Multiple Features Fusion for Front-View Vehicle Detection

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***Abstract*-With the rapid increase of vehicle holdings, urban transport is facing a severe test. Driver-assistance systems (ADAS) can effectively avoid happening of traffic accidents. Real-time detection of moving vehicle based on vision has become a research focus of ADAS. A method of multiple features fusion for front-view vehicle detection is proposed in this paper. Firstly, in RGB color space, license plate position is located using color conversion and Otsu threshold segmentation method is improved to confirm the vehicle's candidate area. Secondly, geometrical characteristics of the license plate is adopted to eliminate distraction regions and to verify the extracted license plate. Finally, rear lamps of vehicle are detected and matched in candidate license plate regions, so vehicle area is further determined. The experimental results show that the proposed method in this paper can be used to detect vehicle in real-time and false detection rate is low.**

Keywords-rear-view vehicle; RGB color space; Otsu threshold segmentation

I INTRODUCTION

Driver-assistance systems require real-time and reliably to detect vehicle and pedestrian around the vehicle driving direction, to remind the driver or vehicle to automatically take corresponding measures to avoid potential dangers. In ADAS, front-view vehicle detection is one of the ways to improve security, it can effectively avoid the rear-end collisions of traffic accidents due to lack of safe distance between vehicles.

Vision-based vehicle detection method mainly consists of vehicle models [1], the optical flow methods [2] and feature methods [3]. In [4], Zeng zhihong established a 'U' model and a rectangular model, which were used to detect the long distance and short distance vehicle, respectively. A fine vehicle model, which has seven parameters, was built according to the features of car body [5] to search and match of vehicles by using genetic algorithms and energy function. Model-based vehicle detection has a great dependent on model, so that this scheme is not good for real-time detection. Vehicle detection based on optical flow can not detect slow or stationary vehicle. Feature-based vehicle detection method using significant features of vehicle, such as color, edge symmetry and vehicle's shadow, to segment vehicle area [6, 7]. When there is a large impact on image from surroundings light and noise, single feature detection will be weakened, so multi-feature combination is able to improve the accuracy of vehicle detection.

Detecting the candidate area of vehicle based on color feature is a popular method. Cheng et al. [8] used a new model for the color conversion, transformed the three color components to two components, one of which represents the color model of vehicle, and the other represents a color model of non-vehicle, the method is appropriate for detecting aerial images, which reduce the effect on billboards and buildings of the road. Yan et al. [9] made binary image processing by setting H and S components threshold, this man-made threshold does not have universal adaptability. To avoid a single color model of image misjudge segmentation, Zhou et al. [10] proposed a multi-color model determined the vehicle candidate regions, selected threshold range in RGB color space, which to make sure H and S components thresholds in converted HSV color space. However, this way also need man-made threshold. Bin et al. [11] proposed a characteristic color transformation method, the extracted target areas are more significant for employment most real-time image detection, and the results are robust.

In this paper, we propose an adaptive extraction method of license plate based on the literature [11] and [12] feature extraction method with an improved Otsu algorithm to generate vehicle assumption areas. To verify and detect vehicle area, we apply the vehicle license plate and car tail lights geometric spatial relationships, and propose a multi-feature fusion for detecting forward vehicle.

II VEHICLE CANDIDATE REGION DETECTION

According to the People's Republic of China Public Security standards about the vehicle, the vehicle must be linked to the license plate when they are traveling on the road [13]. The Chinese license plates composed of a blue background and white character plate, or a yellow background and black character plate, or a white background and black character plate. Taking a white-blue pair as an example, this type of plate is the most common in China.

A Candidate license plate localization

The histogram of R, G, B, three components of license plate, is shown in Fig.1. For the blue plate, the blue components is greater than the red and green component, the histogram of B component has the largest peak among the histogram of three component in Fig.1, these extremes except for the peak value is caused by the white characters of license plate. Subtracting the red and green components from the blue components can eliminate background information and remain the license plate area. Bin et al. converted the image into a specific color space as in

$$C(x,y) = B(x,y) - \min\{R(x,y), G(x,y)\} \tag{1}$$

Where $C(x,y)$ is the converted color of (x,y) pixel, and $R(x,y)$, $G(x,y)$, $B(x,y)$ are the values of red, green, and blue channel. The converted color image is shown in Fig. 2(b). This conversion of the blue channel is very fuzzy, so the result will be missed some plate area.

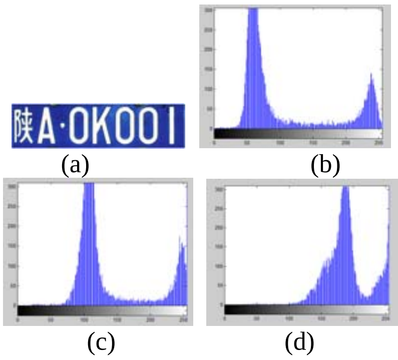

FIGURE I. THREE CHANNELS STATISTICAL HISTOGRAM OF BLUE LICENSE PLATE. (A) LICENSE PLATE. (B) R COMPONENT HISTOGRAM. (C) G COMPONENT HISTOGRAM. (D) B COMPONENT HISTOGRAM

Zheng [12] regard blue feature as the weighted sum that other two color channels subtract each other. General blue feature formula as defined in

$$C(x,y) = k_1(B(x,y) - R(x,y)) + k_2(B(x,y) - G(x,y)) \tag{2}$$

The formula (2) can be expressed as formula (3), and the converted color image is disturbed by some non-blue feature noise in Fig. 2(c), as calculated in

$$C(x,y) = 0.33748(B(x,y) - R(x,y)) + 0.66252(B(x,y) - G(x,y)) \tag{3}$$

In this paper, determines the better coefficients on the basis of experiments, and proposes a new blue feature transformation, as in

$$C(x,y) = 1.3B(x,y) - 0.3R(x,y) - G(x,y) \tag{4}$$

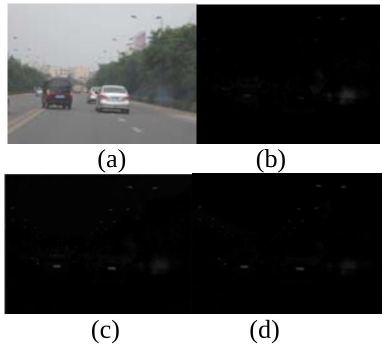

FIGURE II. COMPARISON RESULT OF BLUE FEATURE TRANSFORM. (A) INPUT IMAGE. (B) LITERATURE [11] CONVERTED RESULT IMAGE. (C) LITERATURE [12] CONVERTED RESULT IMAGE. (D) THIS PAPER CONVERTED RESULT IMAGE

B Improved Otsu threshold

Threshold segmentation plays a vital role in vehicle detection, and effect the accurate of detecting plate. The key of a binary image is choosing a appropriate threshold which is better to adaptive.

The between-class variance method, a self-adaptive threshold obtaining method, was proposed by N. Otsu in 1978. When the image histogram appears obvious peaks and troughs, the segmentation result is satisfied. However, the difference between background and foreground is not obvious, the segmentation result is bad. The Otsu's method is based on the statistical properties of the histogram, considering only gray information of pixels and ignoring its edge information. In this paper, gradient denote significant gray differences of image edges on both sides. Thereby, we combine the gradient with Otsu algorithm to integrate gray level information and edge correlation information for the pixels.

Now suppose that $G(x,y)$ represents the gradient of pixel $f(x,y)$. $G_x(x,y)$,

$G_y(x,y)$ and $GMag(x,y)$ are horizontal gradient, vertical gradient and gradient mode, respectively, as the gradient mode formal in

$$GMag(x,y) = \max\{|G_x(x,y)|, |G_y(x,y)|\} \tag{5}$$

Assuming an image is represented in L gray levels $[0,1,\cdots L-1]$, the number of pixels at level i is denoted by n_i , and the total number of pixels is denoted by N. The probability of gradient level i is denoted by

$$p_i = n_i / N,\ p_i \geq 0, \sum_{i=0}^{L-1} p_i = 1 \tag{6}$$

Assuming that the image gradient of pixels are divided into two classes C_0 with gradient levels $\{0,1,...,t\}$ and C_1 with gradient levels $\{t+1,...,L-1\}$ by the threshold t .Then the gradient level probabilities for two classes are class mean levels, respectively, are give by

$$\omega_0 = \sum_{i=0}^{t} p_i \quad , \quad \omega_1 = \sum_{i=t+1}^{L-1} p_i \qquad (7)$$

The means of class C_0 and C_1 are

$$\mu_0 = \sum_{i=0}^{t} GMag(x,y)\cdot p_i/\omega_0 \qquad (9)$$

$$\mu_1 = \sum_{i=t+1}^{L-1} GMag(x,y)\cdot p_i/\omega_1 \qquad (10)$$

As the total mean of gradient and between-class variance shown in

$$\omega_0\mu_0 + \omega_1\mu_1 = \mu_T \qquad (11)$$

$$\sigma^2 = \omega_0(\mu_0 - \mu_T)^2 + \omega_1(\mu_1 - \mu_T)^2 \qquad (12)$$

In order to choose the optimal threshold t^* by maximizing the between-class variance, since the total variance is constant for different partitions.

$$t^* = \arg\max_{o\le t\le L-1}\{\sigma^2(t)\} \qquad (13)$$

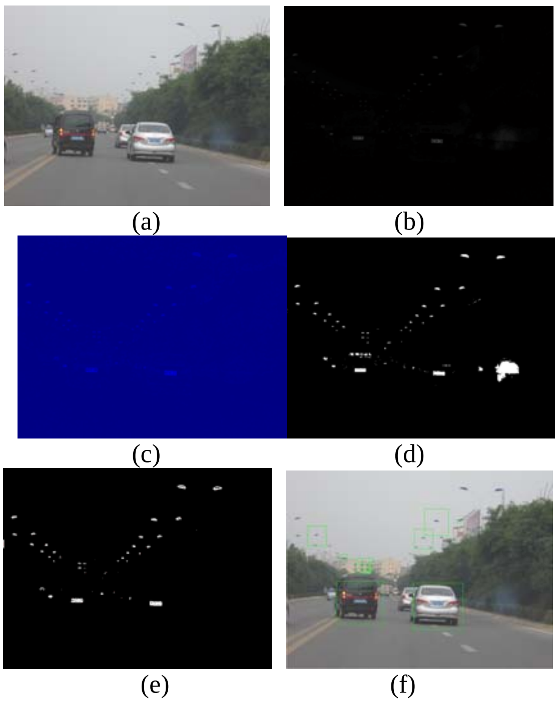

FIGURE III. COMPARISON RESULT OF THRESHOLD SEGMENTATION. (A) INPUT IMAGE. (B) BLUE FEATURE TRANSFORM. (C) GRADIENT MODE IMAGE. (D) TRADITIONAL OTSU SEGMENTATION. (E) IMPROVED OTSU SEGMENTATION. (F) CANDIDATE AREAS LOCALIZATION

The Otsu threshold segmentation result in Fig. 3(d), the proposed method can improve segmentation result for non-obvious in background and foreground Fig. 3(e). However, there are some street lights and billboards impact object localization. In order to further determine the vehicle location, the candidate areas are verified by rear lamps.

III VEHICLE LOCATION

A Rear lamp detection

A vehicle rear lamp is an obvious feature of the vehicle. According to the Chinese national standard, the color of the vehicle rear lamp is red and falls within a specified range. We operated rear-lamp localization under the RGB color space [11], the value of the red channel is large, the values of the green and blue channels are small. The conversion is called the rear-lamp color image, as calculated in

$$C(x,y) = R(x,y) - \max\{G(x,y), B(x,y)\} - 2\|G(x,y) - B(x,y)\| \qquad (14)$$

This paper adopted the improved Otsu threshold segmentation method, a binary image indicating the position of red lamp pixels in the image. Due to some disturbance factors, such as billboards, traffic lights and street lights, we adopted mathematical morphological operators to remove noises and merge together closely located lamp segments in the binary image, as shown in Fig. 4(c).

B Light candidate pairing

Although the shape of rear-lamp is not specified by regulations, rear-lamp pairs must be symmetrical. Segmentation processing could lose some information of rear-lamp, so this condition may not confirm two lamps candidates belong to a vehicle. In this paper, image cross correlation is exploited based on template matching, and considering lamp shape information, we proposed lamps matching based on position and shape information.

Assuming connected region after threshold segmentation is $D_i,(i=1,...N)$, so the set of connected is $D=\{D_i\}$ .Supposing $h_{i,j}$, $v_{i,j}$ are horizontal distance and vertical distance of D_i to D_j, respectively, B_i is a minimum external rectangle of connected region D_i, imcrop (B_i) is interception region of D_i, and the average gray value, length and width ratio of the region are $W(D)$, $H(D)$ and $Area(D_i)$, respectively, as shape constraints following in

$$0 < h_{i,j} \le \alpha\cdot\min(W(D_i), W(D_j)) \qquad (15)$$

$$0 \le v_{i,j} \le \beta\cdot\min(H(D_i), H(D_j)) \qquad (16)$$

$$sd_{ij} = Aear(D_i)/Aear(D_j) \le \tau \qquad (17)$$

Where sd_{ij} is similar ratio of the region shape. α, β, τ are experience threshold.

The cross-correlation matrix λ is calculated between two lamp images by[14]

$$\gamma = \frac{\sum_{(x,y)} (D_l(x,y) - \overline{D_l})(D_r(x,y) - \overline{D_r})}{\sqrt{(\sum_{(x,y)} (D_l(x,y) - \overline{D_l})^2)(\sum_{(x,y)} (D_r(x,y) - \overline{D_r})^2)}} \tag{18}$$

Where $D_l(x,y)$ and $D_r(x,y)$ represent the values of the gray in (x,y) pixel location corresponding to the left and right lamps of a candidate region, respectively. $\overline{D_l}$ and $\overline{D_r}$ are the mean values of $D_l(x,y)$ and $D_r(x,y)$. A lamp pair is classified as valid vehicle, if the maximum value in the cross-correlation matrix γ is greater than a threshold $\gamma_{\min}$, the experimental results show that a pairing correlation threshold is $\gamma_{\min} = 0.8246$.

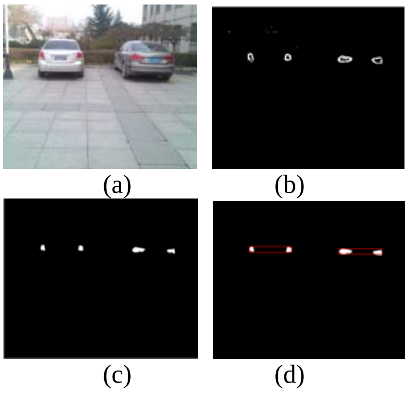

FIGURE IV. REAR LAMPS MATCH VERIFICATION IN HYPOTHESIS GENERATION. (A) INPUT IMAGE. (B) THRESHOLD SEGMENTATION. (C) MATHEMATICAL MORPHOLOGICAL. (D) REAR LAMP PAIRING

IV EXPERIMENTAL RESULTS AND ANALYSIS

Experimental data were captured using a forward-view camera mounted inside the host vehicle. The color video was captured using a regular camera with sensor. The video was processed at a resolution of 600×800.

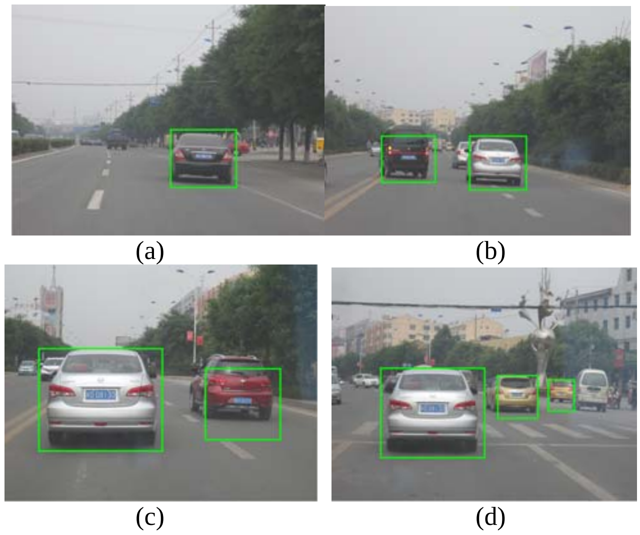

FIGURE V. DETECTION RESULTS IN VARIOUS ROAD CONDITIONS. (A) SINGLE-LANE DETECTION. (B) TURN VEHICLE DETECTION. (C) DOUBLE-LANE DETECTION. (D) THE CROSSROADS DETECTION

The detection result in Fig.5. We calculate the detection rates about the false negative rate and the false positive rate, the false negative rate is the total number of omit vehicle in proportion to the total number of frames, the false positive rate is the total number of false detections in proportion to the total number of frames.

In the paper, the false negative rate is 24.67%, and the false positive rate is 0.88%.the detection results has low rate of false positive than Bin Tian[11] method.

V CONCLUSION

In this paper, a front-view vehicle detection method based on multiple features fusion is proposed. The first processing localized the salient parts of the vehicle, including the license plate and rear lamps, color thresholds have been derived from automotive regulations and adapted to real-world conditions utilizing the RGB color space. Then segmentation adopted the improved Otsu method for color conversion image, both shape and color information are used to detect vehicle, which improves the accuracy and robustness of vehicle detection. The experiments showed that the proposed method could achieve real-time performance, the algorithm still exists the phenomenon of high false negative rate in experiment, so needs to improve the performance of the algorithm.

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