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LITERARY REVIEW ON FORWARD BRAKE LIGHT RECOGNITION

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ABSTRACT
Advanced vehicle safety is a recently emerging issue appealed from the explosive population of car owners. Increasing driver assistance systems have been developed for warning drivers of potential hazards by analyzing the surroundings with sensors and/or cameras. Here we have conducted a literary review on the previous methods for forward vehicle brake light detection. The review was done on three different papers. Most of the brake detection algorithms are suitable for night time vision only. During the daytime, vehicle brake lights areas are compared with the surrounding environment of vehicle, the brightness is not very different and certain methods are greatly affected by the light. Even though previous methods show fair results, they do have certain disadvantages.

Keywords- *image processing, survey ,vehicle safety.*

I. INTRODUCTION

Advanced vehicle safety is always a critical issue that ordinary people are fervently concerned about and numerous researchers are devoted to. With the explosive growth in car ownership worldwide, increasing drivers desiderate, more keenly than ever, all sorts of automatic/ semi-automatic vehicle-mounted systems for driver assistance. For accident prevention and safety promotion, most driver assistance systems are designed to call the driver's attention to potential dangers, since distracting driving is one of the main causes of traffic accidents. For the ultimate goal of accident prevention, pre-collision sensing has become a hot research topic among automotive manufacturers. Over the last decades, many existing state-of-the-art systems rely on active sensors, e.g., radars, or beam forming techniques. However, the rapid development and reduced cost of digital cameras have made it feasible to deploy driving video recorders (DVRs), which tend to be worldwide used. Moreover, due to the exponential growth in computing power and the availability of advanced computer vision techniques, various vision-based sensing can be conducted with low-cost algorithms. Compared to device-based sensing, vision-based approaches have the main advantage that different tasks can achieved merely by means of software operating on existing hardware, requiring no additional devices.

II. VISION BASED METHOD FOR FORWARD BRAKE LIGHT DETECTION

This paper presents a recognition algorithm combining the vehicle detection and the color difference of RGB color space to recognize the brake-lights state of moving vehicles in order to achieve the intelligent-car's rear-end collision warning about the vehicle in front of it. Firstly, we train and build AdaBoost cascade classifier by haar features samples and scaling sub-windows are used to detect the target vehicle from the region of interest of the resized image. Then we compare the adjacent frames to recognize brake light status, which including using color, shape, structural features to identify the third brake light; comparing the center of gravity coordinates and the color difference threshold to rear brake lights when vehicles are not red or yellow; according to subtraction of each RGB corresponding channel, binarization, and the color difference threshold of RGB color space to identify the red or yellow vehicles' brake lights. Finally, experiments show that the algorithm can detect the front vehicle's braking quickly and accurately.

1. Proposed Method

AdaBoost algorithm is used for detection of potential vehicle candidate from a given image. For a set of training set, firstly, obtain different training set Si by changing the probability distribution of each sample, then training each

Si to obtain a weak classifier hi, and lastly combine these weak classifiers according to the different weights to get the strong classifier, meanwhile, for the weights of each classification, the higher accuracy of its classification, the higher of its weights. After repeated iterative training several times, the classification error approach to zero. The object detection has been initially proposed by Paul Viola and improved by Rainer Lienhart. First of all, using samples of haar feature to train classifier, we can get a cascade Adaboost classifier. Training samples are divided into positive samples and negative samples. Positive samples which refer to the target samples to be tested, contains only the samples of the rear close-up images; Negative samples that do not contain the target of another images, such as the images containing the roads, traffic signs, buildings, billboards, cars, motorcycles, tricycles, pedestrians and bicycles, etc. All positive sample images have been normalized to uniform size. So the training sample selection process should take into the diversity of the samples account. Negative training samples are representative and each sample is not identical. The training process is divided into three steps: first of all, we need to extract Haar features; then we convert them to the corresponding Haar feature weak classifiers; finally optimal weak classifier is selected iteratively from a large number of weak classifiers.

2. Image Similarity Detection Between Two Frames

This paper uses EMD to judge the similarity of two images by resizing the Pic1 and Pic2 to the same size (a*b).The smaller of the results (0) value represents that the matching degree is higher, it means that the vehicle in the two picture is the same car Here we utilize a measurement criterion that is how to transform a histogram for another histogram including transform all or part of histogram to a new position, this kind of measurement can be done in any dimension histogram. Light can cause drift of image color values, although these drift does not change color histogram, but the drift makes the color value position change, resulting in some histogram matching strategy failure. If we use the histogram distance measuring instead of color histogram matching strategy, then we can still compare the distance of two histogram images just as histogram comparison, even if the second histogram drift occurs, we also can find the smallest distance metric. The brake light recognition algorithm is shown in Fig.1.

3. Non Red and Non Yellow Car Brake Light Recognition

In the paper, t1 = 1 means that the third brake light is detected in the previous frame image, t2= 1 means that the third brake light is detected in the next frame image. By making subtraction between R channel and G channel in color space for Picture Pic1 and Picture Pic2, binarization and calculation of the proportion of white of binarized images, we can finally get k1, k2 respectively, if k1 <0.2 && k2 <0.2, go to step 1 otherwise go to step D.

Third Brake Light Recognition): Searching the contour of the two binary image of the upper part in the two frame images respectively, detecting the third brake light, features mainly including color, shape, structure. By finding contours, if the contour features meet the rectangular outline conditions and in the vicinity of the center of the axis, then the third brake light is detected.

Rear Brake Light Recognition): Searching the contour of the two binary image of the lower part in the two frame images respectively to find two most closed coordinates of the center of gravity of the two contour sequences between two frame images.

4. Red or Yellow Car Brake Light Recognition

- By making corresponding subtraction in R channel, G channel, and B channel for Picture Pic1 and Picture Pic2 respectively, binarization and conducting and operation, we can finally get candidate region of brake lights
- By finding contours, we can obtain the coordinates of the center of gravity of contours, then we extract the feature vector of the 5x5 rectangular region of Pic2, which is compared with a standard feature vector to make determination.

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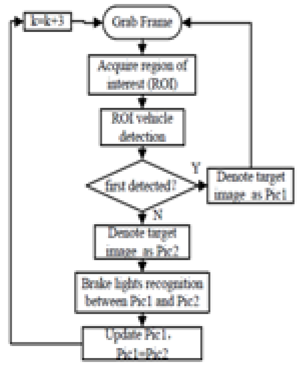

Fig. 1. ***Brake Light Recognition Algorithm.***

Outputs of Brake Lights Status: If it detects inserting road warning, the third brake light or rear brake light, which indicating that the vehicle in front brakes or insert road , alerting the rear vehicle and it would make intelligent driving decisions automatically, slowing down or stopping by itself..

5. Disadvantages

The above paper has got certain disadvantages. These need to be avoided in order to get an accurate system. In this paper different step is used for red and yellow color vehicles. The prescribed method produces a high false detection rate when detecting the brake light of red and yellow colored vehicles. Another problem is that the taillights of two distinct vehicles are not properly distinguished. This shall become a serious issue when a vehicle in the other lane applies brake.

III. REAR LAMP VEHICLE DETECTION AND TRACKING IN LOW EXPOSURE COLOR VIDEO FOR NIGHT CONDITIONS

This paper presents a recognition algorithm combining the vehicle detection and the color difference of RGB color space to recognize the brake-lights state of moving vehicles in order to achieve the intelligent-car's rear-end collision warning about the vehicle in front of it. Firstly, we train and build AdaBoost cascade classifier by haar features samples and scaling sub-windows are used to detect the target vehicle from the region of interest of the resized image. Then we compare the adjacent frames to recognize brake light status, which including using color, shape, structural features to identify the third brake light; comparing the center of gravity coordinates and the color difference threshold to rear brake lights when vehicles are not red or yellow; according to subtraction of each RGB corresponding channel, binarization, and the color difference threshold of RGB color space to identify the red or yellow vehicles' brake lights. Finally, experiments show that the algorithm can detect the front vehicle's braking quickly and accurately.

Red Light Detection

1. In this section, we describe the structure of our image processing algorithm that extracts and pairs rear vehicle lamps from frames of forward-facing automotive video. Bright objects such as street lamps, traffic signals, turn signal lamps, oncoming headlamps, and reflections from road infrastructure are filtered out while retaining the rear lamps of target vehicles as regions of interest (ROIs). Segmented red lamps are then paired to associate them with a target vehicle. The proposed algorithm is shown in Fig.2.

Deriving HSV Color Threshold: A database of 300 tail and brake lamp images was created to observe the color distributions of rear-lamp pixels. It can be observed from this scatter plot that red rear-lamp pixels do not directly conform to the derived regulation region. To adapt the regulation color region to real-world images, we convert it into the hue–saturation–value (HSV) color space as it is more intuitive to adjust and manipulate the threshold parameters than RGB. HSV is best represented as an inverted cone, with hue (tint) as the angle (0◦–360◦), saturation (shade) as the radius (0–1), and value (tone) as the perpendicular height (0–1). The color red is located around the hue value of 0◦. We convert the regulation color region from RGB to the HSV space. The H threshold limits were directly extracted from the limits of this distribution. The V component of the distribution spans the entire range of possible values. However, it is undesirable to allow the entire range of V values through the color threshold, as hue and saturation are inaccurate and unpredictable at very low levels of V, and many background pixels would be allowed through. We therefore block the lowest V values from the threshold. While the regulations specify fully saturated color for rear lamps, the saturation component of a color is somewhat dependent on the intensity of the incident light. We derive the S threshold limit from a histogram of these saturation levels.The input frame is median filtered to reduce noise before performing a color threshold with these values. This produces a binary image indicating the position of red lamp pixels in the image. This is morphologically closed to remove noise and merge together closely located lamp segments, which may have been segmented by the color threshold. Red tail and brake lamp light sources are successfully extracted, whereas other common light sources, such as street lamps and signs, are excluded.

2. Light Candidate Pairing: Although the shape of automotive rear lamps is not specified by regulations, rear-lamp pairs must be symmetrical. Image cross correlation has previously been used in automotive vision systems for headlamp detection and template matching of vehicles. We use fast normalized cross correlation to measure the symmetry between rear-lamp candidates. Correlation is calculated along the direction of a line adjoining the center of each light. This compensates for differences in roll angle between host and target vehicles caused by subtle variations in road surface and camera placement. One of the lamp regions is horizontally mirrored and used as the template T; this is then compared against the image of the potential matching lamp I.

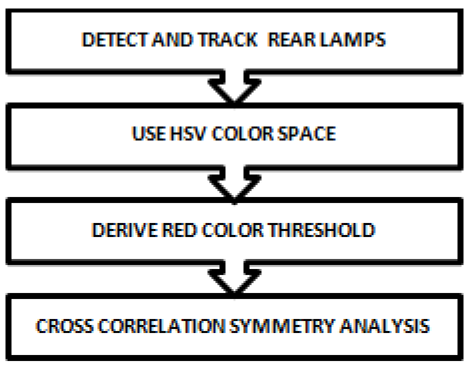

Fig. 2. Proposed Algorithm.

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$$\gamma = \sum_{x,y} \frac{(T(x,y) - \overline{T})(I(x,y) - \overline{I})}{\sigma_T \sigma_I} \qquad (1)$$

The cross-correlation matrix γ is calculated between two lamp image segments by where ⍰ and Ī are the mean values of T and I, respectively, and σT and σI are the standard deviations of T and I, respectively. To utilize color information, correlation matrices are calculated for R, G, and B channels, and the mean is calculated. A lamp pair is classified as a valid vehicle if the maximum value in the cross-correlation matrix γ is greater than a threshold γmin. The value for this was derived from the distribution of the correlation coefficients for a database of 300 images containing valid vehicle lamp pairs, as shown in Fig. 3. A Gaussian curve was fit to the histogram data, and the threshold was established at the lower 95.4% probability point (μ − 2σ). This results in a pairing correlation threshold of γmin = 0.8538. This approach is a size- and shape-independent method of pairing detected lamps.There are many benefits to using cross correlation to pair light candidates. This method is not directly dependent on the result of the threshold stage The binary result of the threshold is used only to generate ROIs in the source image for correlation. Some pairing algorithms apply heuristics to the properties of the binary thresholded regions such as comparison of vertical position or centroid, region size or area, and bounding box aspect ratio. These methods are dependent on, and sensitive to, the result of the threshold.

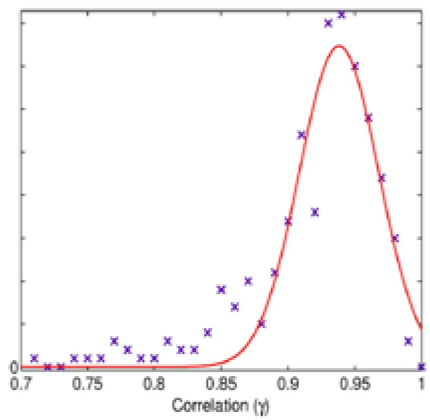

Fig. 3. Histogram illustrating the distribution of cross- correlation values γ and a Gaussian curve fit to the data

Disadvantages

These methods are dependent on, and sensitive to, the result of the threshold. Further issues with these methods are that they do not consider color or intensity information and that they may not produce a numerical parameter that is representative of how well two regions are matched. If they do, and several properties are analyzed, a method must be formed to weigh or average the parameters. Our cross correlation utilizes the color data from the source image and produces a single numerical parameter, indicating how well the regions are matched. These methods can also be sensitive to the size and shape of target regions. These methods are applicable only during night time.

IV. NIGHT TIME BRAKE LIGHT DETECTION USING NAKAGAMI IMAGING

Given the rapid expansion of car ownership worldwide, vehicle safety is an increasingly critical issue in the automobile industry. The reduced cost of cameras and optical devices has made it economically feasible to deploy front-mounted intelligent systems for visual-based event detection for forward collision avoidance and mitigation. While driving at night, vehicles in front are generally visible by their taillights and brake lights. The brake lights are particularly important because they signal deceleration and potential collision. Therefore, in this paper, we propose a novel visual-based approach, based on the Nakagami-m distribution, for detecting brake lights at night by analyzing the taillights. Rather than using the knowledge of the heuristic features, such as the symmetry, position, and size of the rear-facing vehicle, we focus on finding the invariant features to model brake light scattering by Nakagami imaging and therefore conduct the detection process in a part-based manner. vehicles' brake lights. Finally, experiments show that the algorithm can detect the front vehicle's braking quickly and accurately.

Brake Light Detection

This section describes the detection of brake lights in rear facing vehicles without complete knowledge of the vehicle's tail shape

1. Preprocessing: Contrast Enhancement: The color intensity image is defined as

$$Ci = Max(R, G, B)/255 \qquad (2)$$

where R, G, and B are the three color channels in the RGB color space. The color intensity image Ci can then be obtained using

2. In addition to employing the property of the large contrast between the taillight regions and other lights, the scattering property of brake lights is investigated. In the real world, scattering is a general physical process, where some forms of radiation, such as light, sound, or moving particles, are forced to deviate from a straight trajectory by one or more localized non uniformities in the medium through which they pass. Scattering is very significant in the area of braking lights. Therefore, we focus on discovering the invariant features from the regions of brake lights based on the scattering property and thus aim to conduct the detection process in a part-based manner. Prior to the model scattering property, a simple step function T(u) is first applied to the color intensity image Ci to reduce the noise generated from non taillights and is defined as

$$T(u) = \begin{cases} 1, & u > \theta_x \\ 0, & otherwise \end{cases} \qquad (3)$$

Using (3), the color intensity image Ci is filtered by

$$UT = Ci \times T(Ci) \qquad (4)$$

It is obvious that preprocessing using the step function can raise the contrast in the intensity image Ci, particularly the contrast between the taillight regions and the background.

However, the distributions of brake lights and taillights are highly similar and thus difficult to distinguish. To overcome this problem, we propose an approach that can discriminate brake lights from taillights based on Nakagami imaging..

Modeling Taillights by Nakagami Distribution

The Nakagami statistical model was initially used to analyze returned radar echoes and be applied to ultrasound by using two associated parameters, i.e., them-parameter and the scaling parameter. The Nakagami statistical model is briefly introduced as follows: The probability density function of the Nakagami distribution is defined asto the size and shape of target regions. These methods are applicable only during night time.

$$f(r) = \frac{2m^m r^{2m-1}}{\Gamma(m)\Omega^m} \exp(-\frac{m}{\Omega} r^2),\ r > 0 \qquad (5)$$

where Γ($\cdot$) is the gamma function. Symbol r indicates possible values of random variable R in the ROI. The scaling parameter Ω and the Nakagami parameter m associated with the Nakagami distribution can be obtained from

$$\Omega = E(R^2) \qquad (6)$$

$$m = \frac{\Omega^2}{E[(R^2 - \Omega)^2]} \qquad (7)$$

respectively, where E(•) denotes the statistical mean. The Nakagami parameter m is a shape parameter determined by the probability distribution function of the random variable R.

To detect one or more brake lights present in the image UT, the Nakagami imaging can be employed. The Nakagami image is obtained based on the Nakagami parameter map and thus can be obtained. However, a scanning window Wn with size n × n pixels should be defined first to estimate the local Nakagami parameter mL, which is assigned as the new pixel located at the center of the window. Therefore, variable R is the pixel set of the ROI selected by Wn, i.e., pi ϵR, i = 1, 2, . . . , n^2, where pi is the pixel in the square window Wn. Based on sliding window Wn in the image UT , each local Nakagami parameter mL in ROIs is computed, thus obtaining the Nakagami image. Due to the scattering from brake lights, the red lights appear wider and brighter than non brake lights. The area covering part of the taillight and the scattering regions is emphasized by Nakagami imaging, which can also assist in differentiating between the brake light areas (including the scattering region) from the non brake light areas. In the Nakagami image, it is worth noting that the density of the remaining pixels of the brake light area is higher than that of the non brake light area and the spatial consistency of pixel value in the scattering area is also higher than that in the non brake light area due to the scattering intensity, which can be modeled by

$$I_s = (1/2) I_0 (1 + \cos 2\theta) \qquad (8)$$

where I0 is the intensity of the incidental light, and θ is the scattering angle. We can see that the scattering intensity varies with the scattering angle. Therefore, based on this property, the brake lights can be differentiated since the scattering intensity of the brake lights would be much larger than that of non brake lights. In addition to taillights, some non taillights such as traffic lights or street lights can also be expected in the general road environment and should be recognized as noise. According to the scattering property, the scattering intensity of taillights would generally be larger than that of non taillights since the angle between the camera and the taillight is smaller than that between the camera and the non taillights. This means that a higher scattering intensity would result in a larger light source scattering region. Therefore, to model the scattering of brake lights, the variable R in window Wn in the Nakagami image is used to compute the density DR of pixels and the spatial consistency Sr of the Nakagami image. The characteristics of the brake lights in the Nakagami image are accordingly modeled by density DR and consistency Sr as

$$D_R = \left(\sum_{i=1}^{n^2} \left[\frac{B(P_i)}{n^2} \right] \right) \times 100 \qquad (9)$$

$$S_R = \sum_{i=1}^{n^2} \sum_{j=1}^{n^2} \left| p_i - p_j \right| \qquad (10)$$

respectively, where piϵR, B(pi) ϵ {B(pi < 0.9) = 0, B(pi ≥ 0.9) = 1}, and n^2, is the total number of pixels in Wn. It can be observed that local Nakagami parameter mL significantly changes when density DR exceeds 90%. This behavior reflects the fact that, when a vehicle brakes, the percentage of pixels within the larger mL in the Nakagami image is relatively high; meanwhile, the region covering the part of the taillight and the scattering regions is highly similar in value to the Nakagami image. Therefore, the detection of the brake lights can be conducted by using the value of density DR and consistency Sr obtained from the Nakagami image. The brake recognition scheme is shown in Fig.4.

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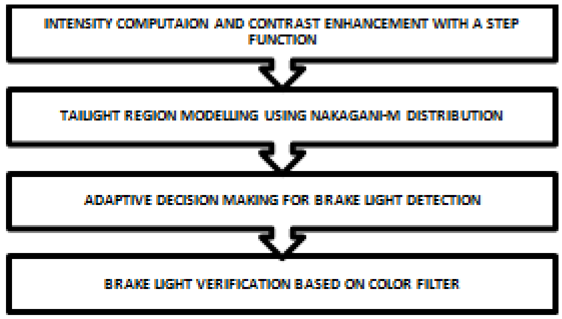

Fig. 4. Brake Recognition Scheme

Adaptive Decision Making for Brake Light Detection

To adaptively determine the threshold, a randomly generated data set is used to simulate brake light behavior. Each data set consists of n × n random values p_ri ϵ Rr, i = 1, 2, . . . , n^2,, where 0 ≤ p_ri ≤ 1. To simulate brake light behavior, we set p_ri such that DR ≥ 93%. As Wn increases, the mean value stabilizes while the standard deviation among the estimated mL in the data set decreases. The ideal size of scanning window Wn is between 17 and 19. Furthermore, the varied distance between the taillights in front and the camera is also critical since the taillight signal would attenuate with increased distance. Therefore, the threshold TM used to detect the brake lights should adapt to distance. The distance between the taillights and the camera can be approximately estimated based on the computation of the vanishing point by lane line detection. The horizontal line going through the vanishing point, is thus used to evaluate the distance to the taillights in front, the evaluated distance, a set of 500 taillights is collected at distinct distances between the vehicles and the camera and used to approximate the signal variations using curve fitting. Sometimes, the chosen curve passes through the data points, but, at other points, the curve approaches the data points without passing through them. In most cases, we use the least square curve fitting to minimize the square error of the data points. We can thus obtain an adaptive threshold TM according to distance Ddis by

$$T_M = \begin{cases} 20, & \text{if} \quad D_{dis} \geq H_d \\ aD_{dis}^2 + bD_{dis} + c, & \text{otherwise} \\ 1.5 & \text{if} \quad D_{dis} < L_d \end{cases} \qquad (11)$$

where the weighting set {a, b, c} is evaluated in the training data set, and D_dis is the distance between the candidate regions to the horizontal lineH_dand L_d are the upper and lower bounds of the distance, respectively.

Detection Brake Light Verification Based on Color Filter

To reduce the interferences from environmental lighting sources such as street lights and signboards, a color filter is used for verifying the detected brake lights.

Disadvantages

The light scattering effect becomes inconspicuous under a high ambient light condition and thus is not applicable to daytime brake light detection. Another problem is that the taillights of two distinct vehicles are not properly distinguished. This shall become a serious issue when a vehicle in the other lane applies brake.

V. CONCLUSION

Here three previous papers have been reviewed. In the first paper, by extracting color features, shape features and structural features from the brake lights area and making color difference threshold determination in the RGB color space to output the brake lights status information of the frontal vehicle immediately and accurately, this can be applied to driver assistance and autopilot. In the second paper, red-color thresholds have been derived from automotive regulations and adapted to real-world conditions utilizing the HSV color space, as opposed to subjective color thresholds or hardware color filters used in related research. We have presented a shape- and size-independent color image cross correlation approach to pairing detected lamps. In the third paper, we have proposed a novel visual-based approach to detect brake lights at night by analyzing taillights based on the Nakagami-m distribution. Rather than using knowledge of heuristic features, such as symmetry, position, and size of rear-facing vehicles, we have focused on finding the invariant features modeling brake light scattering by Nakagami imaging and, thus, have been able to conduct the detection process in a part-based manner. These papers have got some disadvantages. In the first paper output varies depending on the color of vehicle. In the second paper cross correlation is used and it is sensitive to size and shape of target regions. In the third the light scattering effect becomes inconspicuous under a high ambient light condition and thus is not applicable to daytime brake light detection. The common problems in the above papers are that the tail lights of two distinct vehicles are not properly distinguished and do not give a good result during daytime. A new method that overcomes the above difficulties needs to be implemented.

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