plate and so on determines the area of interest, then extracts it, and then classifies and recognizes it.

In the existing research, on the image preprocessing, especially on the color pre-processing, Xue *et al*. used histogram equalization, locally contrast enhancement and homomorphism filtering to adapt to the vehicle image processing and recognition. [1], [2] But it takes a lot of time. Jun-Wei et al. used the saliency mapping kernel function in the image to reduce highlight and color distortion. [3] In addition, in the overall classification and recognition, Chen Pan *et al*., Chuanping Hu *et al*. first carried out a certain amount of fog removal processing on the vehicle's image, and then carried on the invisible or dominant location of the salient region

on this basis, and then carried on the color classification, and then carried on the color classification, such as the word packet model. [4], [5] But the selection of its salient region is not very accurate, and then affect its recognition effect.

Additionally, there are also some direct uses of in-depth learning to classify vehicle colors, However, it needs a large amount of data, large requirements for computer hardware conditions, the recognition area is not fine enough and sometimes the recognition results do not improve very well.

Given the above situation, to obtain a more accurate vehicle recognition region and color classification reults, this paper proposes a method using image saliency and locality-sensitive histogram to pre-process the vehicle's image. Through the image saliency transformation, the vehicle's position is located from the image containing more background at one time, and the main part of the body is retained by detecting the windhield and other parts that have obvious influence on the color recognition. Then a locality-sensitive histogram and an adaptive KNN classification algorithm are designed to make it have a good classification and recognition effect in different illumination.

2. Color Classification Algorithm Based on Two-Layer Saliency, Illumination-Invariant Transformation, and Adaptive KNN

In this paper, an improved method for vehicle color classification is proposed. To begin with, a method based on two-layer saliency is proposed to detect the body of vehicle images on three color channels, R, G, and B respectively, and to set different control parameters on each channel. Then three channels are fused, so that the target region is segmented more accurately, the interference target is removed, and then the locality-sensitive histogram transformation is carried out. After that, the illumination-invariant transformation will be used to preprocess and improve robustness. Additionally, adaptive KNN is used to sort out the color of vehicles.

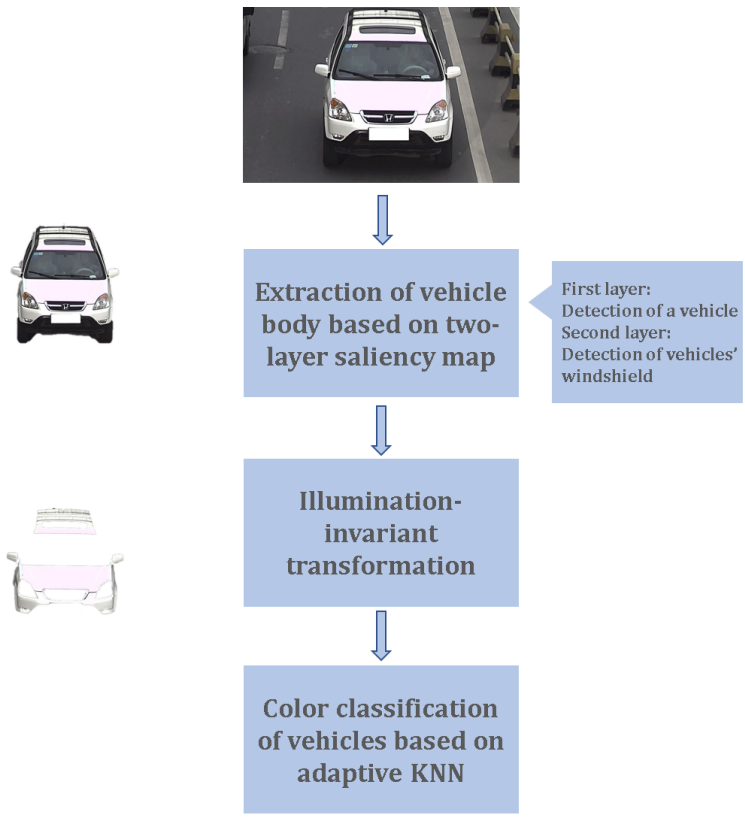


Fig. 1. Flow chart of color classification of vehicles.

2.1. Extraction of Vehicles Body Based on the Two-Layer Saliency Map

In the vehicle's image, one is the background of the vehicles, the other is the windshield in the body area, which affects the accurate segmentation of the color region. Therefore, this paper proposes a two-layer saliency map based on regional salient detection, the vehicle's image to do two salient detection. One layer is a single channel, the other is a multi-channel. The former removes the background part by salient detection, while the latter removes the windshield part that affects color recognition by retaining the non-salient region, achieving the segmentation effect.

Generally, the image saliency value of a pixel in an image is defined as:

$$\mathrm{S}(\mathrm{I_k}) = \sum_{\forall \mathrm{I_i} \in \mathrm{I}} \mathrm{D}(\mathrm{I_k}, \mathrm{I_i}) \tag{1}$$

where $D(I_k, I_i)$ is the color distance measurement of pixel $I_k$and pixel I_i in R*G*B space, and its expansion is as follows:

$$S(I_k) = D(I_k, I_1) + D(I_k, I_2) + \cdots + D(I_k, I_N) \tag{2}$$

where the image I contains the total number of pixels N, $N = x * y$. In the image, because the salient detection of the color does not need to consider the spatial position of the pixel, the saliency value of each color can be obtained:

$$S(I_k) = S(c_l) = \sum_{i=1}^{n} f_i D(c_l, c_i) \tag{3}$$

where c_l is the pixel color value of pixel I_k, n is the total number of pixel color values in the image, and f_i is the probability of c_i appearing in the image I .

Once the saliency value is obtained, on this basis, by designing a selector, the desired pixel is preserved:

$$S(I_k) = \begin{cases} 1, |S(I_k) - p| < \alpha \\ 0 \end{cases} \tag{4}$$

where p is the peak value bins in the statistical histogram of saliency value bins, and α is the selection parameter, which is the range of saliency values selected.

When removing the background of the vehicles, c_l is the gray value of pixel I_k and n is 256; when removing interference areas such as windscreen, c_l is the color value of pixel I_k and n is the total number of colors contained in the image. When the background is removed, because the background of the vehicles is consistent in general, we use this feature to detect the single-channel saliency, that is, the saliency target detection in the gray-scale image. When the interference is removed in the vehicle's area, if the full color space is used, 256^3 kinds of colors will be used. Aiming to reduce the computational complexity and spatial complexity, the color of the three channels is quantized here, each channel gets 10 different values, and the final number of colors is reduced to 1000. In the calculation of the saliency value of each image, the similar colors are merged and their number is controlled less than 50 to reduce the time complexity.

2.2. Illumination-Invariant Transformation

For the sake of solving the problem of image color recognition error in dark night, a transform algorithm based on the locality-sensitive histogram is designed in this paper. The histogram statistics of pixel comparisons are made, and the influence of other pixels in the image is calculated. Finally, a transformation weight matrix is obtained for each pixel to form a new image, so as to have a certain constant illumination under the condition of dark night and keep the original pixel color unchanged.

If an image I is used as an image, its corresponding statistical histogram is $\boldsymbol{H}$, that is:

$$\boldsymbol{H}(b) = \sum_{q=1}^{N} Q\left(\boldsymbol{I}_q, b\right) \quad , b = 1, \ldots, B \tag{5}$$

Among them, N is the number of pixels in the image, B is the maximum number of bins group distance,

in this paper, it is set to 32, that is, the gray value 255 is divided into 32 groups, every 8 pixels of gray scale corresponding to a vector, $Q(\boldsymbol{I}_q, b)$:

$$Q(\boldsymbol{I}_q, b) = \begin{cases} 0 & ,other \\ b & ,\frac{I_q}{8} \in [b-1, b] \end{cases} \tag{6}$$

Here, the two-dimensional matrix of each color channel in the image is simplified to one-dimensional, and $\boldsymbol{H}(b)$ iterates based on the p-1 pixel in front of it, that is:

$$\boldsymbol{H}_p^{\boldsymbol{I}}(b) = Q(\boldsymbol{I}_p, b) + \boldsymbol{H}_{p-1}^{\boldsymbol{I}}(b) \quad , b = 1, \dots, B \tag{7}$$

In the actual operation, the two-dimensional matrix of the image is divided into x and y directions, each direction is simplified to one-dimensional calculation, that is:

$$\boldsymbol{H}_p^{\boldsymbol{I}}(b) = \boldsymbol{H}_p^{\boldsymbol{I}_x}(b) + \boldsymbol{H}_p^{\boldsymbol{I}_y}(b) \tag{8}$$

Because the influence between a pixel and its surrounding pixels is relatively large, and the distance is almost negligible, a locality-sensitive statistical histogram is used to replace the statistical histogram, that is:

$$\boldsymbol{H}_p^{LS}(b) = \sum_{q=1}^{N} \alpha^{|p-q|} \bullet Q(\boldsymbol{I}_q, b) \quad , b = 1, \dots, B \tag{9}$$

Here, $\alpha \in (0,1)$ is a weight matrix, decreasing from near to far according to the position of the pixel.

After the transformation of a locality-sensitive statistical histogram, the intensity values of pixels are superimposed on each other to form the local aggregation of the whole image, that is, ignore the interference of non-important pixels.

Then, by one of the following transformations, it has a certain color invariance to the light:

$$\boldsymbol{I}_p^{'} = \mathcal{A}_p(\boldsymbol{I}_p) = a_{1,p}\boldsymbol{I}_p + a_{2,p} \tag{10}$$

Among it, $\boldsymbol{I}_p$ and $\boldsymbol{I}_p^{'}$ represent the color values of pixels before and after the transformation respectively, while $\mathcal{A}_p$ is a transformation function and $a_{1,p}$ and $a_{2,p}$ are two parameters.

2.3. Color Classification of Vehicles Based on Adaptive KNN

K-nearest neighbor, KNN is one of the classification algorithms and one of the classification algorithms based on space vector model (VSM). [6], [7] KNN classifies by calculating the similarity between the sample data to be tested and the data points of different categories in the training sample data, that is to say, the distance from the nearest k sample points of the sample point to be tested is used to determine its classification. And in the process of calculation, adaptive KNN algorithm automatically selects the nearest k sample points according to the instance, so that it has self-adaptability to different instances, and does not have to set k sample points in advance to compare. [8], [9]

The algorithm flow for this adaptive KNN is as follows:

1: Make k the nearest neighbor number and initialize to 10, D is the set of training samples

2: For each test sample $z = (R_z, G_z, B_z)$:

(1) according to the value of z , the training samples $D_z \in D$ are selected by the method of minimum interception.

(2) calculating the Euclidean distance d_i between z and each sample $(R_i, G_i, B_i) \in D_z$

(3) choose the first k samples with the smallest distance and output the type with the largest number of Y_i

(4) the value of k is added by 1, until the next classification result is consistent with the results of the previous two, then the k value takes the intermediate value.

3. Output classification results for test sample z

Among them, $D = (R_i, G_i, B_i, Y_i)$ is the largest training sample and R_i, G_i, B_i, Y is the value and classification mark of the three color channels. And the minimum interception method, that is, in the initial data sample point setting, through the RGB three-channel color division of the detailed class, each channel is divided into 10 sampling points, combined is 1000 sample points. The 1000 sample points are then divided into 10 categories, that is, the total number of categories of vehicle colors. The minimum truncated sample point method, which is based on the value of z, outputs the test sample D_z through the following equation:

$$D_z = \begin{matrix} D, max\{|R_z - R_i|, |G_z - G_i|, |B_z - B_i|\} \leq 40 \\ \emptyset \end{matrix} \tag{11}$$

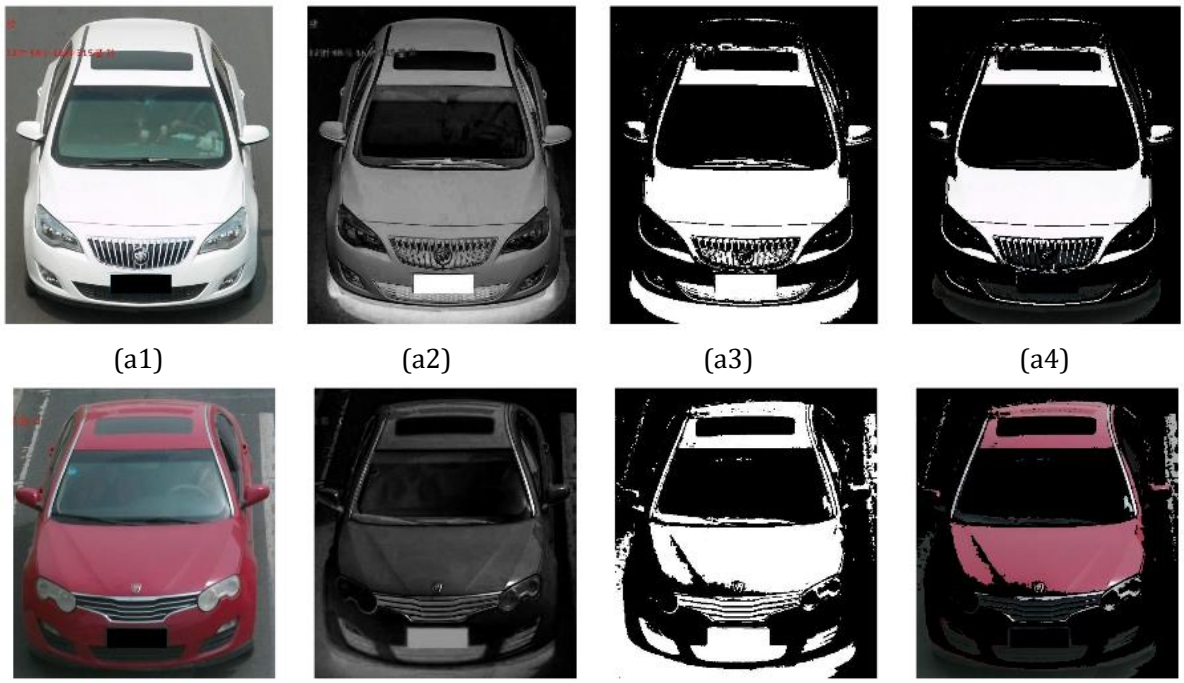
3. Experimental Results

This section tests the proposed method through Python and runs it on an Intel i7 2.5ghz CPU and 12GB RAM computer, mainly to evaluate the effectiveness, classification accuracy and efficiency of the test algorithm.

In this paper, we collect urban road traffic images, classify and label the corresponding color vehicles, and complete the collection and labeling of 5,000 images of 10 kinds of colors, which can be used to verify whether the algorithm is accurate or not. Also, for the KNN classifier, the text data containing 1000 sample points are made, and the classification visualization is carried out.

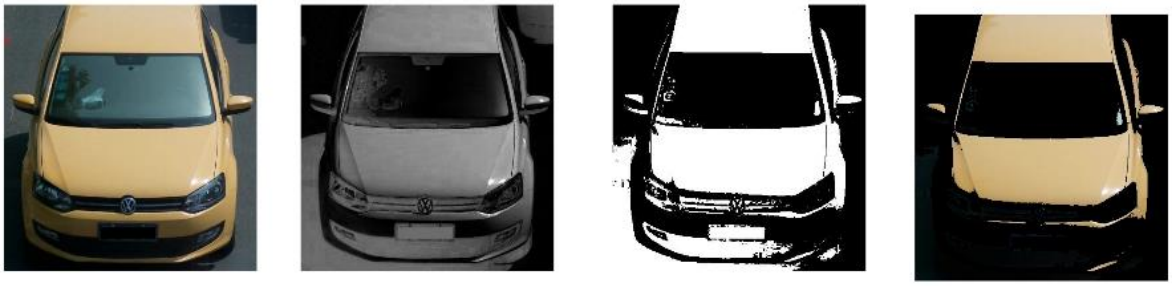
3.1. The Test of the extraction of Vehicles Body

In this step, the vehicle images with a partial background are selected as the input. After the salient feature graph is obtained, a fixed threshold between [0,255] is set to segment the binary image. Finally, the segmentation result is combined with the original image to output the final result, and the non-target area is set to black to display as shown in the following illustration:



(a1) (a2) (a3) (a4)

(b1) (b2) (b3) (b4)

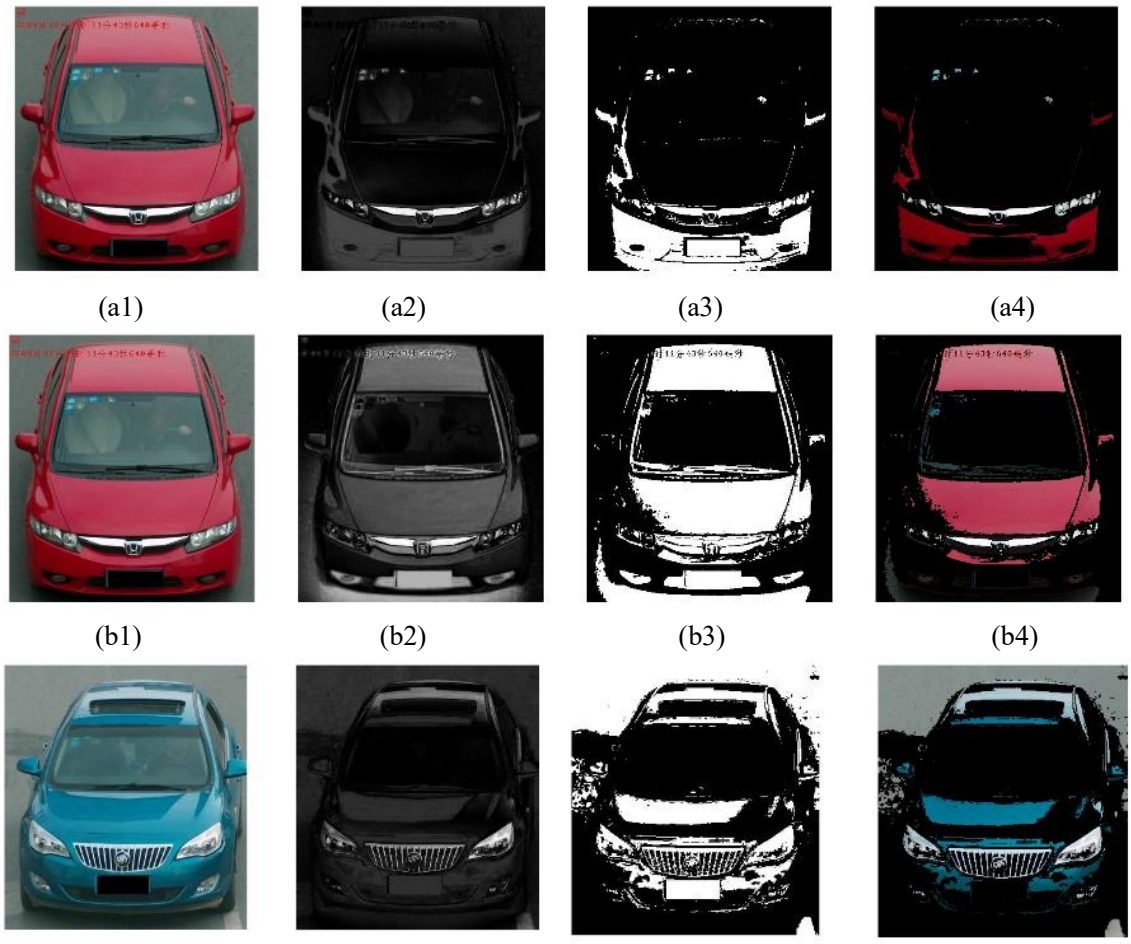


(c1) (c2) (c3) (c4)

Fig. 2. Process chart of salient detection, from no.1 to 4, the original drawing, saliency detection, salient cutting, and the cut drawing are respectively.

Take (a) as an example to illustrate: first of all, the salient detection is carried out. (a1) is the original picture. (a2) is the salient saliency map. You can see that the background and the window part of the car will become different from the color part of the main body. And as can be seen in the (a3), the salient cutting diagram, it has already cut out the color part of the body obviously, and (a4) is the final effect. The final result is that only the body color is retained and the rest is removed as a useless background.

Comparing the salient detection effect of the original method with the method of this paper, the method in this paper is more suitable for vehicles detection of different colors, and the effect is shown in the following diagram:



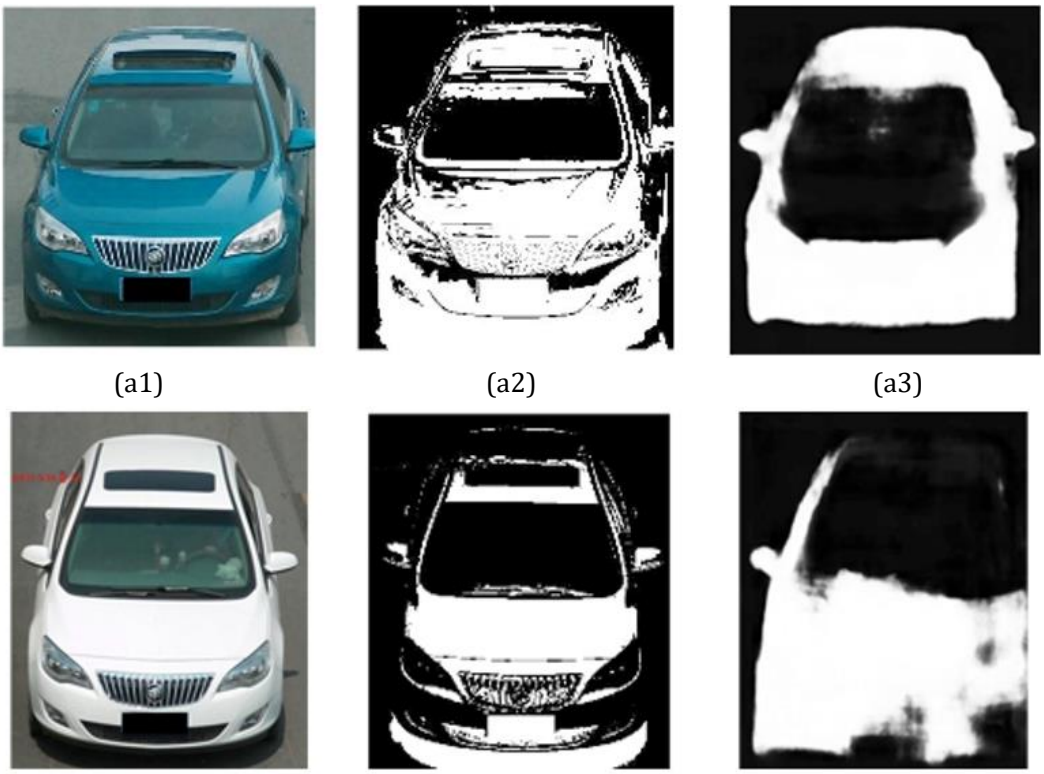
(a1) (a2) (a3) (a4)

(b1) (b2) (b3) (b4)

(c1) (c2) (c3) (c4)

(d1) (d2) (d3) (d4)

Fig. 3. The comparison between the original method and this method is as follows: a and c are the original method and b and d respectively are the comparison of the experimental results of the method in this paper. It can be seen that the method in this paper can be applied to the detection of vehicles of different colors. While, the original method only works well for a single color.



(a1) (a2) (a3)

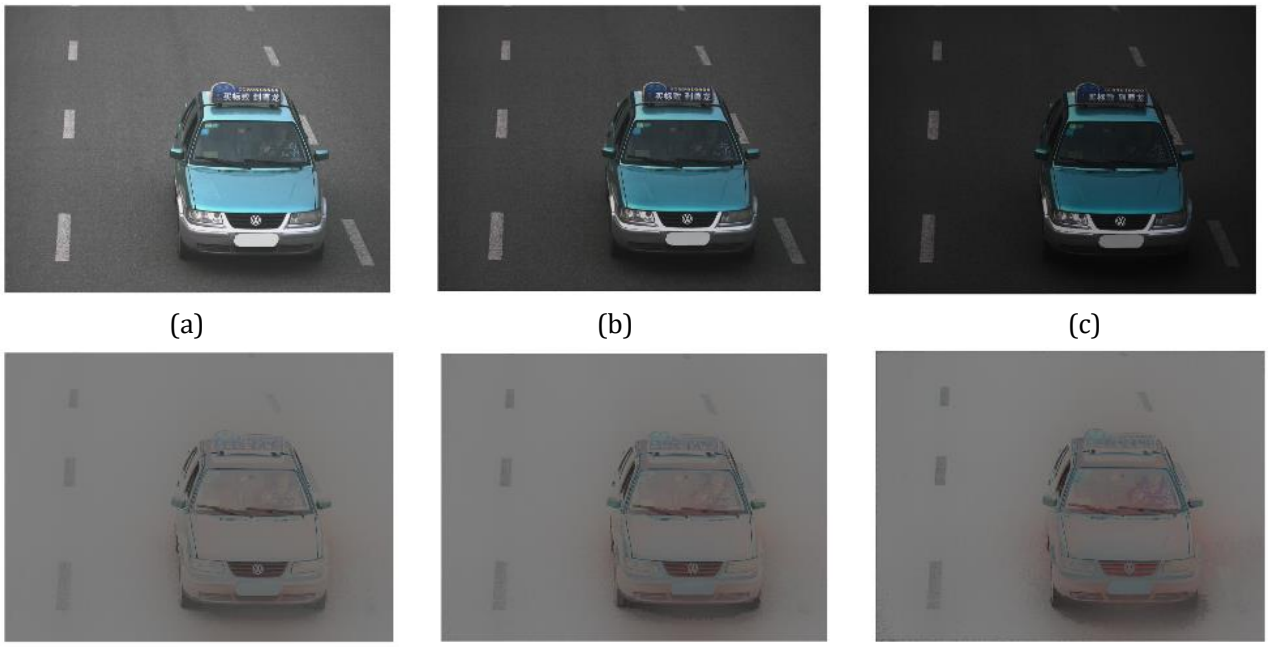
(b1) (b2) (b3)

Fig. 4. The comparison between the other method and this method is as follows: a1 and b1 are the original picture and a2 and b2 are the graph obtained by salient cutting with the method in this paper and a3 and b3 respectively are the graph obtained by using another method.

Compared with another method, we can see that our method can achieve fine segmentation. [10] It is advantageous to segment the window glass and other parts when locating the second segment after the vehicles.

3.2. The Test of Illumination-Invariant Transformation

Images are collected from urban roads. Since it is difficult to collect photos of the same car at different times, the brightness of the collected images is transformed to imitate the images of urban road vehicles under different lighting conditions. The original images, transformation images under different lighting conditions, and constant multi-channel illumination transformation images are shown as follows:



(a) (b) (c)

(d) (e) (f)

Fig. 5. Multi-channel luminance constant transform feature, figs. a to c are input images under different illumination, and figs. d to f are transformed diagrams for comparison.

From the experimental results, under different illumination, the main part of the vehicles is relatively intact. Although the color aspect becomes relatively light, its basic characteristic will still exist. The classification in the next step only needs to set a conversion coefficient, so our algorithm can basically achieve the characteristic constant effect in different illumination.

3.3. The Test of Color Classification of Vehicles

To investigate the effectiveness of extraction of the vehicle's body and preprocessing, 500 samples were used to detect the accuracy of color classification of vehicles based on different algorithms. Table 1 shows the results of the experiments.

Table 1. The Result of Experiments

Algorithm	Test Sample	Accuracy
Classical KNN (k=10)	500	66.00%
Adaptive KNN	500	73.00%
Adaptive KNN +Two-layer saliency map	500	86.70%
Adaptive KNN + Illumination invariant transformation	500	84.30%
Adaptive KNN +Two-layer saliency map +Illumination invariant transformation	500	95.60%

4. Conclusion

In this paper, an algorithm for color classification of vehicles based on a two-layer saliency map, illumination invariant transformation, and adaptive KNN is proposed in this paper It's shown that the algorithm is superior to other color classification of vehicles methods in terms of accuracy, robustness, and stability. Of course, this paper also has shortcomings. The experimental results demonstrate that the shallow features have little influence on the final saliency detection results, but the operation consumption of the shallow features is very large. Therefore, the further work of this study is to extract slightly deeper features and directly obtain the preliminary saliency graph based on the decoder processing.

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