# License Plate Recognition Using MSER and HOG Based on ELM

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***Abstract*—In this paper, an effective method for automatic license plate recognition (ALPR) is proposed, on the basis of extreme learning machine (ELM). Firstly, morphological Top-Hat filtering operator is applied to do the image pre-processing. Then candidate character regions are extracted by means of maximally stable extremal region (MSER) detector. Thirdly, most of the noise character regions are removed according to the geometrical relationship of characters in standard license plates. Finally, the histograms of oriented gradients (HOG) features are extracted from each character of every plate detected and the characters are recognized by the classifier trained though the ELM. Experimental evaluation shows that our approach significantly performs well in the ALPR systems.**

***Keywords*—license plate recognition; extreme learning machine (ELM); maximally stable extremal region (MSER); histogram of oriented gradient (HOG)***

## I. Introduction

Intelligent transportation systems (ITSs) have had a wide impact on peoples life in the past years. With the rapid development of computer vision and pattern recognition, more and more vision-based technologies are applied in ITSs for traffic control and management. Automatic license plate recognition (ALPR) plays an important role in ITSs for numerous applications, such as road traffic monitoring, electronic payment systems and traffic law enforcement [1], [2].

Although the ALPR has a long research history, it is still a challenging task in complex traffic scenes because many factors affect the final recognition result, such as uneven lighting conditions, partial blurry license plate characters, etc. ALPR algorithms are generally composed of two major steps: license plate detection and character recognition.

License plate detection, corresponding to detect the rectangular area of the license plate in an original image, is most crucial to the ALPR system. Many researchers are committed to the field of license plate detection. Color-based approaches are used to detect license plates because color combination of license plate and characters occurs almost only in a plate region [3]–[5]. Shi *et al.* [4] extracted license plate region based on hue, saturation, and lightness (HSL) and verified the plates according to the aspect rations. However, the color-based methods are sensitive to illumination conditions especially in full-day monitoring scenes. Moreover, edge-based methods are more likely to be used for they are more effective and fast [6], [7]. In [6] the vertical edges are extracted by a Sobel operator and the noise edges are removing. As a result, the plate regions can be easily detected. These methods based on edge information may detect the real license plate regions in relatively simple environments, but they are very sensitive to noise and computationally complex when there are many edges in traffic scenes with complex backgrounds.

After license plate detection, each character is segmented from the license plate regions and recognized by classifiers. Many techniques to segment each character have been developed. It is easy to segment after real license plates binarization. The binary-based approaches transform the images to the binarized images and adopts the filters to eliminate noises. In [8], local thresholding is used for each pixel since binarization with one global threshold cannot always produce acceptable results. The threshold is calculated by subtracting a constant from the mean grey level in an window centered at the pixel. Qian *et al.* [9] used imensions of each character for segmentation and the prior knowledge of the Chinese license plate layout to construct a classifier for recognition. In addition, to recognize the characters efficiently, optical character recognition (OCR) is the method that has been primarily applied. A wide variety of character recognition methods are reported including conventional neural networks in [10] and a support vector machine (SVM) in [11]. Chen *et al.* [12] proposed a multi-stage classifier with a feature-salience algorithm to recognize characters. These recognition methods have high adaptability, good study ability and can result in a high correct level, but they are also time-consuming for training and testing.

In this paper, an effective method for ALPR is presented, on the basis of extreme learning machine (ELM).The flowchart of the method is illustrated in Fig.1. Firstly, we use top-hat transformation to preprocess the input image which helps restrain background noises. Then extract the MSERs, pick out the candidate character regions and choose the real license plate

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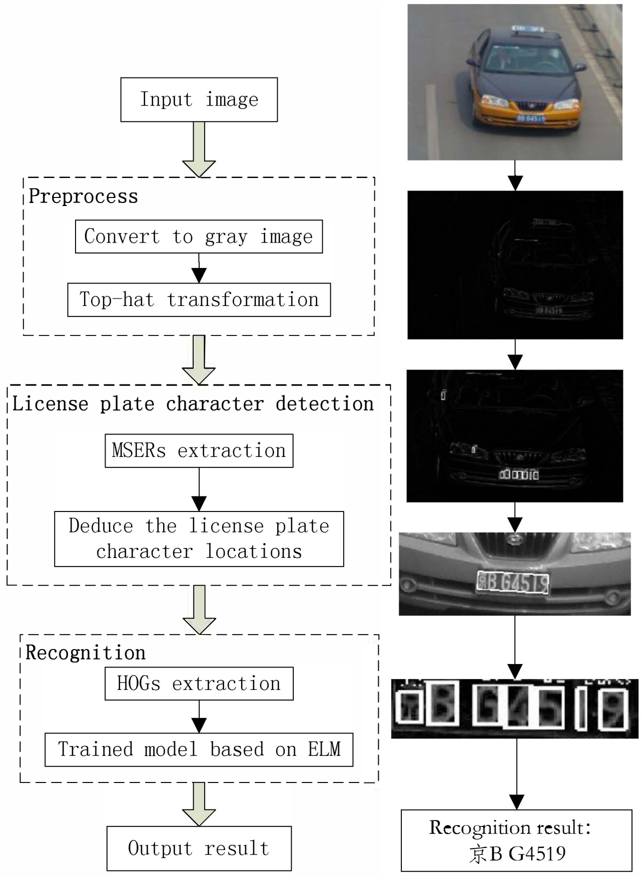
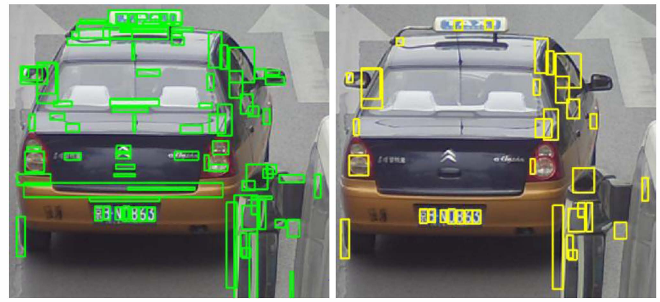



Fig. 1: The flowchart of the proposed method



(a) (b)

Fig. 2: Extracted MSERs. (a)Candidate MSERs. (b)MSERs after filtration

character regions according to the geometrical relationship of characters in standard license plates. Lastly, the character regions features named HOG descriptors are extracted from the input image and the characters are recognized by using the neural network based on ELM.

This paper is organized as follows. In sect. II, license plate character detection is described, followed by the image preprocessing and MSER extraction. License plate recognition using HOGs and neural network based on ELM is discussed in detail in Sect. III. The experimental results are described in Sect. IV. Finally, a brief conclusion is made in Sect. V.

## II. License Plate Character Detection

### A. Image preprocessing

For most of the images with license plate acquired from real environments are color images, we should change them into gray ones to cut down the amount of calculation. Moreover, we did the top-hat operation which is a kind of mathematical morphology transformation. For the mathematical morphology [13], it is a non-linear filter, with the function of restraining noises, extracting features and segmenting images etc.

### B. Character Regions Extraction

*1) Maximally stable extremal region:* The MSER feature allows a wide range of different applications such as scene classification, object recognition and target tracking. Originally, MSER was proposed in [14] to denote a set of distinguished regions, which are defined by an extremal property of its intensity function in the region and on its outer boundary. Maximum intensity region is a region that all the value of pixels are less than the gray level of pixels in this regions boundary, and minimum intensity region is greater than that. The extremal regions including maximum intensity regions and minimum intensity regions are denoted as $Q_1, ..., Q_{i-1}, Q_i, ...(Q_i \subset Q_{i+1})$. If the area of an extremal region is stable in a wide range of gray level, this region is a maximal stable extremal region (MSER). The mathematical expression is shown in (1).

$$q(i) = \frac{|Q_{i+\Delta} \setminus Q_{i-\Delta}|}{|Q_i|} \tag{1}$$

Compared with other region features, MSER is affine-invariant to scale transformation, rotation transformation and transformation of the view-point. Similar to [15], [16], we use MSER detector in our implementation to detect the license plate characters and get a good performance.

*2) Character and plate localization:* The pixels in license plate characters vary steadily and these regions meet the maximally stable extremal condition. Although we have done the preprocessing to remove some interference regions, other noisy MSERs in the image are also extracted meanwhile. While extracting the MSERs, we find that the interference regions have diversity in shape as shown in Fig.2(a). Taking the geometrical relationship of characters in standard license plates into consideration, we can choose the right corresponding parameters to remove interference regions as shown in Fig.2 (b). As the standard Chinese license plate shown in Fig.3, the length-width ratios of license plates and their characters are all within a certain range. According to the priori knowledge described above, we can locate the license plate and segment each character region simultaneously.

## III. License Plate Recognition

### A. Extreme Learning Machine

Extreme learning machine (ELM) was proposed by Huang *et al.* in [17] as an efficient learning algorithm for single-hidden layer feedforward neural network (SLFN). For multiclass classification, the architecture of SLFN with L hidden nodes and


Fig. 3: Standard Chinese license plate

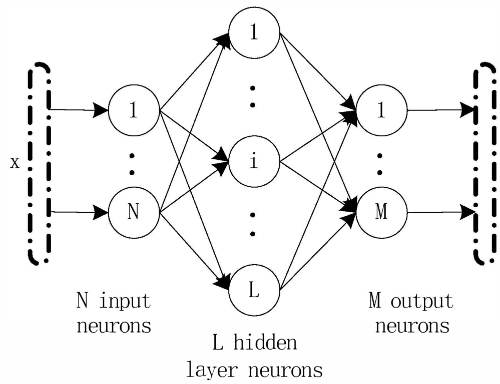



Fig. 4: Architecture of the SLFN

M outputs is shown in Fig4. The ELM aims at minimizing the training error and the norm of the output weights. The key point of ELM is that it needs no iteration when determining the parameters, which results in less computational time for training the SLFNs.

For a training set consisting of N arbitrary distinct samples $S = \{(x_j, t_j)|x_j \in R^n, t_j \in R^m, j = 1, 2, ..., N\}$,a standard ELM with $\tilde{N}$ hidden nodes is formulated as below

$$f_{\tilde{N}}(x_j) = \sum_{i=1}^{\tilde{N}} \beta_i g(w_i \cdot x_j + b_i) = t_j, j = 1, 2..., N \quad (2)$$

where $g(x)$ is an activation function and is n-dimensional weight vector connecting $i$th hidden node and input neurons. For using $\tilde{N}$ hidden nodes to approximate $N$ samples, $\beta_i$, $w_i$ and $b_i$ are supposed to exist if zero error is to be obtained. Hence the (2) is modeled as the (3) with a more compact format.

$$H\hat{\beta} = T \quad (3)$$

where

$$H = \begin{bmatrix} g(w_1 \cdot x_1 + b_1) & \cdots & g(w_{\tilde{N}} \cdot x_1 + b_{\tilde{N}}) \\ \vdots & \ddots & \vdots \\ g(w_1 \cdot x_N + b_1) & \cdots & g(w_{\tilde{N}} \cdot x_N + b_{\tilde{N}}) \end{bmatrix}_{N \times \tilde{N}} \quad (4)$$

$$\hat{\beta} = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_{\tilde{N}^T} \end{bmatrix}_{\tilde{N} \times m} \quad \text{and} \quad T = \begin{bmatrix} t_1^T \\ \vdots \\ t_{N^T} \end{bmatrix}_{N \times m} \quad (5)$$

Fig. 5: Examples of training samples

$H$ is called the hidden layer output matrix of the neural network, the $i$th column of $H$ is the output of the $i$th hidden node with respect to inputs $x_1, x_2, ..., x_N$. Considering the hidden nodes $\tilde{N}$ will always be less than the number of training samples $N$ in practical application, Huang *et al.* [17] proposed randomly assigning values for parameters $w_i$ and $b_i$, and thus the system becomes linear so that the output weights can be estimated by $\beta = H^{\dagger}T$, where $H^{\dagger}$ is the Moore-Penrose generalized inverse of the hidden layer output matrix $H$. Consequently, there are three steps to learn the model as shown below.

*1)* Assign randomly input weight vectors or centers $w_i$ and hidden node bias of impact factor $b_i$, $i = 1, 2, ..., L$ and $L$ is the number of hidden nodes.

*2)* Calculate the hidden layer output matrix $H$.

*3)* Calculate the output weight: $\beta = H^{\dagger}T$.

### B. Recognition

We have trained the classification model off-line on the basis of ELM aforementioned. Tamura *et al.* [18] and Huang *et al.* [19] pointed out that SLFNs (with N hidden nodes) with randomly chosen sigmoidal hidden nodes (with both input weights and hidden biases randomly generated) can exactly learn N distinct observations. In this paper, we set hidden nodes to 1100 to get a better recognition result.

Chinese license plate characters consist of 31 Chinese characters, 10 digits and 24 alphabets. In this paper, we manually collect 1358 character samples for training(see Fig.5). We extract the Histogram of Oriented Gradients (HOG) [20] as the feature descriptor to represent the license plate characters. Furthermore, we set the cell size, block size, block stride, and number of orientations to 10*10, 20*20, 5*5 and 9, respectively. Accordingly, we get a feature vector of 180 dimensions to represent the character region. Then we train a network with 1100 hidden nodes and 65 output neurons as the classifier on the basis of ELM.

## IV. Experimental Results

All the experiments are performed on a standard PC with 2.66-GHz Intel Core 2 Quad CPU and 2-GB RAM. The complete testing image database consists of 286 digital images with 408 plates from the full-day traffic surveillance videos. Only the plates with height above 20 pixels are counted for 20

TABLE I: Experimental Results of Database

| Evaluation Indicator | Rate(%) |
|---|---|
| LPLRR | 94.85(387/408) |
| LPLPR | 95.56(387/405) |
| CRR | 97.90(2652/2709) |


Fig. 6: Examples of Location and Recognition Results

pixels is typically the lowest height of identifiable characters in most OCR engines [21]. Some detection and recognition results are illustrated to show the validity of our proposed system(see Fig.6).

To evaluate the performance of our proposed approach, the license plate location recall rate (LPLRR), license plate location precision rate (LPLPR), character recognition rate (CRR) are used. In this paper, the location is correct only if the overlap of the detected and ground truth bounding box of the license plate is above 0.8. The experimental results are listed in TABLE I. The rates of locating the plate, recognizing the characters achieve 94.85% and 97.90%, respectively. Moreover, it reaches the requirement of real-time application for it takes less than one second to process a $1280 \times 736$ image. The experimental results show our proposed method is real-time, robust and efficient. However, most wrongly recognized characters are Chinese characters for their complex structures with more strokes and the test images from the full-day traffic surveillance videos are with complex backgrounds and under different light conditions.

## V. Conclusion

In this paper, an effective approach for ALPR is presented, on the basis of ELM. Firstly, top-hat transformation is applied to restrain background noises followed by the extraction of MSERs. Then, suitable MSERs are selected as the candidate character regions according to the geometrical relationship of characters in standard license plates. In addition, the license plates are also located simultaneously only if five or more adjacent characters are detected. Finally, we extract the HOG descriptors and recognize the plate number though the off-line trained net work based on the ELM. Our future work will focus on adding more robust training samples and discovering more abstract and useful representations of license plates by using deep architectures.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