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License plate detection based on multistage information fusion

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ABSTRACT

Adaboost detector has been successfully used in object detection. In this paper, we propose a new License Plate (LP) detection technique based on multistage information fusion, which is adopted to reduce high false alarm rate in the conventional Adaboost detector. The proposed multistage information fusion system is composed of an enhanced Adaboost detector, a color checking module and an SVM detector, where the latter two stages further check whether the image patch that gets through the Adaboost detector is an LP. Test results of the dataset that consists of 950 real-world images show that the fusion reduces the false alarm rate. The proposed Fusion detector outperforms the conventional Adaboost detector throughout the ROC (Receiver Operating Characteristic) curve. The AUC (Area Under the Curve) of the best Fusion detector reaches 0.9081; however, the AUC of the best Adaboost detector is only 0.8441, which shows that the modification on feature extraction and the multistage information fusion significantly improve the LP detection performance.

1. Introduction

A license plate recognition (LPR) system is an important part of intelligent transportation systems (ITSs). It is used in a wide range of applications including parking charges, pay-per-use road usage and traffic law enforcement, etc. In general, a license plate recognition system is divided into three steps: (1) detecting the license plate; (2) extracting the characters from the license plate one by one; and (3) recognizing the characters from (2). Among the above three steps, License Plate (LP) detection is the most difficult step. If an LP is precisely detected, further processing becomes rather simple. In a practical context, LP detection in an inconstant environment is difficult. The variable factors include illumination variance, complex background, unpredictable weather and tilts caused by viewing angle. These problems are particularly intolerable when the system is used in an outdoor environment.

In the past few decades, LP detection has generated much research. There are three major categories of methods for LP detection: The first category is statistical or morphological operations of low level visual features, such as color, edge, etc. [1–5]. This is the most frequently used LP detection method in the early LPR systems. Visual attention model presents an appropriate framework to integrate the low level features [6]. The second category utilizes middle level features for LP detection, in which shape [7] and symmetry [8] are taken into consideration. Texture analysis by Gabor filter [9], wavelet transform [10] and Hough transform [11] also give impressive results in LP detection. The last category is the methods based on artificial intelligence (AI), including neural networks (NN) [12,13], Adaboost [14], etc. Support vector machine (SVM) is a powerful texture classifier [15]; however, due to its heavy computation requirements, SVM has not been used in LP detection directly. In reference [16], the authors first estimated LP region by motion information, then verified the result by SVM. In an AI based LP detection method, the classifier scans the whole image patch by patch, and determines whether it is an LP. Most of these works perform well in simple and constant backgrounds; but they suffer performance degradation if the background is complex or the environment (such as illumination, climate, viewing angle, distance) changes. Simply put, the challenges of LP detection are still far from being solved.

Since Adaboost has had great success in face detection [17], Dlagnekov tried to apply it to detect license plates and achieved a detection rate of 95.6% with a false alarm rate of 5.7% [14]. Pan et al. tried to detect Chinese license plates using Adaboost [18], whose test results on 200 frames yielded a detection rate of 81% with a false alarm rate of 6.5%. Their results are with a high false alarm rate, not as good as expected. From all the above we can conclude that, the Adaboost LP detectors are far from practical use.

This paper presents a multistage information fusion detector for LP detection, in which information fusion is applied to improve the conventional Adaboost LP detector. The direct contributions of this work are improved feature extraction and multistage information fusion of detectors. The feature extraction of [14,18] for LP detection does not look into the details of LPs. In our implementation, the Harr-like features are restricted in the scale of characters and

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strokes, which are more meaningful for LP detection. Besides modifications and restraints on feature extraction, a multistage information fusion detector, which is composed of an enhanced Adaboost detector, a color checking module and an SVM detector, reduces the false alarm rate effectively. Tests on 950 real-world car images in complex background show encouraging results, which proves that the modifications on feature extraction and the multistage information fusion do improve the performance of LP detection.

The rest of the paper is organized as follows: Section 2 describes details of a license plate detection algorithm based on Adaboost. In Section 3, a multistage information fusion procedure composed of an Adaboost detector, a color checking module and an SVM detector is presented. Test results on a dataset consisting of real-world car images are shown and discussed in Section 4. Finally, we conclude this paper and look forward to future work in Section 5.

2. Adaboost detector – training and detection

This section provides a detailed description of Adaboost detector. Section 2.1 presents the Harr-like feature extraction for LP detection. Section 2.2 establishes a method of training the Adaboost LP detector offline. And Section 2.3 outlines the online work procedure of the Adaboost LP detector.

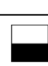
2.1. Harr-like feature extraction

In Ref. [17], Viola and Jones proposed four types of Harr-like features for an Adaboost detector to detect faces. Lienhart and Maydt [19] extended the detector by rotating the Harr-like feature. Meanwhile, they extracted another type of feature called center-surround feature. All the types of features mentioned above can be calculated fast by accumulation image, more details about accumulation image could be found in Ref. [17]. The features extracted by [14,18] for LP detection are horizontal and vertical deviations, and all of the features are extracted in the scale of LP. In other words, only coarse Harr-like features are extracted; the feature extractors do not look into details.

The Harr-like features are modified to accommodate our application of license plate detection. The 4-section (diagonal) feature is removed; center-surround feature is added. There are 5 types of feature; all of which are shown in Table 1. Each feature is the sum of pixels which lie within the black sections subtracted by the sum of pixels in the white sections. Harr-like features in our scheme are restricted in the scale of character and stroke, since these Harr-like features are more meaningful for LP detection.

According to the LP standard in China [20], the LPs have an aspect ratio of about 3. All LPs can be scaled to the same size as shown in Fig. 1. The only constraint on the LP size is the aspect ratio of 3, which means that an LP is of size $H * 3H$. LP with smaller H is in low resolution, which would result in information loss; whereas, LP with larger H is in high resolution, which contains meaningless details for LP detection and induces complex computation. As the tradeoff decision, H is set to 20. All the training samples are scaled to $20 * 60$. Consequently, the trained detector could only identify LP of size $20 * 60$.

Table 1
Harr-like features.

Features					
Feature type	1	2	3	4	5
Horizontal range	1–3	1–3	2–7	2–7	5–7
Vertical range	2–14	2–14	1–3	1–3	12–14
Total number	23,595	22,737	14,715	12,753	141

As mentioned above, the feature extraction focuses on stroke scale and character scale. The constraints on scale significantly reduce the computational cost. Through simple measurement we can draw the following conclusions. When an LP is scaled to $20 * 60$, the size of a horizontal stroke is about $2 * 6$, the size of a vertical stroke is about $13 * 2$, and the size of a character is about $13 * 6$. The horizontal and vertical range (in pixel) of white sections are shown in Table 1. For each type of feature, the size of the white section can be any value within an interval given in the table.

Given the basic resolution of $20 * 60$, there are 73,941 features in the exhaustive feature set. The number of each type of feature is also shown in Table 1. It is worth mentioning that the features of type 5 (whose white section is surrounded by black) are extracted in character scale only, and the center section (white color) should be a single character. So the number of center-surround feature is 141, much less than the other types of features.

2.2. Adaboost offline training

LP images (the positive samples) for training are cropped manually; whereas nonLP images (the negative samples) are cropped automatically and randomly from the whole image. There are totally 1800 negative samples and 200 positive samples in the training dataset. Fig. 1a shows some LP images, and Fig. 1b gives some nonLP images. All the images are scaled to $20 * 60$. Given the training images, 73,941 features are extracted from each sample. As shown later, each feature forms a weak-classifier for the Adaboost detector.

The offline training procedure is presented as Algorithm 1.

Algorithm 1. Adaboost offline training procedure

1. Given sample x_i with label y_i, $w_{t,i}$ is the weight of ith sample in tth training round, m and l are the number of positive and negative samples, respectively.
2. Initialize sample weights $w_{1,i} = \frac{1}{2m}$ if $y_i = 1$; $w_{1,i} = \frac{1}{2l}$ if $y_i = 0$.
3. For $t = 1, \ldots, T$

   (1) Normalize the sample weight $w_{t,i} = \frac{w_{t,i}}{\sum_{j=1}^{n} w_{t,j}}$.

   (2) For each feature j, train a weak-classifier h_j, determine threshold

   θ_j and bias p_j by minimizing weighted error $\varepsilon_j = \sum_i w_{t,i} |h_j(x_i) - y_i|$.

   where $h_j(x_i) = sgn(p_i \cdot (x_i - \theta_i))$, $p_i = \pm 1$,

   $$sgn(x) = \begin{cases} 1 & x > 0 \\ 0 & \text{otherwise} \end{cases}.$$

   (3) Get weak-classifier h_t with minimum error ε_t.

   (4) Update sample weights by $w_{t+1,i} = w_{t,i}\beta_t^{1-e_i}$, in which

$$e_i = \begin{cases} 0 & x_i \text{ is correctly classified} \\ 1 & \text{otherwise} \end{cases}, \quad \text{and} \quad \beta_t = \frac{\varepsilon_t}{1 - \varepsilon_t}.$$

4. The final strong classifier is

$$h(x) = \begin{cases} 1 & \sum_{t=1}^{T} \alpha_t h_t(x) \geqslant 0.5 \sum_{t=1}^{T} \alpha_t \\ 0 & \text{otherwise} \end{cases}, \tag{1}$$

   where $\alpha_t = log\left(\frac{1}{\beta_t}\right)$.