Tail Light Based Vehicle Detection and Self-Adapt Scale Vehicle Tracking

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Abstract—**This paper proposes a vehicle detection and real-time tracking system based on forward looking CCD camera, where vehicle tail light location information is employed to generate vehicle candidate, also tail light pair distance is used to adjust vehicle tracking window size. In vehicle detection step, a back propagation neural network (BPNN) which is trained by Gabor feature set is used to verify vehicle candidates. A strong BPNN classifier guarantees system robustness. In vehicle tracking step, mean shift tracking algorithm using color feature space is proposed. In the experiment, total 104 images are tested for vehicle detection, 87 vehicle images are detected successfully; a 175 frames video is tested for real-time vehicle tracking. These results show the proposed system is effective for vehicle detection and real-time tracking in the day time.**

Keywords-vehicle detection; vehicle tracking; color segmentation; mean shift

I. INTRODUCTION (HEADING 1)

An increasing number of car accident happened everyday, which has drawn great attention from the public, almost every minute, at least one people dies in vehicle crash [1]. Recently, many new technologies are developed to avoid or mitigate vehicle accident through sensing the significance and nature of danger which aim to improve human safety, such as intelligent transportation, intelligent driver assistance systems.

This paper proposes a vision based vehicle detection and real-time tracking system. Vehicle tail light information is employed in the entire algorithm. In vehicle detection step, many features can be selected. For instance, article [2-3] extracted shadow information between the vehicle and road for vehicle candidate generation, article [4-5] investigated edge histogram information. However, the shadow information is very sensitive to illumination and edge histogram is influenced easily by environment, which makes algorithm quite difficult to implement. In this paper, vehicle tail light location is use to generate vehicle candidate, these candidate is verified by BP neural network which is trained by Gabor feature set before. Vehicle detection robustness is guaranteed by BPNN classifier [6]. In real-time vehicle tracking step, mean shift algorithm is proposed. The kernel window bandwidth is very essential in mean shift tracking algorithm, it determined the sampling quantity of mean shift iteration, furthermore, it related to the tracking windows size. Original mean shift object tracking with fixed window size. Article [7] employ use kernel bandwidth increment for scale adjustment, this approach process one frame use 3 different bandwidth kernel, it will increase system runtime. In order to solve multiple scales tracking problem, this paper employed the distance between light pair which is determined by vehicle detection result for tracking windows adjustment.

The main architecture of vehicle detection and tracking system is described in figure 1.

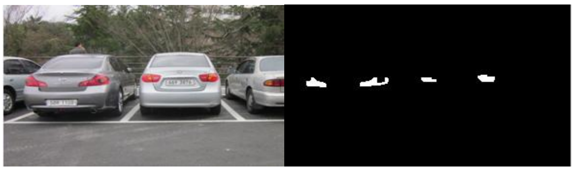
Figure 1. system architecture

II. VEHICLE DETECTION

A. *HSV color model based light blob segmentation*

HSV stands for hue, saturation and value, and is also often called HSB (B stands for brightness), these are often used by human for color object description. Based on HSV color model, red light blob can be detected easily with appropriate threshold. After that, morphological method is employed to remove some small points which come from color segmentation. Figure 2 shows Vehicle real light blob segmentation result.

(a) Signal vehicle light blob segmentation



(b) multiple vehicle light blob segmentation

Figure 2. Vehicle real light blob segmentation

B. *Light pairs candidates generation*

This step consists in finding the corresponding light pair. Vehicle tail light pair candidates can be extracted by the following conditions. See figure 3, denote the left tail light as c1 and right side tail light as c2.

Figure 3. Vehicle tail light pair

a) The distance between c_1 and c_2 should be limited to a range.

$$w_{\min} \le w_{c_1c_2} \le w_{\max} \quad (1)$$

w_{c1c2} represents the width between vehicle light pair. In this paper, w_{min} and w_{max} equal to 45 pixel length and 500 pixel length respectively.

b) The height of the corresponding light pair should be almost the same. This condition can be formulated by the equation:

$$\left| h_{c_1} - h_{c_2} \right| \le d \quad (2)$$

Where h_{c1} and h_{c2} represent the height of c_1 and c_2 respectively, d is a constant, 8 pixels were chosen in this process.

Due to the parameters which are mentioned in the above step, this algorithm is able to extract vehicle candidates based on tail light distribution. However, in some cases where cars are next to each other, as shows in figure 2(b), this process will extract non tail light pairs. As shown in figure 4, each rectangle determines one light pair

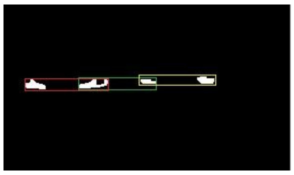


Figure 4. Light pair candidate

Because the proportion of same type vehicle is almost same, so based on lights pairs location and distance information, vehicle candidates can by extracted as figure 5 shows:

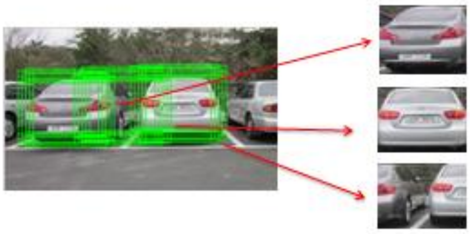


Figure 5. Vehicle candidates generation

C. *Gabor feature extraction and training process*

In order to obtain detail vehicle feature for BPNN training process, Gabor feature is investigated. Gabor feature can effectively describe local feature of image with different direction and scales. Gabor transform [8] can be formulated by the following equation:

$$G(\mathrm{x,y},\omega,\sigma) = \frac{1}{2\pi\sigma_x\sigma_y}\exp^{-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2}\right)}\exp^{-j\omega(x+y)} \quad (3)$$

This paper chooses 8 orientation and 5 scales Gabor filters to build database.

In vehicle verification step, back propagation neural network is proposed. BPNN is applied extensively in practical application, in particular, superior effectiveness in model recognition [9]. This paper uses BPNN which is trained by Gabor feature to identify vehicle in vehicle candidates. In this case, the robustness of vehicle detection is guaranteed by a strong BPNN classifier. Figure 6 shows Vehicle detection result example.

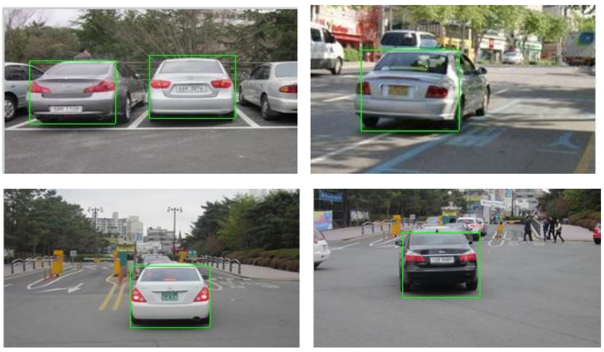


Figure 6. Vehicle detection result

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III. REAL-TIME VEHICLE TRACKING

In order to follow detected vehicle in video, this system implement mean shift algorithm for vehicle tracking. The mean shift algorithm is a nonparametric statistical method for seeking the nearest mode of point sample distribution [10] which has been proven to be very effective and efficient for object tracking.

A. Color feature space representation

In the current frame, the detected vehicle can be represented based on RGB color model, see figure 7 (b). We assume the target color model can be split several uniform histogram bins, target vehicle can be represented in RGB color space by the color probability density function (PDF) q which is calculated by the following equation, this paper proposed 16x16x16 bins, result is shown in figure 7(c).

$$q = R \times 256 + G \times 16 + B \tag{4}$$

R,G,B denote different color channel

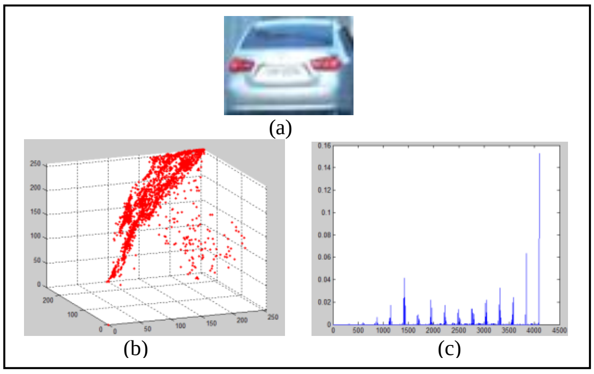

Figure 7. (a) Target vehicle, (b) RGB color space, (c) color PDF

In next frame, starting from the position of the target in the previous frame, the same process is applied, the candidate color PDF is defined as p. In order to find best matching candidate in the target's neighborhood, similarity function between q and p is proposed.

B. Similarity function

To define similarity, Bhattacharyya coefficient is proposed in this paper. The Bhattacharyya coefficient is an approximate measurement of the amount of overlap between two statistical samples. This coefficient can be used to describe the similarity of two discrete and normalized distributions q and p. The Bhattacharyya coefficient can be defined as following equation.

$$\rho[p,q] = \sum_{u=1}^{m} \sqrt{p_u q} \tag{5}$$

In the tracking system, denote p(y) is the distribution of the candidate object at position y. so the Bhattacharyya coefficient function can be formulated as

$$\rho[p(y),q] = \sum_{u=1}^{m} \sqrt{p(y)_u q} \tag{6}$$

Best candidate can be found by maximizing similarity function.

C. Mean shift vector

Mean shift is a non-parametric feature-space analysis technique which can be use for locating the maxima of a density function [11].

Let y_0 denote as model location, y denote as candidate location. The similarity function can be linearized use Taylor series as:

$$\rho[p(y_0,q)] \approx \frac{1}{2}\sum_{u=1}^{m}\sqrt{p_u(y_0)q_u} + \frac{1}{2}\sum_{u=1}^{m} p_u(y)\sqrt{\frac{q_u}{p_u(y_0)}} \tag{7}$$

$$where: \quad p_u(y) = C_h \sum_{b(x_i)=u} k\left(\left\|\frac{y-x_i}{h}\right\|^2\right)$$

C_h is normalization coefficient, h is kernel bandwidth. From the above equation, the first term is independent of candidate location y, the second term is a kernel probability density estimation with profile function k. so the similarity function maximization can be realized by the following iteration.

$$y_{k+1} = y_k + \frac{\sum_{i=1}^{n_h} \omega_i (x_i - y_k) k'\left(\left\|\frac{y_k - x_i}{h}\right\|^2\right)}{\sum_{i=1}^{n_h} \omega_i k'\left(\left\|\frac{y_k - x_i}{h}\right\|^2\right)} \tag{8}$$

$$where \quad \omega_i = \sum_{i=1}^{m} \sqrt{\frac{p_u}{q_{u(y_k)}}}$$

x_i (i=1,…,n_h) denotes the candidate spatial coordinates, h denotes the scale of the kernel. The best candidate which is most similar to the detected vehicle can be sought by mean shift iterations. The mean shift iteration example is shown in figure 8.

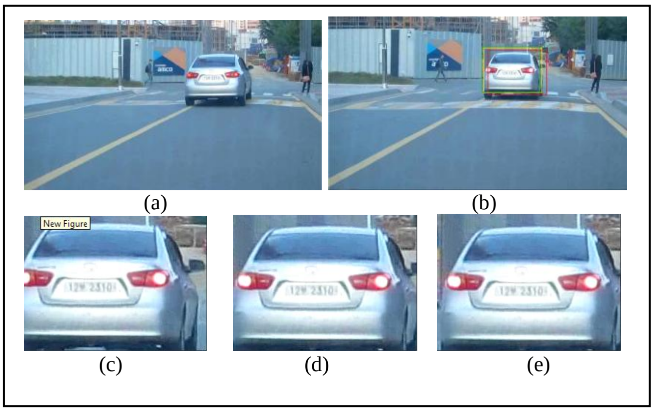

Figure 8. Mean shift iteration

Figure 8 (a) and (b) is frame t and frame t+1 respectively. The red rectangle is the first iteration, it starts from initial position which is target vehicle position at frame t, and the candidate is shown in figure 8(c). Yellow rectangle and green rectangle represent the forth iteration and ninth iteration respectively, the candidates is shown in figure 8 (d) and (e), and the ninth iteration is the final iteration which means figure 8 (e) is the best candidate for matching with the target vehicle.

D. Scale adjustment

The size of target vehicle is variable, when the distance between target vehicle and camera changing. Consequently, Window scale adjustment is essential. In order to obtain a dynamic tracking window, distance between corresponding light pairs is investigate. Light pairs are detected in vehicle candidate generation step, and it can be finally determined in vehicle verification step by trained BPNN. After apply vehicle tracking process, the best candidate is obtained. Based on this candidate, the window scale is enlarged 10%, light blob is detected by color segmentation on HSV space which has been introduced in section 2 A and B. in order to determine the corresponding light pair, the following constraints is proposed, c_1 and c_2 represent left and right light which is determined before. $c_1^{'}$ and $c_2^{'}$ represent left and right light which is detected after tracking process.

a) The area of the corresponding light is almost proportional

$$\frac{S(c_1)}{S(c_1^{'})} \approx \frac{S(c_2)}{S(c_2^{'})} \quad (9)$$

b) The shift of the corresponding light's position almost same

$$P(c_1) - P(c_1^{'}) \approx p(c_2) - P(c_2^{'}) \quad (10)$$

After corresponding light pairs are found, the distance between lights which is determined in vehicle detection step is defined as d_0, the distance between light which is detected after mean shift iteration is defined as d_t, so the size of the tracking window at frame t can be obtained by following equation:

$$L_t = \frac{d_t}{d_0} L_0 \quad (11)$$

L_0 is initial window size, L_t represents the window size at frame t.

IV. EXPERIMENTS

In this section, the experimental results obtained for the proposed method is laid out. 104 images are tested for vehicle detection; vehicle movement video is tested for combine with real-time vehicle tracking. The images sequence which comes from vehicle movement video has 175 frames of 720x1280 pixels for each. The target vehicle histogram has been derived in the RGB space with 16x16x16 bins. The detected vehicle window size was 338x444 pixels. The vehicle detection result is shown in figure 9.

Figure 9. Vehicle detection result at 1st frame

The tracking algorithm start from the 1st frame, the tracking results are presented in figure 10

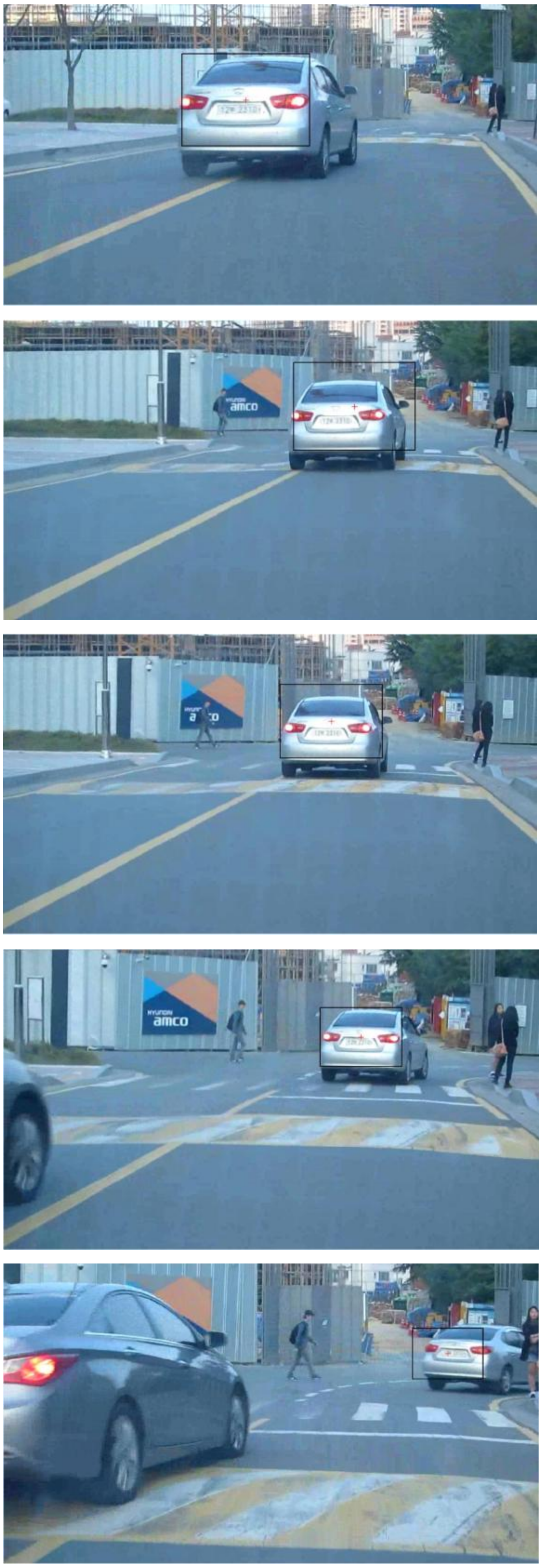

Figure 10. Vehicle tracking results. The frames 25, 79,100,143,175

These above results show the proposed system is effective for vehicle detection and real-time tracking in the day time. The tracking window scale is able to self-adapt to the changing of the target vehicle size.

V. CONCLUSIONS

This paper presents an effective system for vehicle detection and vehicle tracking. Vehicle tail light is employed in the entire algorithm, not only for vehicle candidate generation, but also for vehicle tracking window adjustment. Back propagation neural network which is trained by 8 orientation and 5scales Gabor feature set is used in vehicle candidate verification step. Mean shift tracker is implemented in vehicle tracking step.

The result shows this system has good performance for vehicle detection and tracking, especially for target vehicle nearby, because of the color information in not always stable, it influence from illumination, and the tail light is so week when target vehicle is very far from camera. Also in vehicle tracking process, because of view angle of the camera, the tracking window may not perfect matching with target vehicle.

For future work, it is necessary to utilize any other features which are stronger and more suitable for vehicle representation both in detection and tracking algorithm.

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