License plate detection using Haar-like features and histogram of oriented gradients

Article · May 2012

DOI: 10.1109/ISIE.2012.6237313

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License Plate Detection Using Haar-like Features and Histogram of Oriented Gradients

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***Abstract*-The Haar-like cascaded classifier has been used in license plate detection and yields a high detection rate, but it often has high false positives. We introduced a classifier which was trained through histogram of oriented gradients (HOG) features to judge the likelihood of candidate plates detected by Haar classifier, and selected the candidate with highest likelihood as the final plate, in order to reduce the false positives. This method was tested on 3000 images to obtain a recall rate of 95.2%, and accuracy of 94.0% as opposed to 66.4% without using HOG features. It was shown that the proposed method is able to eliminate most of the false candidate plates, such as barriers and incomplete plates.**

I. INTRODUCTION

License plate detection plays an important role in the automatic license plate recognition system. Various techniques have been proposed in previous works. Generally, detecting methods employed edge statistics, morphology, color classification or neural networks, and they have been reviewed explicitly [1, 2].

Recently, Viola and Jones reported that the strong classifier trained through AdaBoost and Haar features has a good performance in face detection [3]. They proposed to calculate Haar features with "integral image" to speed up, introduced the AdaBoost to select a small number of distinctive features from tens of thousands of Haar features, and trained one cascaded classifier which has several layers and allows background regions of the image to be quickly discarded to keep those face-like regions for further processsing. Real time face recognition is made possible using cascaded classifier.

Many other object detecting methods based on Haar cascaded classifiers were proposed afterwards. AdaBoost method was introduced into the license plate detection by Dlagnekov [4]. One strong classifier was constructed with 100 weak classifiers, and the false candidate plates were eliminated by a clustering method. As a result, the detection rate is 95.6% and the false positive rate is 5.7% in a 158-image test. Later, Cui et al. [6] enhanced the method of Viola and Jones [3] with gentle AdaBoost (GAB) and an extended set of Haar features to license plate detection. Eventually they proved experimentally that GAB is the best among GAB, discrete AdaBoost (DAB) and real AdaBoost (RAB).

The Haar-like cascaded classifier yields a good performance in object detection [3, 4, 5], but it often has high false positives. Although increasing the number of layers can decrease false positives, the computational cost will be increased and the detection rate will be decreased. In this paper, we proposed an algorithm in which a Haar-like cascaded classifier was used to detect license plate, while a classifier based on histogram of oriented gradients (HOG) was introduced to set the likelihood of candidate plates detected by the Haar-like cascaded classifier. By doing so, a high detection rate and a low false positive rate have been achieved.

The rest of this paper is organized as follows. Section II will describe the framework of the algorithm, detailed on Haar features, AdaBoost and HOG features. Section III will present some experimental results. Section IV is devoted to discussions and conclusion.

II. FRAMEWORK

Our license plate detection algorithm includes two main steps. First, candidate plate regions are detected through a cascaded classifier. Second, a HOG classifier is adopted to calculate the likelihood of candidate plates. The framework of the algorithm is given in Fig. 1, and the detailed steps are described below.

A. Preprocessing

The original RGB image is converted to a grayscale image. As Dalal and Triggs [6] reported that the Gaussian filter might change the details in the images which will degrade the performance of a HOG classifier, a median filter with a 5*5 sliding window is chosen for noise removal.

B. Haar features

Haar-like features are simplified from Haar wavelet, and some basic types are enumerated in Fig. 2. Due to their insensitivity to illumination and strong ability in representing textures, Haar-like features have been applied widely, since Lienhart and Maydt [7] introduced the rotated Haar-like features into the feature set.

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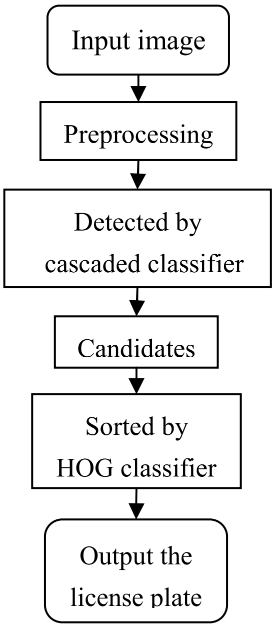

Fig. 1 Detection framework using cascaded classifier and HOG

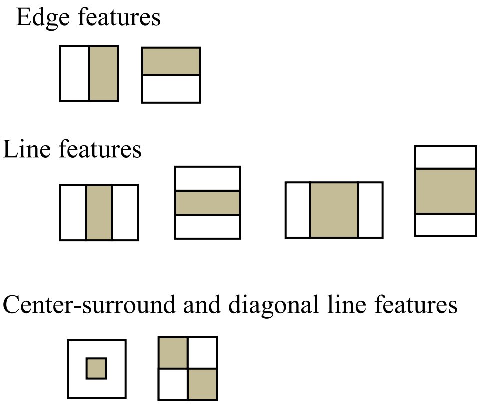

Fig. 2 Several basic Haar features

The Haar-like feature is equal to the grayscale sum of pixels in shaded rectangles minus the grayscale sum of pixels in white rectangles.

C. Gentle AdaBoost

Millions of Haar-like features are contained in an image of 47*17, so an effective feature selecting method is necessary.

AdaBoost has been proven to be an effective method in selecting classifiers from millions of weak classifiers. Among the three types of AdaBoost commonly used, GAB has advantages of both DAB and RAB, and is adopted in this paper for its lowest false positive rate, as Lienhart et al. [8] demonstrated. In Fig. 3, the process of GAB is shown. A strong classifier F(x) is constructed with M weak classifiers from a set of N weak classifiers, and x is a vector composed of Haar-like features.

Gentle AdaBoost ([9, 10])

1. Start with weights $w_i = 1/N$, $I = 1, 2, \ldots, N$, $F(x)=0$.
2. Repeat for $m=1,2,\ldots,M$
   (a) Fit the regression function by weighted least squares fitting of Y to X with weights w_i
   (b) Update $F(x)=F(x)+f_m(x)$
   (c) Update $w_i= w_i \exp(-y_i f_m(x))$
3. Output the classifier F(x).

Fig. 3 Gentle AdaBoost training

D. Training of the cascaded classifier

Here we give a short description about the training of cascaded classifiers. Each classifier on subsequent layer is trained using the samples from immediately previous layer. The strong classifier on every layer is trained using GAB until it meets the accuracy requirements [3, 5] including the detection rate and false positive rate.

E. HOG classifier

The images of candidate regions detected through the cascaded classifier are normalized to a size of 152*56. The calculation of HOGs is described as below.

We divide 360 degrees into 9 bins, and set the cell size as 8*8, block size as 16*16, and the step size of blocks as 8. In a 152*56 image, there are 108 blocks, each block has 4 cells, and each cell has a HOG of 9 bins. The gradient direction of each pixel is calculated according to the formula (1).

$$Angle(x, y) = \arctan[(I(x,y+1)-I(x,y-1))/(I(x+1,y)-I(x-1,y))] \quad (1)$$

Here, I(x, y) is the grayscale at (x, y). Then the Angle(x, y) is projected onto the closest one of 9 bins with angles being 0, 40, 80, 120, 160, 200, 240, 280 and 320 respectively, as illustrated in Fig. 4. The HOG of each cell will be used in adjacent blocks repetitiously and normalized in different blocks by L2 [11].

An image of 152*56 has a vector of 3888 HOG features. Using those vectors, the HOG classifier was trained by a GAB method. While predicting, the Boost classifier would output a weight which was considered as the likelihood of candidate region being a plate.

During the plate detection procedure, candidate regions are detected by the Haar-like cascaded classifier and sorted according to their likelihood predicted by HOG classifier. The candidate with highest likelihood will be taken as the eventual plate.

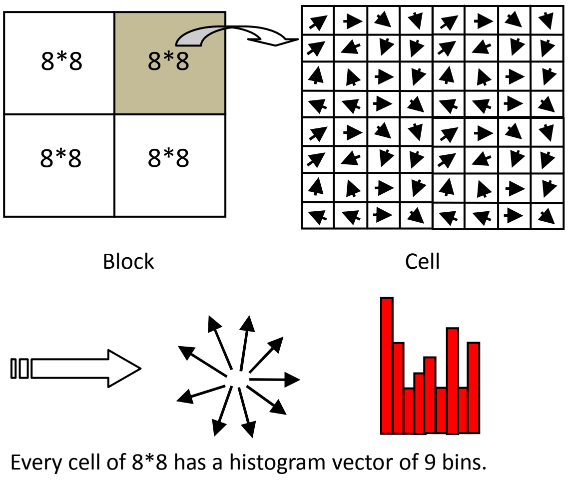

Fig. 4 The calculation of HOG features

III. EXPERIMENT

A. Training of cascaded classifier

6500 license plates segmented from pictures captured from car parks in China during day and night and 12000 images without a license plate were used as the positive and negative samples for training Haar-like cascaded classifier.

We normalized the samples to a unified size of 47*17, and set the detection rate on each layer of cascaded classifier as 99.9%, the false positive rate 0.5. It takes about a week to train such a cascaded classifier with 18 layers on a 3.3GHz, 16GB RAM, 64-bit computer.

B. Training of HOG classifier

After a positive sample set of 6000 manually-segmented plates and a negative sample set of 9000 non-plate images were used to train a HOG classifier at first, 12308 images of candidate plates detected from 2000 images through a cascaded classifier with 11 layers were classified by the previous HOG classifier.

Typical samples wrongly classified were selected to add into the positive sample set and the negative sample set. The HOG classifier was retrained over the new sample set and tested against the rest of those 12308 images. This process was repeated until the accuracy of the HOG classifier reaches 98.0%. The terminal training data consisted of 6905 positive samples and 9968 negative samples.

C. Test result of HOG

We tested 3000 images each of which contains only one complete plate. Fig. 5 shows six typical pictures, in which the green and the red rectangles are, respectively, detected candidate plates by the cascaded classifier with 16 layers, and the eventual plates after sorting likelihood from HOG classifier. Fig. 5 b shows several false candidates detected by cascaded classifier, but classified as non-plate by HOG.

From Fig. 6, we see that for a cascaded classifier with the same number of layers, the detection accuracy increases substantially by using HOG classifier. When the number of layers of the cascaded classifier is 16, the recall rate is 95.2%, and the detection accuracy is respectively 66.4% and 94.0%, without and with sorting the candidate regions by HOG classifier.

Fig. 7 shows the detection recall rates of the two methods (cascaded classifier with or without HOG). There is almost no difference in recall rate for both methods when the number of layers is 15 or above. The recall rate reaches maximum when the number of layers is 15 and remains quite large when the number of layers is 16-19.

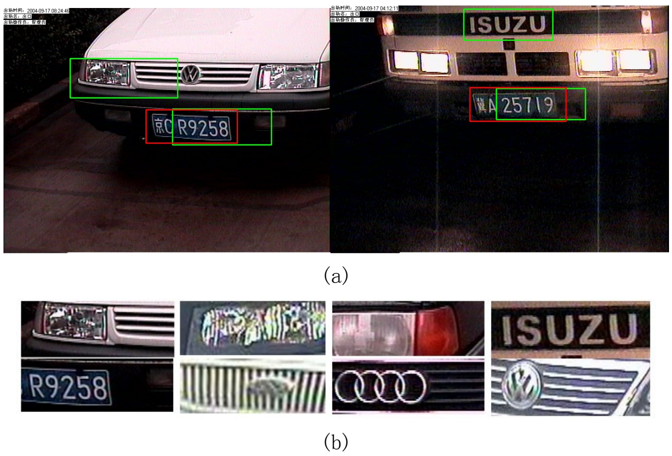

Fig. 5 Detection process: (a) the detection results of 6 typical images; (b) 8 false candidates which are classified as non-license plates by HOG classifier.

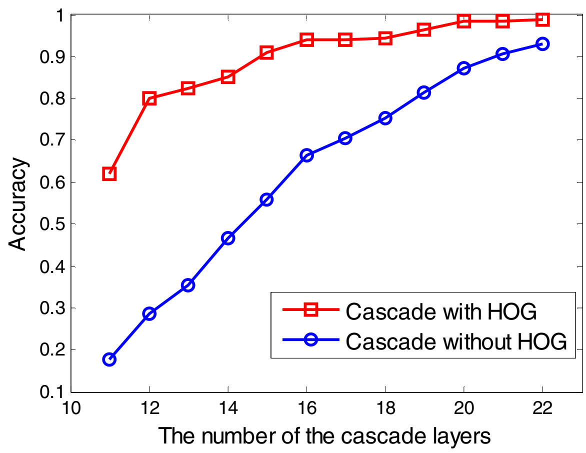

Fig. 6 Performance comparison between the two methods (cascaded classifiers with or without HOG). Accuracy is defined as the ratio between the number of real plates in all candidates detected and the number of all candidates detected.

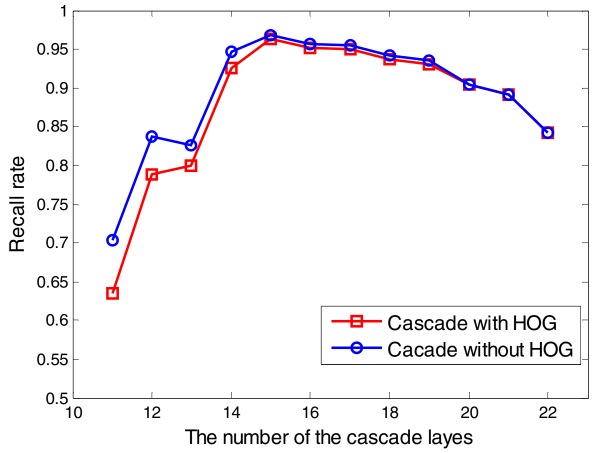

Fig. 7 Performance comparison between the two methods (cascaded classifiers with or without HOG). Recall rate is defined as the ratio between the number of real plates detected and the number of all real plates in 3000 images.

Here, Open Computer Vision Library 2.0 [12] is used for the convenience.

IV. DISCUSSIONS AND CONCLUSION

A classifier with many layers usually require some days for training on a common computer. However it takes less than an hour to train a HOG classifier, so the HOG classifier is combined with Haar-like cascaded classifier to enhance without adding layers of Haar classifier that will increase substantially the training time.

As shown in Table I, it takes about 76 ms to detect the plate in a 320*240 image by the Haar-like cascaded classifier on a 2.3GHz Dual Core processor, RAM 2GB. The step size of the sliding window, and the scaling factor, to increase the size of the sliding window, are 2 and 1.1 respectively. When the number of layers is increased, the number of candidates detected is reduced so that the sorting time is decreased. It takes about 2.8 ms to calculate a likelihood of one candidate plate which is much shorter than the detection time, so the computational cost of sorting with HOG is negligible.

TABEL I

TIME COST IN LICENSE PLATE DETECTION

Number of layers		12	14	16	18	20	22
Average time (ms/image)	Detect	75.5	76.4	76.5	76.1	75.7	76.2
	Sort	7.3	5.0	4.0	3.5	3.2	3.0

All the images in the experiment were collected from car parks. When the angle between the plate and the X axis of the image plane is less than 10 degrees, the plate could always be detected.

Our experiment shows that the HOG feature is an effective feature to differentiate a complete plate from barriers, incomplete plates, vehicle lamps and most textures similar to those of license plate. However HOG is sensitive to inclined plates like Haar-like features. We tried and failed to find a critical value of likelihood of a HOG classifier that can judge a candidate plate as true or false.

To summarize, we have presented an approach for license plate detection, which achieved high detection accuracy and low false positives. The HOG classifier is efficient in eliminating false positives from candidate regions detected through the Haar cascaded classifier. In the future, we will be working on detecting inclined plates (larger than 10 degrees) for static images grabbed from car parks and detecting plates from videos.

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