A Vehicle Logo Location Method Based on Sub-block Pixel Intensity and Weight Matrix

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Abstract. Vehicle logo, as the key information of vehicle, combined with other vehicle characteristics will make vehicle management more effective in the intelligent transportation system. However, it is still a challenging task to detect vehicle logo due to its variations in geometry, location and illumination. In this paper, we propose a method to locate the texture type, which is based on the sub-block pixel intensity and weight matrix. This method is suitable for the target location under various backgrounds, and has a faster location speed in the complex background. It has a high robustness and strong anti-interference to the illumination. Finally, our method was verified effectively through the experiment compared to other methods.

1. Introduction

Vehicle logo detection is a kind of technology to exactly detect the vehicle logo position from picture or video. It is the key step before vehicle logo recognition. Vehicle logo detection problem usually has the following feature: (1) usually vehicle logos have kinds of shapes, commonly including circle, rectangle, and character and so on. (2) The location of vehicle logo is usually in cooling network, this adds the complexity of detection. (3) It is easily affected by illumination, such as reflecting problem under glare and low resolution problem at night, both will add interference. Due to the particularity of vehicle logo, some mature target positioning technology like license plate positioning technology does not suit for vehicle logo. So it attracts a lot of attention from scholars home and abroad.

In 2008, Apostolos P.Psyllos et al. [1] Firstly researched a vehicle logo detection technology which combined detection and phase congruency model to locate logo. In 2009, Wenju Li and Ling Li [2] use a method based on prior knowledge and background texture. In 2012, Kai Zhou, Karthik Mahesh Varadarajan et al. [3] proposed a vehicle symmetry axis detection method based on SIFT descriptors. It firstly calculates the symmetry axis, and then use the phase congruency to locate vehicle logo according symmetry axis. This method has a low detection speed although it has good detection effect. In 2014, Quan Sun [4] et al. proposed an improved edge detection algorithm. It introduced attenuation coefficient in vehicle precise positioning and can detect without discriminating texture type. Literature [5] proposed a detection method based on Adaboost. This method extracts a lot of wavelet moment of vehicle logos and non-vehicle logos, and composes a strong classifier with weak probability classifiers. It needs to detect the
image in different scales, so it will be detrimental to real-time processing. In Literature [6], after precisely positioning the vehicle logo and normalizing, the author mapped the vehicle logo into the feature space generated by PCA to get the reconstructed image. And then eliminate non-vehicle logo area by plausibility function to reduce the positioning error.

This paper proposed a precisely location method that does not need to judge texture type, this method can be used to locate vehicle logo in condition of various background. And even under abstract background it still has fast localization rate and good robustness to illumination. At the end of this paper it shows the advantages of this method compared with other existing methods through experiments.

2. Vehicle Logo Precisely Location Algorithm

From a point of human visual view, the vehicle logo shapes are mostly circular or oval, with rich edge texture information, and the texture directions include variety of directions other than horizontal and vertical directions. However, the edge texture of cooling fan network has fewer directions, generally mainly in horizontal and vertical directions, and a few other parts are in the form of a mesh. However, compared with these texture features, vehicle logo features are more prominent. Therefore, based on the above features, we first detect the edge of the image, remove the background texture information greatly, and keep the key structure information of the vehicle logo to facilitate subsequent processing.

2.1 Edge Detection with Sobel Operator

Edge detection refers to extracting edge information that has significant changes in the image by a certain way, so as to highlight the significant edge changes part. The common forms of edge detection are first-derivative edge detection and second-derivative edge detection. Among the currently used edge detection operators, the Sobel operator is widely used in many field. It can highlight the horizontal and vertical edge information of the image respectively and greatly reduce the edge information of the other direction. In recent years, Sobel operator has also been used as a method of image processing in the field of vehicle logo detection. The template of Sobel horizontal and vertical operator is as follows:

$$\begin{bmatrix}
-1 & 0 & 1 \\
-2 & 0 & 2 \\
-1 & 0 & 2
\end{bmatrix} * A$$

Horizontal edge detection can greatly reduce the vertical texture information to highlight the horizontal edge information, and vertical edge detection is the opposite. Considering that the vehicle logo background texture may be horizontal texture, vertical texture, or both, the texture information needs to be suppressed as much as possible. So here we first respectively use Sobel horizontal or vertical operator to detect the edge of the original image, and then use the other direction of the detection operator to filter out the edge information of the other direction, and finally obtain two edge-detection images. In these two images, besides the vehicle logo itself, a part of the edge information of the background texture that has not been suppressed is preserved, such as the profile of the fin that is not completely eliminated and other stains on the upper edge of the coarse positioning area and so on. This edge information exists in the form of noise. We calculate the noise information, and then select the image with less noise information as the object of subsequent processing.

$$G = \begin{cases}
G_1, E(G_1) \leq E(G_2) \\
G_2, E(G_1) > E(G_2)
\end{cases} \quad (1)$$

$$G_1 = I \otimes G_x \otimes H_y = I \otimes \begin{bmatrix}
-1 & 0 & 1 \\
-2 & 0 & 2 \\
-1 & 0 & 1
\end{bmatrix} \otimes \begin{bmatrix}
-1 \\
0 \\
1
\end{bmatrix} \quad (2)$$

$$G_2 = I \otimes G_y \otimes H_x = I \otimes \begin{bmatrix}
-1 & 2 & -1 \\
0 & 0 & 0 \\
1 & 2 & 1
\end{bmatrix} \otimes \begin{bmatrix}
-1 \\
1
\end{bmatrix} \quad (3)$$
Where, $\otimes$ is the convolution operator, $G_x$ and $G_y$ are Sobel horizontal and vertical operator, $H_x$ and $H_y$ are horizontal and vertical operator, $E(G) = \sum g_{ij}^2$ represents pixel intensity. $G$ indicates that the image with smaller pixel intensity in the two images generated by the original image using edge detection. It has less noise information and can reduce the influence of noise on subsequent operations. As shown in Figure 1, $E(G_1) = 748.96$, $E(G_2) = 704.88$, so the result image $G = G_2$. In Figure 1

![Figure 1](image)

(a) Original (b) Vertical Edge (c) Horizontal Edge (d) Result

**Figure 1.** Edge information suppression of various textures

### 2.2 Image Sub-block Pixel Intensity

After the initial suppression of the texture, we found that the pixels in the vehicle logo area are relatively dense, while the background noise is relatively sparse. Local sub-blocks of images have proven to be suitable for analyzing image features and suppressing image noise [7]. Therefore, in this paper, we introduce the concept of image sub-block pixel intensity, and use it to describe the rough area of the vehicle logo, eliminating noise points. The concept of pixel sub-pixel intensity is as follows: Let $z = (x,y)$ denotes a pixel in image $G$, and sub-block $p(z)$ is a rectangular pixel block, centered at point $z$ and its size is $m \times m$. A sub-block pixel intensity is define as equation 4

$$E(p(z)) = \sum G(w)^{z^{1/2}}$$

(4)

Where $w$ is each pixel in sub-block $p(z)$. We can sample sub-block with any pixel as the central point in image $G$ to obtain a series of sub-blocks. The $m$ is the parameter that determines the size of the sub-block; we find that it can obtain better results when $m = 11$ through experiments.

We can find that vehicle logo and the license plate have same vertical symmetric axis. So according to this feature we can use a gaussian distribution $W_1(z)$ to represent the probability that the pixel whether belong to a vehicle logo equation 5.

$$W_1(z) = \exp\left(-\frac{||x-x_0||^2 + ||y-y_0||^2}{2\sigma_x\sigma_y}\right)$$

(5)

Where the $W_1(z)$ is related to the distance between the pixel and point $(x_0,y_0)$, the smaller the distance is, the value of $W_1(z)$ is bigger and its probability of vehicle logo area is bigger. $(x_0,y_0)$ is the central point of vehicle logo, and the value of $x_0$ can approximately be obtained by the vertical symmetric axis of license plate. And then calculate point $(x_0,y_0)$ and its 8 adjacent pixels average sub-block pixel intensity $E(p(z))$.
\[
\overline{E(p(z))} = \frac{\sum E(p(x))}{9}
\]  

(6)

The location ordinate of max value of all \(\overline{E(p(z))}\) is \(y_0\). \(\sigma_x\) and \(\sigma_y\) are determined by the width and height of vehicle logo coarse area. In this paper, the value of \(\sigma_x\) is width/6, the value of \(\sigma_y\) is height/6.

\[W_2(z) = 1 - \exp(-k \cdot f(p(z), p(z_0)))\]  

(7)

\[f(p(z), p(z_0)) = \frac{E(p(z))}{(1 + D(p(z), p(z_0)))}\]  

(8)

\[D(p(z), p(z_0)) = ||z - z_0||\]  

(9)

Where the value of \(W_2(z)\) is related to the distance between \(z\) and \(z_0\) and the sub-block intensity \(E(p(z))\), the distance is smaller the similarity is bigger; and the intensity \(E(p(z))\) is bigger, the similarity is bigger. \(D(p(z), p(z_0))\) represents the euclidean distance between the central point \(z\) and \(z_0\) of sub-block \(p(z)\) and \(p(z_0)\). \(k\) is constant coefficient, this value is 5 in this paper.

Combine the edge information of the image and the weight matrix information to highlight the vehicle logo area to obtain the saliency image \(T(x, y)\), which contains a large number of vehicle logo area textures and filters out the non-vehicle logo area textures

\[T(i, j) = G(i, j) \ast W_1(i, j) \ast W_2(i, j)\]  

(10)

Finally, use the OTSU threshold algorithm [8] to select a threshold \(T_h\) to threshold the grayscale image. We can obtain the binary image and segment the vehicle logo area

\[T'(i, j) = \begin{cases} 1, & T(i, j) > T_h \\ 0, & T(i, j) \leq T_h \end{cases}\]  

(11)
3. Experimental Results and Analysis

In order to verify the effectiveness of the proposed method for vehicle logo precisely location described in this paper, we designed following experiments. All the images are sampled from actual road. Taking into account the actual circumstances of illumination and weather of road bayonet vehicle pictures, we divided 1436 vehicle logo pictures into three data sample sets, then test the detection correct rate of each sample set in different light conditions respectively. In data samples set I, the illumination conditions of the vehicle pictures are dark, mostly cloudy and rainy weather and night; the illumination conditions of the vehicle pictures in the data samples set II are ideal, and the illumination is uniform and the vehicle logos are clear; illumination conditions are relatively strong, there is reflection on the part of vehicle logos.

Table 1 is the result of the experiment of this paper’s precisely positioning algorithm. Due to the different illumination conditions of the three data sets, the detection rate is slightly different. In the case of dark rainy weather and dark night conditions, it can extract less information from the vehicle logo, and this resulted in the lowest detection rate, but still maintained at more than 90%; In the case of ideal light and clear vehicle logo image, the detection is best and it is up to 97.69%. From the point of view of detection time, the algorithm average operation time is only about 97ms, and it can meet the needs of online real-time processing.

| Data Samples | Samples I | Samples II | Samples III |
|--------------|-----------|------------|-------------|
| Samples Number | 416       | 565        | 455         |
| Correct Number | 381       | 552        | 430         |
| Correct Rate  | 91.59%    | 97.69%     | 94.50%      |
| Average Time  | 94ms      | 102ms      | 97ms        |

In order to verify the effectiveness of the proposed algorithm, we compare the results of three experiments with the method in literature [8] [9] [4]. The comparison of experimental results is shown in Table 2. The literature [8] is the traditional background texture suppression method, and the literature [9] and the literature [4] are respectively improved by the methods in [8]. In the experiment, we took 1436 vehicle logo pictures as test samples, and the main type of vehicles was car, the main types of vehicle logos were common 15 types, and it included horizontal, vertical and mesh types of texture.

As can be seen from Table 2, the detection rate of the literature [8] is relatively low. Before the location, it needs to determine the background texture type of the vehicle logo by using texture recognition algorithm, which will produce a certain degree of error in the experiment. Literature [9] improved the method of reference [8]. This method has a detection rate of 95.59% for horizontal and mesh texture types. However, this method has its limitations. It has poor effect on vehicle logos of vertical texture. So the overall detection rate is only 84.20%. Besides, it consumes more time than other methods because of...
introduction of the template matching. Literature [4] also improved the method in reference [8]. It introduced texture attenuation coefficient, the method does not need to judge the texture for a variety of background texture of vehicle logos, the overall detection rate can reach 90.95%, but it is more sensitive to light, especially in the case of intense reflective light, the location results will be a certain degree of error. But our method applies to a variety of different vehicle logos texture detection, and the detection time also meets the real-time needs. The detection accuracy reaches 94.91%. Generally speaking, the detection method proposed in this paper is superior to the other three methods, so the method is more suitable for vehicle logo detection in practical applications.

| Table 2. Comparison of different method performance |
|--------------------------------|
| Literature [4] | Literature [5] | Literature [6] | This Paper |
| Correct Number | 1262 | 1209 | 1306 | 1363 |
| Correct Rate | 87.88% | 84.20% | 90.95% | 94.91% |
| Average Time | 103ms | 145ms | 87ms | 97ms |

4. Conclusion
This paper proposed a vehicle logo precisely location algorithm based on sub-block pixel intensity and weight matrix. This method is suitable for the positioning of vehicle logos in various contexts, and it is also faster in the case of complex backgrounds. It has high robustness and strong anti-jamming ability to illumination. And finally our method is verified effective by experiments.

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