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Combining Global and Local Features for Detection of License Plates in a Video

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Abstract

This paper presents a license plate detection algorithm using both global edge features and local Haar-like features. Global classifiers using global statistical features are constructed through simple learning processes. After applying these global classifiers, most of license plate background regions are excluded from further training or testing. Then an AdaBoost learning procedure is constructed to obtain local classifiers based on selected local Haar-like features. By combining the global and local classifiers, we obtain a cascaded classifier consisting of 6 layers with only 160 features. Therefore, our cascaded classifier is simple and efficient. Our proposed cascaded classifier is invariant to the brightness, colour, size and position of license plates. Satisfactory detection results showing high detection rate with low false positive rate are demonstrated using a video of moving vehicles. Unlike methods built on either fixed image backgrounds or fixed cameras, our method does not use any inter-frame information and pre-knowledge. Therefore, our method is more flexible for real-time applications.

Keywords: License plate detection, AdaBoost algorithm, Haar-like features, statistical features

1 Introduction

License Plate Recognition (LPR) has found numerous applications in various areas. It can be used for automatically identifying vehicles in a car park, for vehicle access control in a restricted area and for detecting and verifying stolen vehicles. There have been some well-known commercially operational LPR systems around the world. The Perceptics License Plate Reader (PLPR) system is a well-known example used in Melbourne, Australia [1]. The PLPR system provides real-time identification of electronic highway toll violators to ensure that toll collection operates efficiently. The PLPR system can also be used for video-based toll collection and origin/destination studies. The examples of other LPR systems include London Congestion Charge (LCC) for automatic enforcement of fee charged to vehicles entering a specified zone in London [2]. Although few details are released to the public about the accuracy of commercially deployed LPR systems, it has been well known that they all work under controlled-conditions and the cameras are mounted in fixed locations without mobility.

LPR system consists of two major components: license plate detection and license plate recognition. License plate detection is a crucial step in a LPR system. The quality of a license plate detector influences the accuracy of license plate recognition. On the other hand, many factors can affect the accuracy and efficiency of license place detection. For example, the quality of license plate detection may be degraded due to ambient lighting conditions, image perspective distortion, texts on images and so forth. Most of existing license plate detection algorithms are restricted by various controlled conditions such as fixed backgrounds [3], known colour [4], or designated ranges of the distance between cameras and vehicles [5,6]. Detecting license plates under complex environments, therefore, remains to be a challenging problem.

There have been various attempts for license plate detection under complex conditions [5][7][8]. Recently, local Haar-like features have been widely used for object detection especially for face recognition [9,10]. Classifiers based on Haar-like features can extract objects from complex backgrounds independent of variations in colour, illumination, position, and size of the objects. However, one problem associated with these algorithms is the use of a large number of features in the classifier, which makes the system very complex and unstable. Dlagnekov and Belongie [11] constructed a cascaded classifier using Harr-like features for license plate detection. Although this classifier can achieve a satisfactory detection rate, the false positive rate is also high. Chen and Yuille [12], on the other hand, constructed a cascaded classifier for text detection using statistical features. However, the features used in this algorithm cannot be used directly to represent the characteristics of license plates.

In this paper, we use both global statistical features and local Haar-features to construct a cascaded classifier for license plate detection. Two classifiers based on two global statistical features respectively are trained through simple learning procedures. Then, AdaBoost learning algorithm [13] is used to select important local Haar-like features and construct four additional classifiers. The final cascaded classifier with 6 layers is obtained by combining the above two kinds of classifiers. The classifiers based on global features decrease the complexity of detection algorithm. The classifiers based on local Haar-like features further improve the detection rate and reduce the false positive rate.

The rest of the paper is organized as follows. An overview of our algorithm is given in Section 2. The algorithms for constructing the classifiers based on the two global statistical features are presented in Section 3. Classifiers using the local Haar-like features learned by the AdaBoost algorithm are performed in Section 4. Experimental results are demonstrated in Section 5. The conclusions are made in Section 6.

2 The Framework of Algorithm

Like the work shown in [9], the basic idea of the proposed detection algorithm is to use a variable scanning window moving around the input vehicle image. At each position, the image area (region) covered by the scanning window will be classified using a pre-trained classifier as either a number-plate area (a positive decision) or a non-number-plate area (a negative decision). To make the algorithm robust to various sizes of number plates, the size of the scanning window in our algorithm is changeable.

In our algorithm, we construct a six-layer cascaded classifier to increase the detection speed, in which the first two layers are based on global features and the last four layers are based on local Haar-like features. The classification process can be taken as a degenerate decision tree containing multi-layer classifiers as shown in Figure 1.

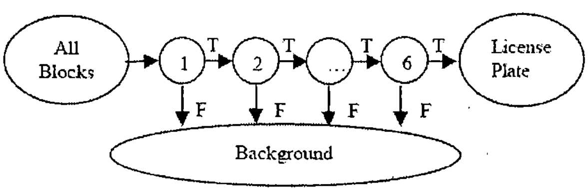


Figure 1: Process of a cascaded classifier for licence plate detection.

A positive result from the first classifier triggers the evaluation of a second classifier. A positive result from the second classifier triggers a third classifier, and so forth. A negative outcome at any layer leads to the immediate rejection of the image region (block). It is worth to note that our detector (classifier) acts on the vertical edge maps of input vehicle images rather than on the raw image intensity values. This further enhances the efficiency of the cascaded classifier.

In the following, the algorithm is further described in two aspects: training and testing. Training is a process to train the classifier and make correct decisions using pre-classified samples. Testing is a process to use the pre-trained classifier to classify individual image blocks.

2.1 Training

To obtain the cascaded classifier which can make correct decisions, pre-classified positive samples (images containing number plates) and negative samples (images containing non-number-plates) are used for training. The individual classifiers that together construct the cascaded classifier are trained independently.

To train the classifier on the first layer, the *value* of the first global feature, called *Edge Density* (to be defined in Section 3), is first computed for each input sample. Statistical methods are used to select a threshold that can correctly classify all positive samples (i.e., using the selected threshold, the edge densities of all positive samples are on the "positive" side). Note that the threshold is not unique. Also note that, for a given threshold, some negative samples may be wrongly classified as "positive", i.e., some non-number-plate blocks may be classified as a "number plate". These are referred as *false positives.* Hence, a threshold which can correctly classify all positive samples and produce the least number of false positives is selected.

For the second layer classifier, another global feature is employed. It is called the *Edge Density Variance* that will also be defined in Section 3. All input samples used to train the classifier on the second layer are from "positive" classification outcomes using the first classifier after training plus some amount of newly added negative samples. By properly selecting another threshold based on the second global feature, we can classify all positive samples as "positive" and produce minimum false positives.

Similarly, the samples used to train the classifier on the third layer are those samples which are classified as "positive" by the classifiers on the first two layers plus some newly added negative samples. The classifiers on the third through sixth layers are all based on local Haar-like features. More details about the features will be given in Section 4. The AdaBoost learning algorithm is used to select best-performing classifiers corresponding to a small amount of most significant Haar-like features selected from a huge amount of features.

The samples classified as positive ones by the third layer are input to the fourth layer, and so forth. Finally, a six-layer cascade classifier is constructed.

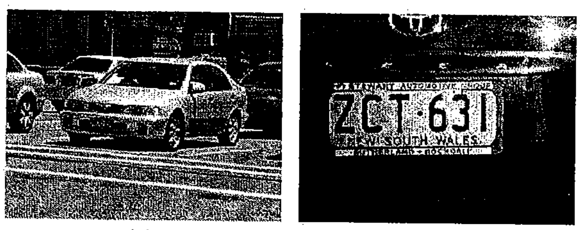
Since both global and local features in this algorithm are generated from vertical edge maps of input images, the vertical edge maps of images are computed first before any feature is extracted. Section 3 defines a new vertical edge map on which our detector acts.

2.2 Testing

In the testing procedure, an input image is selected and a scanning window moves around the whole image space with a horizontal step of half the window width and a vertical step of half the window height. At each position, global and local features of the sub-region (that is covered by the scanning window) are extracted as needed and then the trained cascaded classifier acting on those features classifies the image region as either positive, i.e. a "number plate", or negative, i.e., a "non-number-plate". This procedure proceeds through the whole image until all image regions have been classified.

Furthermore, since our detector acts on vertical edge maps of input images, vertical edge map detection is first performed before the detection begins. This is different from the work shown in [14] where Gradient map is obtained and used for training and testing. After the preprocessing for vertical edge detection, all vehicle images with various appearances are converted to vertical edge maps which are black and white images represented in grey-level intensities indicating the strength of the vertical edge at each image pixel. We can hence employ Haar-like features similar to those that have been successfully used in the systems presented in [9].

To detect number plates of multiple sizes, the detection is carried out using multiple scales. The size of basic scanning window is set to be 48 × 16. The window size is then scaled up to 300 × 100 with a scaling factor of 1.2. This design makes it possible for our algorithm to detect number plates with various sizes. Figure 2 gives an example that shows detectable number plates using our algorithm that have approximately the minimum size of 48 × 16 pixels (see Figure 2(a)) and maximum size of 300 × 100 pixels (see Figure 2(b)).



(a) (b)

Figure 2: Examples of small and large number plates.

3 Global Statistical Features

Our observation on number plate images shows that the regions of number plates have some common, obvious and simple characteristics. Firstly, a number plate region usually contains rich edge information due to the presence of text. Secondly, most edges in the region of a number plate are vertical edges (with direction between -45° and 45° from the vertical direction). Thirdly, the vertical edges are distributed relatively uniformly in the region of a number plate. Therefore, we include global edge features for number plate detection. In this section, two global features are defined, namely Edge Density and Edge Density Variance.

The edge density describes an image region as a whole. It is defined as

$$D_E = \frac{1}{N}\sum_i \sum_j E_V(i, j) \tag{1}$$

where $E_V(i, j)$ is the magnitude of the vertical edge at location (i, j), and N is the number of non-zero vertical edge pixels in the image region. The Sobel gradient operator is employed to produce gradient map, where the resulted gradient magnitudes are normalized by the maximum gradient strength in the image for vertical edge detection.

Note that the foreground characters in a license plate are usually distributed with relatively even interval. As its consequence, the gradients and hence the corresponding vertical edges in the block of a license plate are distributed evenly with similar strength [15], compared with other regions. Figure 3 gives examples of foreground and background images. To obtain the density variance feature, a block is divided into 12 equal-sized sub-blocks as shown in Figure 3. Let g_i denote the mean value of the vertical edge strength at i-th sub-block, and g denote the mean value of the vertical edge strength of the entire block. Then, the density variance of the block, denoted by V_G, is defined as

$$V_G = \frac{\sum_{i=1}^{n} |g_i - g|}{n \cdot g}, \tag{2}$$

where n is the number of the sub-blocks, e.g., $n = 12$ in this paper.

(a) License plate (b) Background

Figure 3: Distribution of vertical edges in two different regions.

4 Local Haar-like Features

The Haar-like features consist of a number of rectangles covering adjacent image regions (see Figure 4). The value of a Haar-like feature is the difference between the average of the pixel values (i.e., vertical edge strengths in this paper) in white rectangles and grey rectangles.

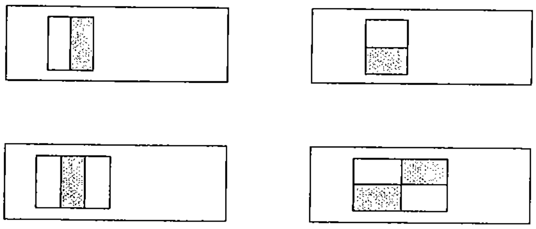


Figure 4: Four types of Haar-like features.

A Haar-like feature is determined by its type, the size and the position of the rectangles in image region. We use four types of Haar-like features in this paper as shown in Figure 4. Haar-like features can capture the interior structure of an object and are invariant to certain transformations [9]. However, the dictionary consisting of all the Haar-like feature values is too large. Clearly, it is too time-consuming to compute all the features for classification.

The AdaBoost algorithm [13] is a good choice for selecting a small number of features from a very large number of features. The classifier trained using the AdaBoost algorithm is a combination of a set of weak classifiers, each using one feature. The basic idea of the AdaBoost algorithm is as follows. After constructing a weak classifier, the samples are re-weighted with higher weights assigned those which are incorrectly classified. Then the next weak classifier is trained with the re-weighted samples. A number of weak classifiers are trained in this way until a given false positive rate is reached. The final classifier (called strong classifier) is constructed by combining these weak classifiers using a set of weights. These weights are determined by classification error of each weak classifier.

5 Experiments

To test the performance of our proposed algorithm, a total of 460 vehicle images are used for the experiments. 300 vehicle images are taken as training images that contain 305 visible number plates. The other 160 images are used as test images that contain 169 visible number plates. Vehicle images used in the experiments were taken in various circumstances under various illuminations conditions and view angles. Some examples of the license plates are shown in Figure 5. From the figure, it can be seen that there is a great variety of colour, view angles and styles of number plates.

Figure 5: Some examples of license plates.

The negative samples used to train the classifiers based on global features are collected by randomly selecting 28,000 regions from 50 images which do not contain any license plate. The negative samples used in AdaBoost learning procedure are randomly extracted from a total of 220 vehicle images that do not contain any number plates.

In the experiments, a six-layer cascaded classifier is obtained. Each of the first two layers uses one of the global features defined in Section 3. On the last four layers, the numbers of the features in the strong classifiers are 19, 34, 47 and 58 respectively. So our final cascaded classifier has 6 layers and uses 160 features. This classifier is much simpler than Viola & Jones' classifier which has 38 layers and uses 6060 features.

In the experiments, of the 169 visible number plates in 160 testing images (in some images there is more than one number plate), 163 number plates were detected, giving a detection rate of 96.4%. At the same time, only 8 false positive regions were detected. Since tens of thousands of background regions were automatically generated during the testing procedure, this false positive rate is actually very low (and less than 0.0001). On a PC with Pentium 2.8GHz CPU, the detector can process a 648*486 image in about 80ms.

Figure 6: Examples of detected license plates.

Figure 6 shows some of the detection results, where the detected license plates are marked by red boxes. From the examples, we may see that our algorithm can work under various complex environments, various illuminations, and various view angles. The algorithm can detect the license plates with various sizes, positions and colours.

Figure 7: A video taken for cars turning at a corner.

To show that our algorithm also works well for video images with lower resolution, a video taken at rate of 20 frames per second is used to show the detection results. Figure 7 shows the examples of detected license plates in a video for cars turning at a corner of a busy road in Sydney. The license plates of all nine turning vehicles in this video are detected with minimum false positive rate. An example of false positive wrongly detected is a part of the bumper bar of a white 4-wheel drive. This false positive, however, is immediately removed (corrected) in the next frame containing the same vehicle.

Compared with the approach shown in [14] where the global features were computed directly from image gradient values and only static images were considered, the cascaded classifier proposed in this paper has increased the detection rate from 93.5% to 96.4% and performed satisfactorily when used to test video images.

Figure 8: An image containing a California license plate.

To compare our algorithm with the algorithm proposed in [11] that also used AdaBoost for license plate detection but did not consider global features, an image containing a license plate of California used by the authors of [11] is taken and shown in Figure 8. In Figure 8, the regions marked by yellow boxes indicate the detected license plate together with a few false positive regions using the algorithm proposed in [11]. Although the algorithm shown in this paper used only the license plates of NSW State of Australia for training and learning, it has shown a much better result than the algorithm proposed in [11] when used to detect the license plate of California. The regions marked by red boxes in Figure 8 show the detected license plate together with only one false positive region using the algorithm presented in this paper. If we use a smaller scale factor for the adjustment of scanning window and reduce the detection speed by half, a perfect detection is obtained and only the license plate in Figure 8 is detected without any false positive regions.

6 Conclusions

In this paper, we have constructed a cascaded classifier consisting of 6 layers for license plate detection using both global edge features and local Harr-like features. The classifiers on the first two layers are based on the two global edge features. These two layers exclude more than 80% non-plate regions from further training or testing and hence greatly increase the detection speed in the next four layers. The classifiers on the next four layers, trained by AdaBoost learning procedure, are based on local Haar-like features. In our algorithm, a real-time detection speed is achieved. With a small number of features, we have achieved a very high detection rate with a very low false positive rate even when the license plate detection algorithm is used under various complex environments.

Our algorithm for detection of license plates in a video does not use motion information and any other pre-knowledge, and is not restricted by any controlled conditions. Therefore, it is more flexible than any existing systems for license plate recognition, and can hence be applied to any areas where the cameras are mobile and the backgrounds are changeable.

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