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Vehicle Detection Method based on Active Basis Model and Symmetry in ITS*

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Abstract—**Vehicle detection is a foundational and significant task in video surveillance systems. In this paper, a vehicle detection method using a deformable model and symmetry is proposed. First, we learn the active basis model (ABM) from the target training sample set by using the shared sketch algorithm. Then, we utilize the edge information obtained by ABM and HSV color information to do symmetry analysis for vehicle objects. The ABM can detect vehicles in various poses, shapes, and sizes for its deformability. By doing edge and color symmetry analysis, subtle difference between two images and environment noises can be adapted. The results of experiments indicate that our approach is capable of detection different vehicles and localization vehicle in bad environment. What's important, the detection results support the capability of the proposed method to enable the introduction of novel intelligent transportation systems applications.**

I. INTRODUCTION

Providing accurate traffic information is becoming a major challenge for the traffic monitoring systems and leads to the great rapid growth of intelligent transportation systems (ITS)[1]. Among the traffic information collection technology, computer vision techniques play an important role in ITS, and according to [2], it can be utilized in parallel transportation management systems. Compared with traditional geography induction coils, ultrasonic, laser detector and other traffic information collection technology, vision based devices have broadly been employed in traffic monitoring of ITS and has many advantages[3]: (1) In a perceptual sense, visual information is easier to understand than other forms of perceptual information (e.g., voices); (2) Video sequences cover a wide range of information which can reflect the status of transportation systems in the most direct way, and it can also be used to detect some time-varying trends, e.g., the collision of vehicles and the red-light violation, an important feature for ITS; (3) Compared with other sensors, video sensors can easily be installed, operated, and maintained; (4) The vision-based devices have a relatively higher price-to-performance ratio.

In the urban traffic video monitoring system, vehicle detection is an essential and challenging task, and it is also the first step to get the traffic parameters. A number of national and international projects have been launched over the past years to investigate new technologies for improving safety and accidents prevention [4]. Many researchers have been attempting to find a robust and reliable vehicle detection method in images. A lot of approaches to vehicle detection is using relative motion information. The main approach to motion-based localization is optical-flow and background subtraction in a continuous image sequence[5][6][7]. And optical-flow-based techniques detect vehicles indirectly by analyzing velocity field while background subtraction methods depend on the estimation accuracy of the background. Unfortunately, these approaches are not suitable for dealing with the parked vehicles for the lack of motion or a vehicle turning into stationary from moving for some time in urban traffic.

Instead of the motion-based methods, many other vehicle detection methods are based on characteristic information such as color, symmetry, texture, shadow, vehicle lights, and geometrical features (e.g., corners, edges). Many researchers have reported their progress in this area. By making use of edge symmetry information, Chi[8] et al. have done the vehicle identification and statistics in the inclement weather. However, edge symmetry estimations are sensitive to noise in homogeneous areas. In [9], the author extracted the vehicle colors and local features as vehicle features and constructed a dynamic Bayesian network to classify vehicles from aerial surveillance images. Chen[10] detect candidates for vehicles at night time by using the vehicle lights and their aspect-ratio constraints. In[11] , Li et al. realized a vehicle detection method based on graphic structure by selecting sophisticated vehicle feature. There is great potential in fusing different feature information to provide robustness in a combined method[12][13]. In [14], the initial bounding boxes for vehicles are generated based on edges, and verified by symmetry and corner detection, which assumes that street clutter does not exhibit similar edge patterns. By minimizing the number of missing detections and false alarms, excellent results were obtained.

Currently, Wu[15] et al. proposed a new method to cope with object detection problems. They use active basis model (ABM) which consists of a small number of Gabor wavelet elements at selected locations and orientations to detect and recognize objects. The shared sketch algorithm applies a gray-value local energy to find a common template together with its deformed versions from the training images. However, the shared sketch algorithm is used when objects in the training images have the same pose and appear at the same location under the same scale. What's more, the ABM completely ignores all symmetry features. So it will be hard

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for an accurate detection in a situation where objects may appear at different unknown locations and scales in the training images, and it is vulnerable to environmental impact.

In this paper, we use the deformable model ABM from a set of training images and to detect vehicles in new images by template matching. We adopt the framework of Wu et al. in the learning, detection, and classification. In order to improve the performance in vehicle recognition, we modify the framework of Wu et al. by using the edge and color symmetry features of the vehicle in template matching algorithms. This is also one contribution of this paper. By using the edge and color symmetry features, we can distinguish vehicles from the road railings environment or part occlusion situation. Furthermore, a series of experiments is studied for performance testing. The experimental results prove that our method can effectively detect vehicles.

This paper is naturally organized as follows. In Section II, we introduce basic theories of the active basis model (ABM) and the symmetry feature. Section III presents the detailed implementation of our method. Then, we will show some experimental results in section Ⅳ, and draw a conclusion in section Ⅴ finally.

II. BASIC THEORY

A. ABM

The ABM is an excellent target expression model, and it has the following two characteristics: (1) Only requiring a small amount of training samples which are approximately aligned and consistent posture; (2) For different samples, the wavelets of ABM can make adaptive changes within a certain range for a better match to the local edge of the target.

The ABM is a deformable model that sketches the shapes of object categories. This model consists of a small number of Gabor wavelet elements that can be locally perturbed at their locations and orientations. According to the sparse coding theory[16], the image I can be expressed as

$$I = \sum_{i=1}^{n} \alpha_i B_i + \gamma \tag{1}$$

where B_i is the Gabor wavelet element, α_i corresponds to the coefficient of wavelet element, and γ is the unexplained residual image.

According to Wu et al, the same samples share a set of wavelet element B_i, *i=1,...,N*. *N* is the number of shared wavelet elements. In the same type of samples, the j_{th} sample can be represented as

$$I_j = \sum_{i=1}^{n} \alpha_{j,i} B_{j,i} + \gamma_j \tag{2}$$

where $\alpha_{j,i}$ and γ_j correspond to the coefficient of wavelet element and the unexplained residual image respectively.

Define a set of active Gabor wavelet elements $B_{i,j} \approx B_j$, assuming that $B_{j,i} \approx B_i$, *i=1,...,N*, $B_i = B_{x_j,y_j,s,\theta_j}$, $B_{i,j} = B_{x_{i,j},y_{i,j},s,\theta_{i,j}}$ (s and θ are the size and orientation of the Gabor wavelet element, respectively,), if and only if the following conditions are satisfied:

$$x_{i,j} = x_i + d_{i,j} sin\theta_i$$

$$\theta_{i,j} = \theta_i + \delta_{i,j} \tag{3}$$

where $d_{i,j} \in [-D_1, D_1]$, $\delta_{i,j} \in [-D_2, D_2]$. B_i can move along its normal position, and rotate over its center. D_1 and D_2 are the upper bound of movement range *d* and rotation angle range θ respectively.

An ABM needs to be learned on a small set of training images before its usage in object detection. During the learning process, several Gabor wavelet elements are extracted to represent the vehicle object using the shared sketch learning algorithm. For the detailed description of the shared sketch learning algorithm, you can look for [15] as reference.

B. Symmetry

Symmetry is one of the basic characteristics of the object shape. Among all the symmetry, bilateral symmetry is the most common and widespread in nature. It can be used for object detection, feature extraction and object recognition.

Assuming the center of an image is at the origin, and using polar coordinates $f(r,\theta)$ to represent the image. If there is a straight line L which gets through the origin and has the angle $\emptyset$ with the x-axis at the same time. If there is a small angle α, it can make $f(r,\theta)$ satisfy the following equation:

$$f(r, \emptyset + \alpha) = f(r, \emptyset - \alpha) \tag{4}$$

Then image f is bilateral symmetry about the line L (see in [17] for detail information). And L is the axis of symmetry. The bilateral symmetry can be easily found in vehicles.

In the following, we will introduce our method in detail.

III. METHOD

Our method includes three steps: (1) the construction of an ABM to represent the vehicle object category in traffic conditions; (2) edge detection and candidates localization; (3) edge and color symmetry judgment. After Gabor filtering, the symmetry analysis is done to edge determine whether a vehicle candidate is a complete vehicle or mixed with environment noise. If and only if, it satisfies the edge and color symmetry at the same time, the candidate is a complete vehicle without the environment influence. Figure 1 shows the framework of the proposed method in this paper. In the following, we will introduce the three steps sequentially.

A. ABM Learning Algorithm

The parameters and location of Gabor wavelets which make up an ABM can be learned by the shared sketch learning algorithm. We get an deformable model $T = \{B_i, x_i\}$,*i=1,...,N*. from the training images, where B_i is the i_{th} Gabor wavelet element , and x_i is the corresponding parameters. The core idea of the shared sketch learning algorithm is to select all the wavelets which share their locations and orientations in the sets. In this paper, the ABM consists of 50 Gabor wavelets. The positive samples include 20 front-view vehicles (cars, vans, and buses). Figure 2 shows several training images.

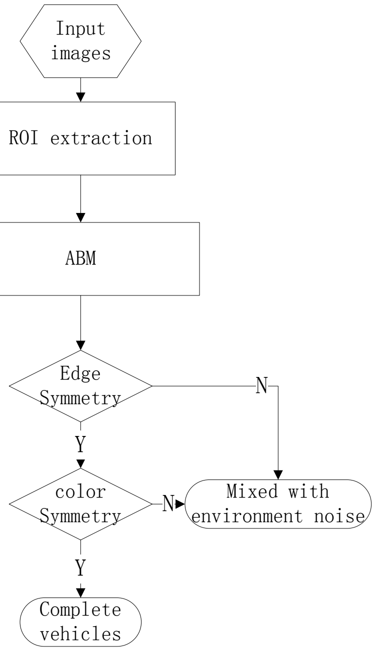


Figure 1.The framework of the whole method

B. Edge Detection and Candidates Localization

For the reason that the edge information remains significant even in variations of ambient lighting, edge based vehicle detection method is often more effective than other background removal or threshold approaches. In this paper, we utilize Gabor wavelets to do the edge detection and candidates localization.

For an image I_i, the matching condition between the model T and image I_i can be calculated as following:

$$P(I_i|T) = log\left(\frac{p(I_i|T)}{q(I_i)}\right)$$

$$= \sum_{j=1}^{N}\left[x_j h\left(\left|\langle I_i, B_{i,j}\rangle\right|^2\right) - log\varphi(x_j)\right] \quad (5)$$

where $T = \{B_i, x_i\}$, *i=1,…,N, N* is the number of Gabor wavelet elements of T, *h(.)* is Sigmoid transform.

C. Edge and Color Symmetry Judgment

As we all know, the bilateral symmetry is the most common and widespread feature of vehicles in nature. It is obvious in the front-view vehicles. The symmetry analysis based on Gabor filter can distinguish subtle difference between two images and environment noises. Hence, we select the edge and HSV color to do the symmetry contrast, for both the two features own the main information of an image.

Assuming L is the axis of symmetry of the image, and $O(x_o, y_o)$ is a pixel point on the line L.

As in (6), the edge symmetry is 1if if two pixels (x_i, y_i) and (x_j, y_j) are both edge points, their distances to point $O(x_o, y_o)$ are equal, the gray-level difference between them is in a certain range, and they have the same ordinate, otherwise it is 0.


(a) (b) (C)

Figure 2. Examples of training images.(a)for bus;(b)for car; (c) for van

$$S_e = \begin{cases} 1 & \begin{array}{c} |x_i - x_o| = |x_j - x_o| \\ |G_v(x_i, y_i) - G_v(x_j, y_j)| < T_1 \\ y_i = y_j \end{array} \\ 0 & others \end{cases} \quad (6)$$

where T_1 is the threshold for edges symmetry judgment, G_v is the gray level of a pixel.

According to (6), there is it a lot of trouble to calculate the symmetry of every pixel. In order to simplify the steps, we make use of the probability by the image cross correlation to do the edge symmetry detection.

Firstly, we separate every single object detected in the ROI (region of interest) from the edge image obtained from the Gabor filter. Then, the left-half edge image and right-half edge image in the separated images are compared to distinguish subtle difference between two images and environment noises. The probability of the edge image symmetry is approximately computed by the image cross correlation. The detailed image symmetry analysis can be found in the work [18]. In the following, (7) is the simplified based on (6).

$$S_e{}' = \begin{cases} 1 & P_{e\_c}|L_i - R_i| > H_1 \\ 0 & others \end{cases} \quad (7)$$

where P_{e_c} is the probability result of the left-half image and right-half image by the image cross correlation for edge symmetry detection and H_1 is the threshold for edge symmetry judgment.

So, as in (7), the edge symmetry is 1if the probability by the image cross correlation for symmetry detection between left-half image and right-half image is above than a threshold, otherwise it is 0.

For color symmetry, we convert images into HSV color space from RGB color space firstly, because it more in line with the human visual. Similar to edge symmetry, the color symmetry is determined by the following:

$$S_c = \begin{cases} 1 & \begin{array}{c} |x_i - x_o| = |x_j - x_o| \\ |H_v(x_i, y_i) - H_v(x_j, y_j)| < T_2 \\ y_i = y_j \end{array} \\ 0 & others \end{cases} \quad (8)$$

where T_2 is the threshold for color symmetry judgment, H_v is the H value of a pixel in HSV color space.

Also, following the judgment of edge symmetry, the color symmetry can be simplified as (9).

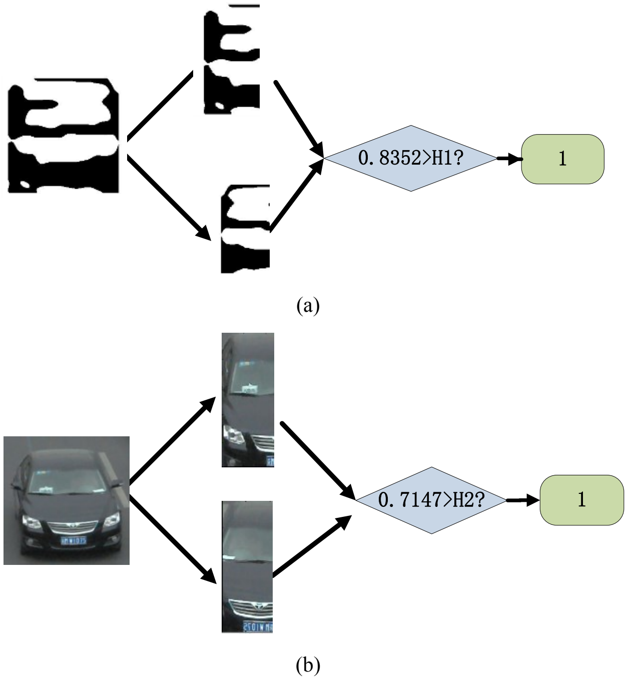


Figure 3. The positive symmetry judgment result for complete vehicle. (a) for the edge symmetry ;(b) for color symmetry

$$S_c{}' = \begin{cases} 1 & P_{c\_c}|L_i - R_i| > H_2 \\ 0 & others \end{cases} \tag{9}$$

where P_{c_c} is the probability result of the left-half image and right-half image by the image cross correlation for color symmetry detection and H_2 is the threshold for edge symmetry judgment.

We separate every single object detected in the ROI according to their locations obtained from the Gabor filter like in the edge symmetry. At last, the left-half color image and right-half color image in the separated images are compared to remove the subtle influence of environment noises. And the discriminative condition for color symmetry is similar to the edge symmetry.

Finally, if both the edge and color symmetry scores are 1, we know that the candidate is a complete vehicle without the environment influence.

IV. Experiments and Results

We have tested performance of our method on a large set of image sequences at various vehicle poses, vehicle shapes, and vehicle types. To do the test, we only focus on this traffic scene where cameras are mounted to the front of vehicles, i.e. the testing images selected are all front-view vehicles.

The total number of the testing images is 180 which are from real traffic scenes. For convenience, the ROI is set from the middle to the bottom of each image without considering the upper area because the objects are too small in that area.

As for the symmetry analysis, we segregate every single candidate object, and do the edge symmetry detection and color symmetry detection one by one. The edge symmetry based on Gabor filter and color symmetry based on HSV color space can adapt to subtle difference between two images and

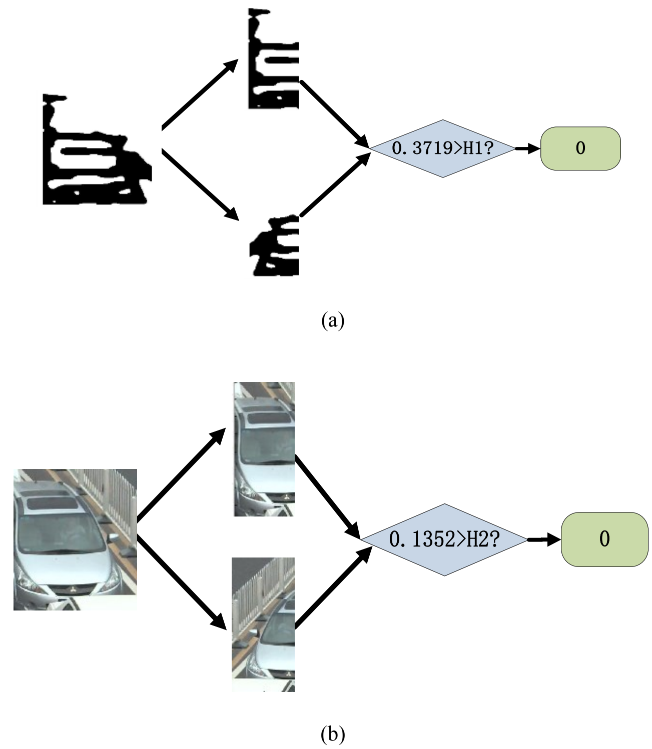
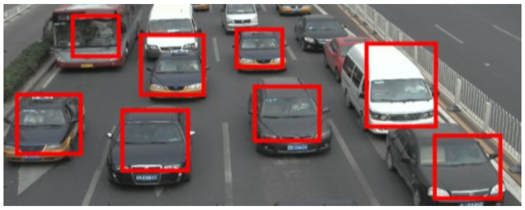


Figure 4. The negative symmetry judgment result for vehicle with environment noise. (a) for the edge symmetry ;(b) for color symmetry

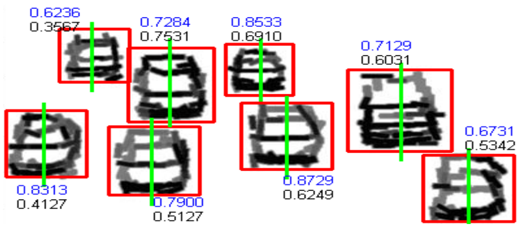
environment noises. We divide every image of the detected objects into two equal parts: the left-half part and right-half part, including the Gabor filter image and the H color image from the HSV color space. Then, a cross correlation contrast is done to judge the symmetry of the two parts, edge and color separately. Finally, the probability results (edge and color) returned from the cross correlation contrast are compared with the threshold H_i, *i=1,2*, individually. Here, we set $H_1 = 0.7$ and H_2 *=0.4,* if and only if the contrast results are greater than $\mathrm{H_i}$ synchronous, the vehicle is not affected by the environment.

Figure 3-5 show some detection results in our experiment. Figure 3 is a positive sample of a complete vehicle detection results without environment effects. In Figure 3, (a) shows its edge symmetry judgment and (b) is its color symmetry judgment result. The digital number in every figure is the probability result of edge or color, correspondingly. Figure 4 is a sample of a vehicle mixed with environment noise. Also, in Figure 5, (a) shows its edge symmetry judgment and (6) is its color symmetry, separately. From the figures, we can easily get the idea that when a vehicle is mixed with ambient noise, the returned number of probability result is quite lower than the complete vehicle without environment. So, by doing the symmetry analysis, we can evaluate the degree of external environmental impact.

In the quantitative experiment, we sequentially process all the testing images and output the bounding boxes of detected vehicles with corresponding scores, and figure 5 shows a detect result of the testing images. In figure 5, (a) shows the detected vehicles and their localization, while (b) shows the edge detection result by ABM for every object and their sym-



(a)



(b)

Figure 5. The detection result of the testing images

metry results: numbers in blue is for edge symmetry, and numbers in black is for color symmetry.

From figure 5, we can easily find that our method can detect different vehicle types, including cars, vans, and buses. At the same time, it can also deal with the vehicle problem of the different poses and shapes. By doing the symmetry judgment, we can evaluate the degree of external environmental impact, and also it supports a new idea to improve the vehicle detection accuracy.

V. Conclusion

In this paper, we propose a vehicle detection method based on the deformable model ABM and symmetry in edge and color. Firstly, the ABM can detect a variety of vehicles which are different from poses, shapes, and sizes. And then symmetry analysis using edge from Gabor filter and color in HSV can be applied to adjust the difference that is not so obvious between two images and environment noises. From the experimental results, it should be evident that our method is meaningful and effective to detect cars, buses, and vans considering noises from environment. In the experiment, our method has focused on only front-view vehicles without taking into more oblique views. To improve the performance of our algorithm, detection of rear-view and side-view vehicles will be done in the future. In addition, different weather conditions (rainy, cloudy, windy) and illumination changes(dusk, night, dawn)will be considered in our future work.

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