Journal of Southeast University (English Edition) Vol. 28, No. 2, pp. 240 - 244 June 2012 ISSN 1003—7985

Vehicle detection based on information fusion of vehicle symmetrical contour and license plate position

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Abstract: An efficient vehicle detection approach is proposed for traffic surveillance images, which is based on information fusion of vehicle symmetrical contour and license plate position. The vertical symmetry axis of the vehicle contour in an image is first detected, and then the vertical and the horizontal symmetry axes of the license plate are detected using the symmetry axis of the vehicle contour as a reference. The vehicle location in an image is determined using license plate symmetry axes and the vertical and the horizontal projection maps of the vehicle edge image. A dataset consisting of 450 images (15 classes of vehicles) is used to test the proposed method. The experimental results indicate that compared with the vehicle contour-based, the license plate location-based, the vehicle texture-based and the Gabor feature-based methods, the proposed method is the best with a detection accuracy of 90.7% and an elapsed time of 125 ms.

Key words: vehicle detection; symmetrical contour; license plate position; information fusion

doi: 10.3969/j.issn.1003 -7985.2012.02.019

In traffic surveillance, vehicle detection from images has a wide range of applications, such as the measurement of traffic volume, traffic event detection and vehicle type classification. The problem of vehicle detection is to distinguish vehicles in images from other objects such as pavement, shadow, sky and other background noise. Sun et al. [1] roughly classified vehicle segmentation into three categories: knowledge-based, stereo-based and motion-based approaches. The background subtraction method can be used for vehicle detection if two or more images are processed or a video sequence is processed[2]. Gao et al. [3] investigated vehicle detection by making reference to the rear-lights regions of vehicles. Techawatcharapaikul et al. [4] exploited the temporal edge intensity to distinguish vehicle region from shadow region. A color cylinder approach was proposed in Ref. [5] to classify a vehicle image into shadow and highlight regions. In some previous studies, different methods of feature extraction and recognition have also been taken into account to assist in effective vehicle detection. For example, Kim et al. [6] utilized the gray level co-occurrence matrix (GLCM) feature and implemented vehicle detection by the support vector machine (SVM). Sun et al. [7] took advantage of the Gabor filters to extract the Gabor feature of vehicle regions and then verified each vehicle candidate using a SVM and a neural network. Knowledge of vehicle symmetry has also been exploited in the past for vehicle detection. In Ref. [8], a method was proposed to allow each pair of pixels on a horizontal line to "vote" for their symmetry axis. The same symmetry operator was used in Ref. [9] to detect a vehicle's vertical axis and its vertical edges, which, however, seems to be computationally extensive. Teoh et al. [10] calculated the vertical symmetry axis of a vehicle by finding symmetry values on the horizontal scan line of multiple windows. Considering the situation that the vehicle color, shadow, lights and symmetry axis of the vehicle contour may be prone to be influenced by illumination changes and background noise, an approach for vehicle detection based on the information fusion of vehicle symmetrical contour and license plate position is proposed.

Received 2011-12-28.

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Foundation item: The National Natural Science Foundation of China (No. 40804015, 61101163).

Citation: Lian jie, Zhao Chihang, Zhang Bailing, et al. Vehicle detection based on information fusion of vehicle symmetrical contour and license plate position[J]. Journal of Southeast University (English Edition), 2012, 28(2): 240 -244. [doi: 10.3969/j.issn.1003 -7985.2012.02.019]

1 Information Fusion Based Vehicle Detection System

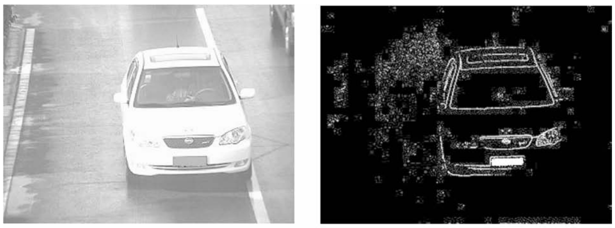
The approach using the vertical symmetry axis of the vehicle contour to locate the vehicle region in an image is effective, but the symmetry axis of the vehicle contour is vulnerable to the influences of trees or traffic signs. According to the characteristics that a vehicle contour has a vertical symmetry axis and the license plate has vertical and horizontal symmetry axes, an efficient approach based on the information fusion of vehicle symmetrical contour and license plate position is proposed in the following.

1.1 Edge detection

The Laplace edge detector, which is a second-order differential operator, is used for the vehicle edge detection in an image. The edge image of a vehicle is smoothed by a median filter. For digital images, the Laplace transform can be implemented by the template,

$$G(i,j) = |4f(i,j) - f(i+1,j) - f(i-1,j) - f(i,j+1) - f(i,j-1)| \tag{1}$$

where $f(i,j)$ is the input image, and $G(i,j)$ is the result of $f(i,j)$ calculated by the Laplace operator. Fig. 1(a) shows an input image, and Fig. 1(b) is the edge image obtained from Fig. 1(a).



(a) (b)

Fig. 1 Vehicle edge detection. (a) An input image; (b) The result of edge detection

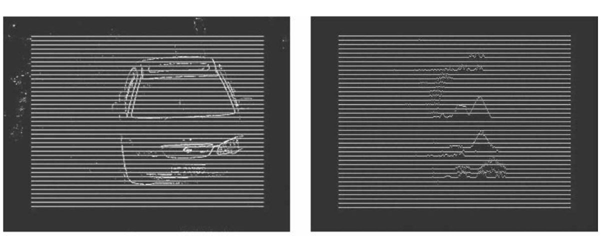
1.2 Contour symmetry axis detection

Taking the camera position and the perspective constraints into account, the region in the captured image, which most probably contains vehicles, is identified first. As the most abundant symmetrical information concentrates in areas, such as vehicle radiator and license plate, the image edge region is ignored in order to reduce computation cost. Fig. 2(a) shows the search area of the symmetry axis. The symmetry value [10] of each pixel on the horizontal scan line is calculated by

$$V(x, y) = \sum_{x'=1}^{W/2} S(x, x', y') \tag{2}$$

$$S(x, x', y') = \begin{cases} 5 & f(x-x', y') = f(x+x', y') = 255 \\ -1 & f(x-x', y') \neq f(x+x', y') \\ 0 & f(x-x', y') = f(x+x', y') = 0 \end{cases} \tag{3}$$

where $V(x, y)$ is the symmetry value at (x, y); W is the width of the symmetry search window; x is the abscissa on the current search line; and y' is the ordinate of the current horizontal scan line. $f(x-x', y')$ and $f(x+x', y')$ are the pixel values at $(x-x', y')$ and $(x+x', y')$, respectively. Fig. 2(b) shows the plot of symmetry values



(a) (b)

Fig. 2 Symmetry value calculation of vehicle contour. (a) Symmetry axis of vehicle contour search area; (b) Symmetry value on the scan line

along the symmetry scan line.

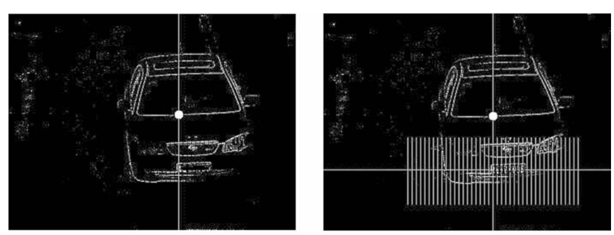
According to the characteristics that the vehicle image is most symmetric at the center and least symmetric at the edges, we assume that the maximum sum symmetry value for each column appears at the symmetry axis of the vehicle contour. The sum symmetry value for each column is calculated by

$$V_{\mathrm{col}}(x) = \sum_{n=0}^{J} V(x, n\delta) \tag{4}$$

where δ is the space between the horizontal scan lines; J is the total number of scan lines; and $V_{\mathrm{col}}(x)$ is the sum symmetry value of the x-column. The column x_{m} corresponding to the maximum sum symmetry value $V_{\mathrm{col}}(x_{\mathrm{m}})$ is regarded as the symmetry axis of the vehicle contour. These pixels on the symmetry axis determine the principal component value of $V_{\mathrm{col}}(x_{\mathrm{m}})$ located in areas that contain most abundant edge information of vehicle, and such areas contain radiators and lights. The section on the symmetry axis that determines the principal component value of $V_{\mathrm{col}}(x_{\mathrm{m}})$ can be calculated as

$$V_{\mathrm{col}}(x_{\mathrm{m}}, n) = \sum_{n=i}^{i+5} V(x_{\mathrm{m}}, n\delta) \qquad i = 1, 2, \ldots, J-5 \tag{5}$$

where n is the serial number of the search line. Finding the maximum value of $V_{\mathrm{col}}(x_{\mathrm{m}}, n)$, we can obtain the starting line of the maximum section n_{m}, and the corresponding ordinate of n_{m} is $y_{\mathrm{m}} = n_{\mathrm{m}}\delta$. The vertical line in Fig. 3(a) is the symmetry axis of the vehicle contour, and the coordinate of the white point in Fig. 3(a) is $(x_{\mathrm{m}}, y_{\mathrm{m}})$.



(a) (b)

Fig. 3 Search area of horizontal symmetry axis of license plate determined by symmetry axis of vehicle contour. (a) Symmetry axis of vehicle contour; (b) Horizontal symmetry axis of license plate

1.3 License plate symmetry axes detection

The point $(x_{\mathrm{m}}, y_{\mathrm{m}})$ on the symmetry axis of the vehicle contour is regarded as a reference point, and it extends the top location of the license plate. The location error will be larger if the vehicle area is estimated by the reference point. As the location of the license plate is fixed, a higher location accuracy can be obtained if the vehicle area is estimated by the license plate. Assume that the distance between the reference point and the bottom edge of the search box of the vehicle contour symmetry axis is d, and the ordinate of the search area of the license plate symmetry axis which is relative to the reference point varies from $\beta_1 d$ to $\beta_2 d$. The vertical scan line in Fig. 3(b) shows the search area of the horizontal symmetry axis of the license plate. The symmetry value of each pixel on the vertical scan line is calculated, and the maximum sum symmetry value for each row appears at the vertical symmetry axis of the license plate. The horizontal line y_s in Fig. 3(b) shows the horizontal symmetry axis of the license plate.

The vertical symmetry axis of the license plate is calculated in the rectangle defined by the upper left point $(x_m - \delta_1, y_s - \delta_2)$ and the bottom right point $(x_m + \delta_1, y_s + \delta_2)$ using the above method. The right vertical line x_s in Fig. 4(a) is the vertical symmetry axis of the license plate. And the intersection point of the vertical and horizontal symmetry axes of the license plate is (x_s, y_s).

1.4 Vehicle area location

Assume that the vehicle area is in the rectangle defined by the upper left point $(x_s - w, y_s - h_t)$ and the bottom right point $(x_s + w, y_s + h_b)$. The horizontal and vertical projection maps of the edge image are calculated to evaluate the presence of the vehicle area. The vertical and horizontal projection vectors $\boldsymbol{v}$ and $\boldsymbol{h}$ of the vehicle edge map in the search region are computed by

$$\boldsymbol{v}_i = \sum_{j=1}^{2w} f(x_i, y_j) \tag{6}$$

$$\boldsymbol{h}_i = \sum_{i=1}^{h_b + h_t} f(x_i, y_j) \tag{7}$$

where $f(x, y)$ is the pixel value at location (x, y). Fig. 4(a) shows the horizontal and vertical projection maps of the edge image.

The maximum values of the vertical and horizontal projection map m_v and m_h are calculated. The top boundary of the bounding box is obtained by finding the first position of the horizontal projection map from the top, which is greater than $0.5m_h$. The left boundary of the bounding box is obtained by finding the position of the first vertical projection map from the left, which is greater than $0.5m_v$. The same technique is used to find the right and the bottom boundaries. Fig. 4(b) shows the result image based on the information fusion of vehicle symmetrical contour and license plate position.

2 Other Vehicle Detection Methods

As a comparison to the information fusion method of vehicle detection proposed in this paper, other four methods are also used for vehicle detection in this paper.

2.1 Vehicle contour-based method

The vehicle detection method based on contour was exploited by Song et al[11-12]. This contour detection method using the Laplace edge detector and the median smooth results in the elimination of noise while preserving image detail parts. The vehicle area can be directly searched by the horizontal and vertical projection maps of the edge image. Considering the situation that there is little noise in the bottom right area of the surveillance images according to traffic rules, the bottom right corner point of the bounding box of the vehicle area is determined first. Then the left and top boundaries of the vehicle bounding box are determined in the hypothesis rectangle using the same method.

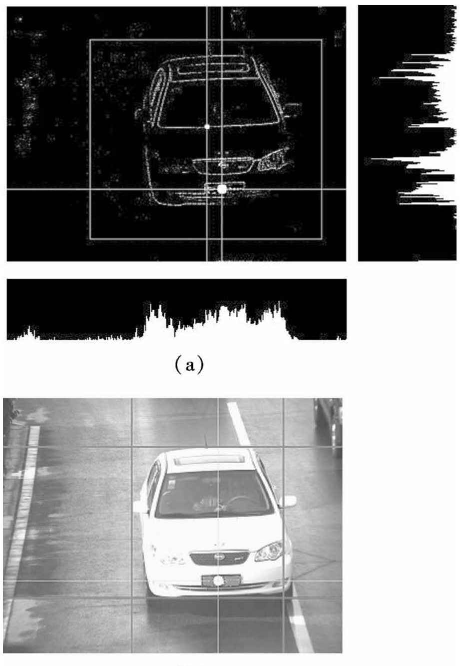


Fig. 4 Vehicle area hypothesis and validation. (a) Vehicle bounding box hypothesis; (b) Vehicle bounding box validation

2.2 License plate location-based method

The method of license plate location was exploited by Ukani et al [13-14]. In this method, the first-order differential of the gray-level vehicle image is calculated to obtain the edge image.

$$g(i, j) = f(i, j+1) - f(i, j) \tag{8}$$

And the following threshold is used to obtain a binary image:

$$T = \frac{1}{2W_e} \sum_{i=1}^{W_e} \max g(i, j) \qquad 1 \leqslant j \leqslant H_e \tag{9}$$

where $f(i, j)$ is the input gray-level vehicle image; $g(i, j)$ is the edge image; m is the m-th column of the edge image; W_e and H_e are the width and height of the edge image, respectively. The horizontal and vertical projection maps of the edge image are calculated to evaluate the presence of the license plate area, and the hypothetical license plate area is verified by the RGB color characteristics. Finally, the vehicle bounding box is defined in terms of the license plate relative to its center and width W_p.

2.3 Vehicle texture-based method

Kim et al. [6] proposed a method by the texture feature described by the gray level co-occurrence matrix (GLCM). An input gray-level image is partitioned into $M \times N$ axis-aligned rectangular areas with the size of width W_t and height H_t. Then the image is quantized into D grayscale levels. The GLCM method is used to build up the co-occurrence matrix of each grid area with $W_t \times H_t$ pixels. We obtain a $D \times D$ square matrix after the feature extraction process, then the obtained GLCM matrix is rearranged in a row-major order to obtain $D \times D$ dimensional vectors. After deciding each grid area of trained images whether it belongs to the vehicle area or the background area, these feature vectors are used as inputs to an SVM classifier proposed by Cortes et al [15].

2.4 Vehicle Gabor feature-based method

An input gray-level image is partitioned into $M \times N$ axis-aligned rectangular areas, and an area with $m \times n$ grids whether belonging to the vehicle area or the background area is sampled. Every $m \times n$ sub-window is traversed in a row-major order. We assign $M = N = 8$, $m = 3$ and $n = 4$, and there will be 30 sub-windows for each input image. The Gabor feature of each sub-window is represented by the statistical feature, the mean μ, the standard deviation θ, and the skewness κ, from a convolution between the sub-window and the Gabor filter[16]. These Gabor features of vehicle areas and backgrounds in the sample images are used as inputs to an SVM classifier, and the trained SVM will distinguish whether a given sub-window of test images belongs to the vehicle area or the background area.

3 Experiments

The proposed vehicle detection method is used to detect vehicle during daytime. We choose the images collected during 8: 00—18: 00 from the Department of Suzhou Transportation. 450 images of 15 vehicle types, including Audi, Buick, Changan, Chery, Chevrolet, Citroen, Ford, Honda, Hyundai, Mazda, Nissan, Peugeot, Toyota, Volkswagen and Wulin, are used for the experiments. The example images with a resolution of 680×512 are shown in Fig. 5.

Fig. 5 Example images of 15 vehicle types

The vehicle detection programs used in the experiments are developed by Visual C++6.0, and the OpenCV image processing library is used in the implementation. The contour-based, the license plate location-based and the information fusion-based methods are used to detect 450 images, and the method proposed by Teoh et al. [10] is also implemented in our dataset. 150 images of the dataset are randomly selected as the training images for the texture-based and the Gabor feature-based methods. We put the GLCM feature of each grid area into an SVM classifier for training, and then the trained SVM will distinguish whether the given grid area of the remaining 300 images belongs to the vehicle area or not. The Gabor responses of vehicle sub-images and background sub-images are calculated from a convolution between the sub-images and a Gabor filter bank. A Gabor filter bank with four scales and six orientations that yields a 72-dimensional feature vector is used. These feature vectors of vehicle and background sub-images are put into an SVM classifier, and the trained SVM will distinguish whether the sub-images of the remaining 300 images belong to the vehicle area or not. The performance of the six methods is shown in Tab. 1.

Tab. 1 The accurate rate and elapsed time of six methods

Method	Accurate rate/%	Elapsed time/ms
The proposed	90.7	125
Contour-hased	82.8	140
License plate location-based	80.9	125
Texture-based	86.4	6 513
Gabor feature-based	77.5	17 609
Ref. [10]	87.6	109

Experimental results show that the detection rate of the information-fusion-based method is 90.7%. The proposed method is 3.1% higher than the single-symmetry-based method proposed by Teoh et al. [10], and the proposed method is superior to the pattern-classification-based methods, such as the GLCM and the Gabor-based methods. The time consumption of the feature-fusion-based method is the shortest among six methods.

4 Conclusion

In this paper, an efficient vehicle detection approach is proposed for traffic surveillance, which is based on the information fusion of vehicle symmetrical contour and license plate position. The vertical symmetry axis of the vehicle contour in images is first detected, and then the vertical and horizontal symmetry axes of the license plate are detected using the symmetry axis of the vehicle contour as a reference. A dataset consisting of 450 images (15 classes of vehicles) is used to test the proposed meth-

od. Experimental results show that the detection accuracy of the feature fusion method is 90.7%, which can effectively eliminate the impact of background noises on vehicle detection.

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基于车辆轮廓对称与车牌定位信息融合的车辆检测方案

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摘要: 为了有效地定位交通监控图像中的车辆区域,提出了一种基于车辆轮廓对称和车牌定位信息融合的车辆检测方法.该方法首先检测图像中的车辆轮廓竖直对称轴,然后以车辆轮廓对称轴位置为基准检测车牌水平和竖直对称轴,最后根据车牌横纵对称轴和车辆轮廓图像的水平、竖直投影进行车辆区域定位.以450 张 15 类车型的图片为测试集进行了基于对称特征融合的车辆区域检测,并与基于车辆边缘、车牌、车辆纹理特征和车辆图像 Gabor 特征的 4 种方法进行了对比,实验结果表明基于车辆轮廓对称与车牌对称特征融合的车辆区域检测方法最优,其检测率和检测时间分别为 90.7% 和 125 ms.

关键词: 车辆检测;轮廓对称;车牌定位;信息融合

中图分类号: TP391