Real-time Recognition System of Traffic Light in Urban Environment

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***Abstract*—detection of arrow traffic light is a focal point research in autonomous vehicle, and in urban environment it is the basic technique. However, most researches mainly concern the circular traffic lights. A novel algorithm is proposed in this paper to resolve the problems of detection and recognition of arrow traffic lights. Two sub-modules, detection module and recognition module, are introduced in the main framework. In detection sub-module, the color space conversion, binarization and morphology features filtering methods are performed to get the regions of candidates of blackboards. For getting the regions of arrow of traffic lights, segmentation based on the YCbCr color space is used in the cropping image, which is cropped from original image by the region of blackboard. In recognition sub-module, Gabor wavelet transform and 2D independent component analysis(2DICA) are used to extract traffic light candidate's features for features of the arrow traffic lights. A library for recognition has been built, and experimental results show that rate of recognition exceeds 91%.**

Keywords-Arrow traffic light; Gabor wavelet; 2DICA; Intelligent vehicle

I. INTRODUCTION

Detection of the traffic lights is very important for autonomous vehicle to make decisions on intersection in urban environment. The arrow traffic lights are more and more popular, and it provides more information than circular traffic lights. Now, detection of arrow traffic lights becomes a focal point of research in autonomous vehicle.

Recently, several approaches were proposed for detection and recognition of traffic light. Park et al.[1] introduced a detector which biased toward circular regions of high intensity surrounded by regions of low intensity to attempt to report the state of light. However, their method did not reliably differentiate between multiple lights, or determine the state of more than one light in a single camera frame. Masako et al.[2] used structural information to detect traffic light. The authors have proposed a model of traffic lights and detected the edge of them. After the pixel clustering and voting, the circle with the maximum vote was selected as the detected traffic light. It was lacked of accuracy as other circle detection algorithm. Charette et al.[3] applied the spotlight detection and template matching method to identify the traffic lights. Although the detection and recognition of this method was accurate, the algorithm was very time-consuming. Chung et al.[4] used fuzzy methods and morphological techniques to estimate background images and average illumination, then the traffic light candidate regions were acquired. This algorithm was only suitable for fixed camera, if the background was changed, it would be failed. In [5], a method considered the structure of traffic light and used the Hough transform for detection. But it lost the traffic lights in complex environment and was also lack of stability. Yung et al.[6] detected the traffic light by its colors such as red, amber and green, also identified the traffic lights with the camera fixed on a shelf. But the limit of the algorithm was that the distance between the camera and the lights was not too far. 6 color thresholds were calculated by Hwang[7] to get the candidate regions of traffic lights. Unfortunately, the red light could not be discriminated from amber light and lacked flexibility. Based on Gaussian distributions the hue and saturation was statistical calculated, then some parameters were learned by training images data in [8]. In test images data, the traffic lights were extracted by these parameters and shape features. Gong et al.[9] also used statistics information in HSV color space to obtain color thresholds for image segmentation, then machine learning was used for classifying and CAMSHIFT algorithm was used for tracking. Some similar systems were failure in varying illumination conditions.

Above algorithms can only detect and recognize the circular traffic lights, and some of them acquired images from the camera fixed on a shelf or building. In this paper, a novel approach is proposed to detect and recognize arrow traffic lights on complex background. Firstly, color and shape information are used to localize the candidates of arrow traffic lights. Secondly, the features are extracted by Gabor wavelet transform and 2D independent component and they used to classify traffic light. Finally, a nearest neighbor classifier is used to identify the arrow type.

The algorithm details and the experimental results are presented in the following sections of this paper.

II. TRAFFIC LIGHT DETECTION

Because of urban environment the background of traffic lights are very complex. The varying ambient light, luminance of traffic lights and size are the interference factors to detect traffic lights from input images. To solve this problem, a framework of arrow traffic light recognition is provided in figure 2. In this framework, two sub-modules, the arrow traffic detection and the arrow traffic light recognition, are the key factors.

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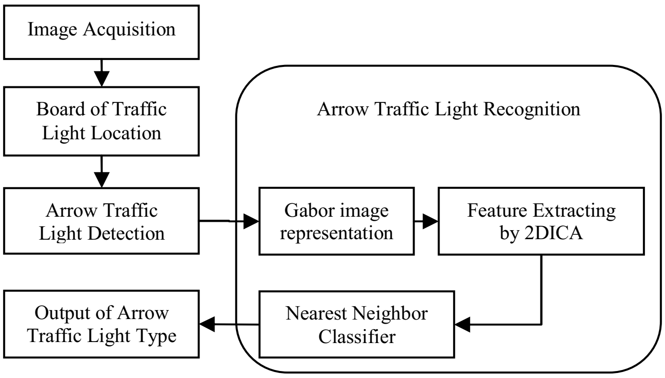


Figure 1. Framework of Traffic Lights Recognition

A. Board of Traffic Light Localization

Let each pixel value $p(x,y)=[p_R,p_G,p_B]$ in the RGB color space, (x,y) means pixel coordinate. To separate the black pixels from the input image, equation (1) and (2) are used. T_1,T_2 are thresholds for image segmentation. The binarization process is performed as equation (3), then the binary image which the blackboard in is get. B means the binary image.

$$B_1(p)=\begin{cases}1, & maximum(p_R,p_G,p_B)<T_1\\ 0, & otherwise\end{cases} \tag{1}$$

$$B_2(p)=\begin{cases}1, & maximum(|p_R-p_G|,|p_G-p_B|,|p_R-p_B|)<T_2\\ 0, & otherwise\end{cases} \tag{2}$$

$$B(p)=B_i\cap B_2 \tag{3}$$

In order to obtain the blackboard of traffic lights, the area, shape and saturation of the candidate region of blackboard are used as features, and they are marked as *Area*, *Rwh* and *Satu* respectively. Usually, the shape of blackboard is regular or nearly rectangle, then the ratio of width to height is calculated to determine whether it is a candidate or not. The *Rwh* means this ratio. Sometimes, a region may be satisfied the conditions of the area and the shape, but it is not a candidates of traffic lights because of a small of number of the valid pixels in bounding box. The saturation marked as *Satu* is the ratio of the area to the convex hull.

For acquiring the valid regions of traffic lights, the algorithm is designed as follow:

step1: The region labeling in the binary image B. Labeled as R_i, i=1…n.

step2: The area, the ratio of width to height and the saturation are calculated by equation (4), (5) and (6) respectively.

$$Area(R_i)=\sum(p(x,y)>0) \tag{4}$$

$$Rwh(R_i)=Height_{R_i}/Width_{R_i} \tag{5}$$

$$Satu(R_i)=Area(R_i)/ConverxArea_i \tag{6}$$

step3: The conditions (10) is used to determinate the candidate regions.

$$Condition_1(R_i)=\begin{cases}true, & T_{la}<Area(R_i)<T_{ua}\\ false, & otherwise\end{cases} \tag{7}$$

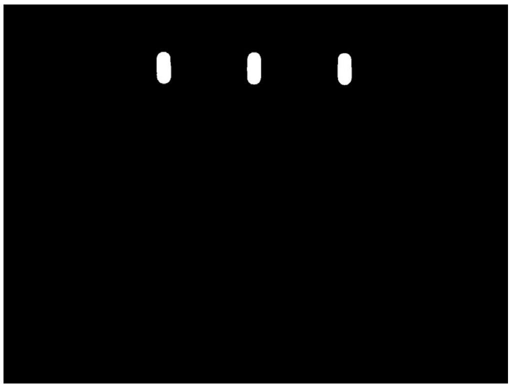
$$Condition_2(R_i)=\begin{cases}true, & T_{lwh}<Rwh(R_i)<T_{uwh}\\ false, & otherwise\end{cases} \tag{8}$$

$$Condition_3(R_i)=\begin{cases}true, & T_{satu}<Satu(R_i)\\ false, & otherwise\end{cases} \tag{9}$$

$$Condition(R_i)=Condition_1\cap Condition_2\cap Condition_3 \tag{10}$$

(a) Input Image

(b) Black Segmentation Image



(c) Result of the Morphology Features Filtering

Figure 2. Results of Traffic Light Board Location

T_{la}, T_{ua}, T_{lwh}, T_{uwh}, T_{satu} are the corresponding thresholds. The Filter is used to remove regions that are not satisfied board morphology. After filtering, the board candidate regions are remained and shown as Figure 2(c).

B. Arrow Traffic Light Detection

For getting the region of the lights, the cropped image based on the size of R_i is converted from the RGB color space to the YCbCr color space. This color space is widely used for digital video. In this format, luminance information is stored as a single component (Y), and chrominance information is stored as two color-difference components (Cb and Cr). Cb represents the difference between the blue component and a reference value. Cr represents the difference between the red component and a reference value.

Assume $p(x,y)=[p_{\mathrm{Y}}, p_{\mathrm{Cb}}, p_{\mathrm{Cr}}]$ represents pixel value in YCbCr color space. Through segmentation in Cb component, the red and amber traffic lights which are hardly distinguished are obtained together.

$$B_{red}(p)=\begin{cases}1, & p_{cb}<T_{red}\\ 0, & otherwise\end{cases} \tag{11}$$

T_{red} is a threshold for image segmentation. Because of the relative position of the red and amber traffic light, it is easy to distinguish them in $B_{Red}(x,y)$.

Regions are labeled on $B_{Red}(x,y)$ to extract connected components with size over 50 pixels and below 1000 pixels, radio of height and width over 0.5 and below 1.5 at the same time. Supposed that there are Ns candidate regions, which are denoted by $SR_j, j=1,\cdots,Ns$. Assume outside rectangular of SR_j is $Rect_j=\{SR_x, SR_y, SR_{width}, SR_{height}\}$. If the relative position between SR_j and light board R_i satisfies:

$$\begin{cases}SR_{width}>R_i(width)/2\\ R_i(height)/5<SR_{height}<R_i(height)/2\end{cases} \tag{12}$$

The SR_j is a traffic light candidate.

If upper left corner coordinate SR_x, SR_y of SR_j satisfies $\max(SR_x, SR_y)<R_i(width)/3$, then SR_j is a red traffic light candidate. Else if coordinate of SR_j meets:

$$SR_x<R_i(width)/3, \text{ and } R_i(width)/3<SR_y<2R_i(width)/3$$

Then SR_j is an amber traffic light candidate, else it is not a traffic light and removed from candidate list.

To detect green traffic light regions in board image, Cr channel image is segmented by threshold T_{green}, binary image is obtained by:

$$B_{green}(x,y)=\begin{cases}1, p_{\mathrm{Cr}}<T_{green}\\ 0, otherwise\end{cases} \tag{13}$$

Region labeling method which is implemented for red light is performed on $B_{green}(x,y)$. Denoted candidate regions as $SR_j, j=1,\cdots,Ns$, Ns is their number. Assume outside rectangular of SR_j, $Rect_j=\{SR_x, SR_y, SR_{width}, SR_{height}\}$ satisfies eq.(12). If upper left corner coordinate SR_x, SR_y of SR_j satisfies $SR_x<R_i(width)/3$, $SR_y>2R_i(width)/3$, then SR_j is a green traffic light candidate.

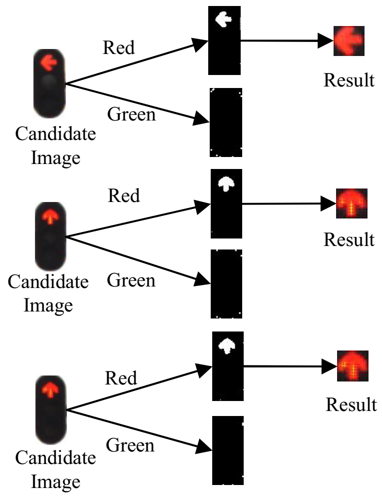


Figure 3 Traffic light Location Process in Board

Figure 4 Traffic Light Location Result

Color image of region SR_j is cropped from board image, transformed gray image and normalized to size 30×30 pixels. The processing image is denoted as $I(x,y)$ and sends to step of traffic light recognition.

III. TRAFFIC LIGHT RECOGNITION

For classifying traffic light candidate image, 2D Gabor wavelet transform and 2D Independent Component Analysis are used to represent image and reduce features respectively.

A. 2D Gabor Wavelet Transform

Gabor wavelet transform is a traditional choice for obtaining localized frequency information, and offers the best simultaneous localization of spatial and frequency information[10]. In detection stage, the obtained image $I(x,y)$ and the Gabor filtered images $O_{u,v}(x,y)$ are calculated together.

$$G_{u,v}(x,y)=\sqrt{\left(real\left(O_{u,v}(x,y)\right)\right)^2+\left(imag\left(O_{u,v}(x,y)\right)\right)^2} \tag{14}$$

As the outputs $G_{u,v}(x,y)$, $u=\{0,1,\cdots,5\}$, $v=\{0,1,\cdots,5\}$ are orientation and scale of Gabor filter, consisting of different image features. All these features are concatenated into a single column vector in order to derive a feature vector $\chi=\{G_{0,0}(x,y)^T, G_{0,1}(x,y)^T,, G_{5,5}(x,y)^T\}$.

B. Traffic Light Feature Extraction by 2D Independent Component Analysis

2D independent component analysis is an improving method of ICA which can eliminate redundancy and reduce dimension of the samples effectively.

Assume that traffic light samples' Gabor image feature were $\chi=\{\chi_i, i\in 1,2,\cdots,Q\}, \chi_i\in R^{n\times n}$, each component may be combined by $P(P\le Q)$ unknown independent component by different coefficient[11]. To reduce dimension of samples, the main task was to obtain optimization projection matrix $S=(s_1,s_2,\cdots,s_m)^T$, according to the method introduced in[12], m was the number of independent components. Independent component s_i must have non-Gaussian distributions with zero mean, unit variance.

$$S=W\times\Lambda_m^{-1/2}\times U_m^T \tag{15}$$

Where Λ_m, U_m were the largest eigenvalues diagonal matrix and their eigenvectors corresponding to covariance matrix $\Sigma=(1/Q)\sum_{i=1}^{Q}(\chi_i-\overline{\chi})^T(\chi_i-\overline{\chi})$, W was named separable matrix. To obtain matrix W , let $W=(w_1,\cdots,w_m)^T$, the steps of weight vector w_i updated by a learning rule as following:

step1: A random initial weight vector $w_i(L)$ is selected.

step2: Let $w_i(N)=E\{\chi g(w_i^T(L)\chi)\}-E\{\chi g'(w_i^T(L)\chi)\}w_i(L)$

step3: Let $w_i(N)=w_i(N)-\sum_{j=1}^{i-1}w_i^T(N)w_jw_j$

step4: Let $w_i(N)=w_i(N)\big/\sqrt{w_i^T(N)w_i(N)}$

step5: If $\left\|w_i^T(N)w_i(L)\right|-1\big|>0.001$, go back to step(2), else go to step(6).

step6: Update over, $w_i=w_i(N)$.

Where $w_i(L)$, $w_i(N)$ were values of last and current update respectively, $g(u), g'(u)$ were selected by:

$$g=\tanh(a_1u), g'(u)=1-(\tanh(a_1u))^2$$

Where $g'(u)$ was the first order derivative of function $g(u)$, $a_1=1$ was taken.

For a given sample $\chi=(\chi_1,\chi_2,\cdots,\chi_n)$, let

$$Y_k=(\chi_i-\overline{\chi}_i)s_k, i=1,2,\cdots,n, k=1,2,\cdots,m \tag{16}$$

Then, projected feature vectors $Y_1,\cdots,Y_m$ are called the independent principal component of the sample χ . Feature matrix of the image sample χ can be reduced to $n\times m$ matrix $B=(Y_1,Y_2,\cdots,Y_m)$.

C. Traffic Light Classification

After feature extracting by 2DICA, a nearest neighbor classifier is adopted for classification. Supposed that traffic light category $c_i(i=1,2,3)$ has N_i training samples $B_j^{(i)}=\left[Y_1^{(i)},Y_2^{(i)},\cdots,Y_m^{(i)}\right]$, $(j=1,2,\cdots,N_i)$, $N=\sum_{i=1}^{p}N_i$ is the total number of training samples, and that these samples are assigned c_p class.

Supposed that sample B would be recognized, distance decision function of category c_i is defined as

$$D_i\left(B,B_j^{(i)}\right)=\sqrt{\left(B-B_j^{(i)}\right)^T\left(B-B_j^{(i)}\right)}=\sum_{k=1}^{m}\left\|Y_k-Y_k^{(j)}\right\|_2 \tag{17}$$

where $\|\bullet\|_2$ denotes the Euclidean distance between two vectors.

If $D_q(B)=\min_{i=1,2,\cdots,p}\left\{D_i\left(B,B_j^{(i)}\right)\right\}$ and $D_q(B)\le T$, then $B\in c_q$, otherwise sample B is not a traffic light region. T is called similarity threshold.

IV. EXPERIMENTS AND ANALYSIS

A. Experiments Data

A camera which equipped with a 25mm fixed mega-pixel lens with 20.4 degree field of view was used to face straight ahead and mounted to front of car roof. Its resolution and frame rate were 1392×1040, 25fps respectively. Since detection algorithm depended primarily on color because no structure was visible at night, the gain and shutter speeds were fixed to avoid saturation of the traffic lights, particularly bright LED-based green lights.

To demonstrate robustness of traffic light recognition system in various traffic light scenarios and under different illumination conditions such as morning, noon, sunset, we drove an intelligent vehicle with the introduced camera on the road of Changsha, China at each of three different times: morning, noon, sunset. The output recognition results included experiment time, date, number of traffic lights and traffic light type (colour, arrow direction) were recorded in a text file.

To test traffic light recognition system, experiments were performed on the 25 typical videos collected on roads in in urban scenes. The length of each sequence was 200 frames. Traffic light categories included red, green and amber arrow traffic lights.

B. Traffic Light Detection and Recognition Results

Figure 5 showed 4 examples in different intersections. A red rectangular box surrounded the detected traffic light plate. Traffic light final state (colour, arrow direction) was represented by a small picture which lied upper left of the red rectangular box. Several parallel traffic lights (red, amber, green) were correctly detected and recognized by our proposed algorithm in these images. Output of our algorithm was correct since 3 arrow traffic lights were boxed by red rectangle and its arrow direction were showed in top left of traffic light boards. False positive cases were valid reduced because board of traffic light was considered before locating the traffic light, however false negative rate will slightly improve since board was difficult to fix position from complex background like sombre constructions, tree.

Figure 5. Traffic Light recognition results

Figure 5 show that the samples which failed to detect traffic lights (far distance from camera, dim light especially green arrow LED light, or occlusions etc.)

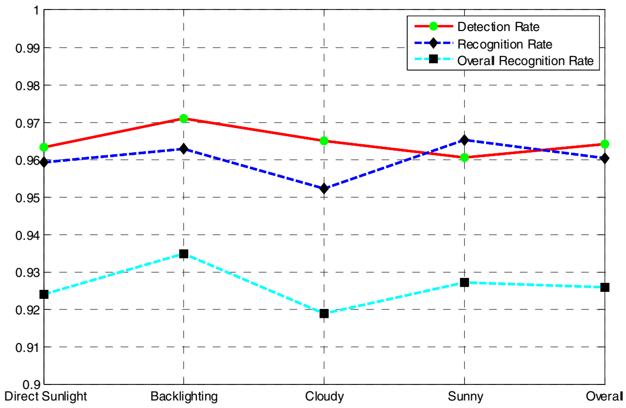


Figure 6. Detection and Recognition Rate of Traffic Light

The frame number of different conditions is showed in Table I.

Overall recognition rate exceeded 91% in our test. In addition to these quantitative results, a significant implication of this work was that our system was able to provide accurate traffic light information for intelligent vehicle driving through intersections.

TABEL I. THE FRAME NUMBER IN DIFFERENT CONDITIONS

Condition	direct sunlight	Backlighting	Cloudy	Sunny	Overall
Frame number	1200	1000	1000	1800	5000

C. *Running environment and Computational Time Analysis*

TABLE I. RUNNING ENVIRONMENT

Device	Type
CPU	Intel I7-3.4GHz
RAM	Kingston 2G*4
DISK	WESTDATA 1T
CAMERA	JAI BB-141M
LENS	NAVITA 25MM

The proposed algorithm was implemented by C++ and OpenCV, and running environment was listed in Table II. The average frame rate was 6.57fps and achieved near real-time performance in experiments. The response time of our algorithm almost satisfied making a proper decision of intelligent vehicle in the intersection.

V. CONCLUSION

Arrow traffic lights are very popular in urban environment of china, and it is helpful for intelligent vehicle to make decision in the intersection. Since most algorithms focus on circular traffic lights, a novel method for detection and recognition arrow traffic light including colour and direction is proposed in this paper. Localization of the blackboards of traffic lights is the first step, and the segmentation and morphology processing is performed for accurate detection. Then candidates of traffic lights are obtained by relative position between candidate and their boards. For identifying the types of arrow traffic lights such as colour and direction, Gabor wavelet transform is used to extract traffic light candidate's features with the best simultaneous localization of spatial and frequency information. 2D independent component analysis is utilized to effectively eliminate redundancy and reduce dimension of the samples. Nearest neighbour classifier is a simple and time saving method to classify object. Experimental results show that the detection and recognition of multiple arrow lights for each intersection significantly are robustness to noise and have higher accuracy.

The chrominance of traffic light images captured by camera vary widely according to the different relative position and distance between camera and traffic light. In addition, the chrominance is influenced by illumination conditions. For promoting the efficiency of detection and accuracy of recognition, our future work is to add tracker or other previous knowledge to estimate an interest region where the traffic lights are most likely to exist in.

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