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Iranian License Plate Character Recognition Using Classification Ensemble

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Abstract

Vehicle license plate recognition system is an important research topic of the applications of intelligent transportation by using computer vision, image processing and pattern recognition technology. In this paper, a set of robust features are calculated from license plate characters based on angle, transit and Kirsch edge detector, and then classified using fusion of SVMs. The proposed recognition method is evaluated on a database of Iranian license plate characters consisting of 10,000 binary images, and the recognition rate of 99.68% is achieved. Also, we obtained 99.75% accuracy using four-fold cross validation technique on 10,000 dataset. Further we evaluated our method on the available dataset that contain 1200 sample. Using 70% samples for training, we tested our method on whole samples and obtained 99.85 % correct recognition rate. In addition, experimental results have demonstrated our method has better performance on Iranian license plate character recognition in comparison with contemporary methods.

Keywords: License plate recognition, intelligent transportation system, character recognition, kirsch edge detector, mixture of SVMs.

I. Introduction

Automatic License plate recognition (ALPR) system in the intelligent transportation system plays a very important role in our lives, which has a wide application, such as unattended parking lots (Zhang, 2014), (Douglas, 2014), video surveillance (Rao, 2014), traffic law enforcement (Anagnostopoulos,2014), congestion pricing, and automatic toll collection (Soomro, 2012). License plate recognition has become very hot in the image processing and pattern recognition, and has deep and extensive research both at home and aboard. The ALPR system that extracts a license plate number from a given image can be composed of four stages (Lotufo, 2013). The first stage is to acquire the car image using a camera. The parameters of the camera, such as the type of camera, camera resolution, shutter speed, orientation, and light, have to be considered. The second stage is to extract the license plate from the image based on some features, such as the boundary, the color, or the existence of the characters. The third stage is to segment the license plate and extract the characters by projecting their color information, labeling them, or matching their positions with templates. The final stage is to recognize the extracted characters by template matching or using classifiers, such as neural networks and fuzzy classifiers. The performance of an ALPR system relies on the robustness of each individual stage. Some of the related works in the field of license plate extraction are as follows.

In (Azad, 2013), the combination of morphology, edge detection and the analysis of the histogram have been used. Primarily, by means of sober operator, obtains the edges of plate image, then these edges are clarified by the analysis of repeated histogram and it considers the most frequent point as a candidate and for detecting the exact location of license plate, the obtained image extended horizontally and vertically, in frequency; then the license plate is obtained by sharing of this development. In (Al-Ghaili,2013) to determine the edges of the image, a new algorithm has been used that, unlike the Sobel and Canny methods, has less time complexity. To find the plate, the number of the drawn lines in each row are counted and then saved in one matrix. Also, the image is divided into several subgroups of 10 rows and the number of the horizontal lines in every group is counted. Then a group is chosen which has less number as candidate and omits the non-candidate points by means of a threshold function and the location of plate is extracted.

In (ZHANG, 2012), firstly, they takes the input image into a grayscale, then for analyzing the location of plate the operations of morphology such as erosion and dilation are applied. Then, the plate is extracted with use of vertical and horizontal projection among various candidates. In (Deb, 2013) the plate has a location with the black background and white writings. In this way, firstly, the image converts into the HIS. Then, due to applying the capability of black color of its background, it uses a mask and segments the image according to HSI color intensity parameter and creates a binary image. For canceling probable noises, it uses the operation of erosion and dilation, and then labels the existing candidates. For canceling the candidates which aren't the location of plate, it applies the geometric capability of the plate and other characters, then for recognizing a primary candidate, it uses the color intensity histogram, and recognizes the location of plate.

In this paper, we focus on a new approach for character recognition step. Character recognition in ALPR systems may have some difficulties. Due to the camera zoom factor, the extracted characters do not have the same size and the same thickness (Comelli, 1995). Resizing the characters into one size before recognition helps overcome this problem. The characters' font is not the same all the time since different countries' license plates use different fonts. Extracted characters may have some noise or they may be broken (Al-Ghaili, A.M, 2013). The extracted characters may also be tilted (Azad, 2013). Based on a survey (Lotufo, 2013) on LPR, existing license plate character recognition approaches in image or video sequence, grouped into two categories:

A. Character Recognition Using Template Matching

Template matching is a simple and straightforward method in recognition. The similarity between a character and the templates is measured. The template that is the most similar to the character is recognized as the target. Most template matching methods use binary images because the grey-scale is changed due to any change in the lighting. Template matching is performed in (Sarfraz, 2003), (Azad, 2013), after resizing the extracted character into the same size. Several similarity measuring techniques are defined in the literature. Some of them are Mahalanobis distance and the Bayes decision technique, Jaccard value (Lee, 1994) and the Hamming distance (Sarfraz,2003). Character recognition in (Lu, 2003) uses normalized cross correlation to match the extracted characters with the templates. Each template scans the character column by column to calculate the normalized cross correlation. The template with the maximum value is the most similar one. Template matching is useful for recognizing single-font, non-related, non-broken, and fixed-size characters. If a character is different from the template due to any font change, rotation, or noise, the template matching produces incorrect recognition.

B. Character Recognition Using Extracted Features

Since all character pixels do not have the same importance in distinguishing the character, a feature extraction technique that extracts some features from the character is a good alternative to the grey-level template matching technique (Lotufo, 2013). It reduces the processing time for template matching because not all pixels are involved. It also overcomes template matching problems if the features are strong enough to distinguish characters under any distortion. The extracted features form a feature vector which is compared with the pre-stored feature vectors to measure the similarity. Some of the related works in this group are (Nejati, 2013), (Azad, 2013).
The rest of this paper is organized as follows: In Section 2, we discuss data collection used in experiments. Feature extraction method and classification stage are described in Section 3 and 4 respectively. The experimental results are demonstrated in Section 5. Finally, conclusions are presented in Section 6.

II. **Proposed Method**

For training and evaluating the classifier presented in this paper, we need to have a database of license plate characters to be recognized. For this purpose, we used a set of gray-scale images of vehicles taken by camera unit of a LPR system, and produced a database consisting 10,000 binary images of Iranian license plate characters. Three samples of gray-scale images used for producing the character database are shown in Fig. 1. The enlarged plate region also has been shown in the right-bottom corner of these images. Fig. 2 illustrates an Iranian car plate with corresponding binary images of its characters which their sizes are normalized to 21*14 pixels.

Figure. 1. Three samples of images acquired from a LPR system; these images are used for producing the character database

Fig. 2. Sample of Iranian car plate and corresponding binary images of its characters with normalized size

A. *Feature Extraction*

The first step in character recognition stage of LPR system is extraction of features from input images to be classified. The selection of the feature set to use is very important for the final classification rate. On the other hand, the feature extraction algorithm should have a low computational cost for real time applications. We use directional Kirsch edge operators, angle and transit technique for feature extraction, as following sections.

B. *Kirsch Edge Detection*

The first-order differential edge detectors are adequate for local detection of a line segment and fast computation. The Kirsch edge detector, Prewitt edge detector, Sobel edge detector, and so on are the representative edge detectors of the first differential edge detectors. However, among these edge detectors, the Kirsch edge detector has been known to detect four directional edges more accurately than other edge detectors because the Kirsch edge detector considers all eight neighbours (Lu, 2003). Kirsch defined a nonlinear edge enhancement algorithm as (1) :

$$G(i,j) = \max \{1, \max (\left|5s_k^7 - 3T_k\right|\} \quad (1)$$

Where $S_k = A_k + A_{k+1} + A_{k+2}$, and $T_k = A_{k+3} + A_{k+4} + A_{k+5} + A_{k+6} + A_{k+7}$, $G(i,j)$is the gradient of pixel (i, j), the subscripts of A are evaluated modulo 8, and A_k $(k = 0,1,\dots,7)$ is eight neighbors of pixel (i, j) defined as shown in Fig. 3.

A_0	A_1	A_2
A_7	(i,j)	A_3
A_6	A_5	A_4

Fig. 3. 4 Definition of eight neighbours of pixel (i, j)

In this paper, we calculate directional feature vectors for horizontal (H), vertical (V), right-diagonal (R), and left-diagonal (L) directions as (2) [20]:

$$G(i,j)_H = \max(|5S_0 - 3T_0|, |5S_4 - 3T_4|),$$
$$G(i,j)_V = \max(|5S_2 - 3T_2|, |5S_6 - 3T_6|),$$
$$G(i,j)_R = \max(|5S_1 - 3T_1|, |5S_5 - 3T_5|),$$
$$G(i,j)_L = \max(|5S_3 - 3T_3|, |5S_7 - 3T_7|) \quad (2)$$

The above calculations can be done by simple convolution of Kirsch masks with character binary image and then, keep the maximum values for each direction. In other words, for producing the directional edge image G_i in direction $i \in \{H, V, R, L\}$, the convolution of character image with two corresponding Kirsch masks of direction i are calculated then for each pixel location in these two convolution results, the maximum absolute value is then saved in G_i. Fig. 4 shows the Kirsch masks used for calculating directional edge images.

$$\begin{bmatrix} 5 & 5 & 5 \\ -3 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix} \quad \begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & -3 \\ 5 & 5 & 5 \end{bmatrix} \qquad \begin{bmatrix} -3 & -3 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & 5 \end{bmatrix} \quad \begin{bmatrix} 5 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & -3 & -3 \end{bmatrix}$$

(a) (b)

$$\begin{bmatrix} -3 & 5 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & -3 \end{bmatrix} \quad \begin{bmatrix} -3 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & 5 & -3 \end{bmatrix} \qquad \begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & 5 \\ -3 & 5 & 5 \end{bmatrix} \quad \begin{bmatrix} 5 & 5 & -3 \\ 5 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix}$$

(c) (d)

Fig. 4. Kirsch masks, (a) horizontal, (b) vertical, (c) right-diagonal, (d) left diagonal

As a final feature extracting step, each 21*14 directional edge image $G_i, i \in \{H, V, R, L\}$, is compressed to 3*2 feature maps by accumulating pixels of each 7*7 sub-region of the input image. In order to consider the global characteristics of the input images, we also compress the 21*14 normalized input images into 3*2 images and use this compressed image as a global feature. The number of the calculated features using Kirsch edge detector are 5*3*2=20 features. These features are rearranged as a vector and concatenated to the feature vector obtained based on directional image projections to construct the final feature vector as the input of classifier.

C. *Transit and Angle Feature Set*

In our system we also computed features based on transit and angle pixels of the images as follows: First we found the bounding box (minimum rectangle containing the character) of each input image which is a two-tone image. Then for better result and independency of features to size and position (invariant to scale and translation), we converted each image (located in bounding box) to a normal size of 30×15 pixels. We chose this normalized value based of various experiments and a statistical study. In Fig. 5 a normalized image with its bounding box is shown. Then, we scanned the image by keeping a window-map of size 5×5 on the image from the top left most point to downright most point (18 no overlapped blocks). Finally for each block the transit and angle features were computed.

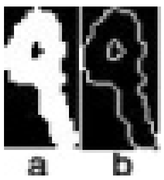

Fig. 5. (a): Bounding box of a normalized image (b): digit '9' contour form

Angle features are very important features in order to achieve higher recognition accuracy and reducing misclassification. These features are extracted from image by the (3) that we mentioned earlier in (Azad, R., Davami, 2013).

$$(a_b) = \frac{1}{n} + \sum_{k=1}^{n_b} \theta_k^b \qquad ,b=1,2,3,.. \quad (3)$$

In the top relation, a_b is angle average for any block and θ_k^b angle of white pixel to block horizontal level. The steps that have been used to extract these features are given: step 1. Divide the input image into n (n=18) number of block, each of size 5×5 pixels; step 2. Calculate for each block of image, angle degree with use of equation (3) and set These 18 sub features as an angle feature; Step 3. Corresponding to the blocks whose angle does not have a foreground pixel, the feature value is taken as zero. Using this algorithm, we will obtain 18 features corresponding to every block.

The third feature extraction investigated in this research was based on the calculation and location of transition features from background to foreground pixels in the vertical and horizontal directions. The transition feature used here is similar to that proposed by Kumar et al (Kumar, 2013). To calculate transition information, image is scanned from left to right and top to bottom. Following steps have been implemented for extracting these features: step I: Divide the contoured image of a character into 18 blocks, each of size 5×5; Step II: Calculate number of transitions for each block. This will give us 18 features for a character image.

III. **Classification**

Over the last decade, ensemble technique is widely used in many different applications. There are different types of ensemble methods. One such type is classification fusion method. In this method, many classifiers are trained on a same feature space. The results of these classifiers are combined to obtain a more accurate classification (Parikh, 2007). In this paper, we have used ensemble of Support Vector Machine (SVM) as classifiers (5 SVM classifiers). The features obtained from kirsch edge detector, transit and angle is applied to each SVM classifier then the prediction of these classifiers is merged using majority-voting technique to correctly classify the sample.

A. SVM Classifier

Support vector machines (SVMs) are very popular and powerful in pattern learning because of supporting high dimensional data and at the same time, providing good generalization properties. Moreover, SVMs have many usages in pattern recognition and data mining applications. At the beginning, SVM was formulated for two-class (binary) classification problems.

B. Binary Support vector Machine Formulation

$X = \{(x_i, y_i)\}^n i = 1$ be a set of n training samples, where$x_i \in R^m$is an m-dimensional sample in the input space, and$y_i \in \{-1,1\}$ is the class label of sample x_i. SVM finds the optimal separating hyper plane (OSH) with the minimal classification errors. The linear separation hyper plane is in the form of (4):

$$f(x) = W^T x + b \quad (4)$$

Where w and b are the weight vector and bias, respectively. The optimal hyper plane can be obtained by solving the optimization problem (7), where $\zeta_i$is slack variable for obtaining a soft margin while variable C controls the effect of the slack variables. Separation margin increases by decreasing the value of C. In a support vector machine, the optimal hyper plane is obtained by maximizing the generalization ability of the SVM. However if the training data are not linearly separable, the obtained classifier may not have high generalization ability, even though the hyper planes are determined optimally. To enhance linear severability, the original input space is mapped into a high-dimensional do product space called the feature space. Now using the nonlinear vector function $\varphi(x) = (\varphi_1(x), \dots, \varphi_l(x))^{\Psi}$ that maps the m-dimensional input vector x into the l-dimensional feature space, the OSH in the feature space is given by (5):

$$f(x) = W^T\varphi(x) + b \quad (5)$$

The decision function for a test data is (6):

$$D(x) = \mathrm{Sign}(W^T\varphi(x) + b) \quad (6)$$

The optimal hyper plane can be found by solving the following quadratic optimization problem:

$$\text{Minimize } \frac{1}{2}||W||^2 + C\sum_{i=1}^{n} \zeta_i$$
$$\text{Subject to } y_i(W^T\varphi(x) + b) \geq 1 - \zeta_i\,,\ \zeta_i \geq 0, i = 1, \dots, n \quad (7)$$

C. *Multiclass Support Vector Machine*

As described before, SVMs are intrinsically binary classifiers, but, the classification of characters involves more than two classes. In order to face this issue, a number of multiclass classification strategies can be adopted. The most popular ones are the one-against-all (OAA) and the one-against-one (OAO) strategies (Azad, 2013). The one-against-one constructs (n (n-1)) ⁄2 decision functions for all the combinations of class pairs. Experimental results indicate that the one-against-all is more suitable for practical use. We use OAA for character classification.

D. *Classification Ensemble*

Our classification ensemble method is summarized in the following algorithm. Also Fig. 6 shows the recognition way for entrance image by applying these classifiers.

Algorithm

Input: a set of training samples and test sample.

Output: the class label for which the test sample belongs.

Method:

Step1: Extract the kirsch edge detector, transit and angle features for the training sample and test sample using previously discussed approaches respectively.

Step 2: Let the extracted feature vector for each character be$f_1, f_2, \dots, f_{56}$: where $f_1, f_2, \dots, f_{20}$ are Kirsch edge feature, $f_{21}, f_{22}, \dots, f_{38}$ are angle features and $f_{39}, f_{40}, \dots, f_{56}$ are the transit features.

Step 3: Divide the extracted features obtained from the training samples to the 5 group and apply them to train the SVM_i i$\in$(1,2,3,4,5) classifiers respectively.

Step 4: Apply the features obtained from the test samples to each of the classifier.

Let the prediction of the classifiers be p1, p2, p3, p4 and p5

Step 5: Predict the class of the test sample as: Class = Majority of {p1, p2, p3, p4, p5}

End

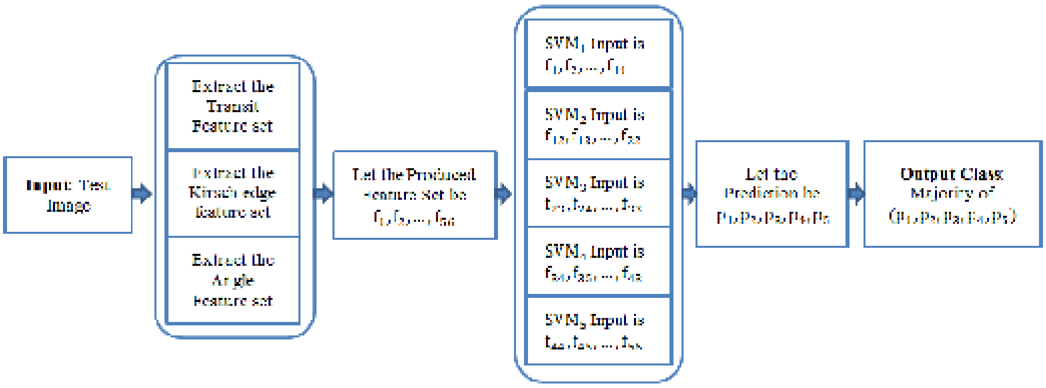

Fig. 6. Applying classification ensemble for character recognition

I.V.Practical Result

To evaluate the performance of our proposed license plate character recognition algorithm, we firstly produce a database consisting 10,000 binary images of Iranian car plate characters with normalized. Using 5,000 samples for training, we tested our scheme on other 5,000 samples and obtained 99.68% accuracy. From the experiment, we got an accuracy of 100% when the10, 000 data were used as training and the same data set was used for testing. In another experiment, we divided our database (10,000 samples) into 4 subsets and testing is done on each subset using rest of the 3 subsets for training. The recognition rates for all the four test subsets of dataset are averaged to get the accuracy. We got the average accuracy of 99.76%. Table 1 shows the result.

TABLE I

PERFORMANCE OF THE PROPOSED METHOD ON THE IRANIAN LICENSE PLATE CHARACTER DATABASE

Number of Images	Iranian License Plate Character Database				
	Method	Data Size		Accuracy	
		Train	Test	Train	Test
10,000	Proposed Method	50,000	50,000	100%	99.68%
		four-fold cross validation technique		100%	99.75%
		10,000	10,000 (Train Set)	100%	100%

Also for further evaluation we applied the proposed method on Persian license plate character database (Parikh, D., Polikar, 2007). This dataset contains numerical and character images and all those image samples are extracted from the real world environment, such as parking lot, freeway and etc. The results are based on three feature extraction techniques, namely, Kirsch edge; angle and transit features are calculated. In this respect we have divided the data set using three partitioning strategies. In the first strategy (strategy A), we have taken 50% data in training set and other 50% data in the testing set. In the second strategy (strategy B), we have considered 70% data in training set and remaining 30% data in the testing set. Strategy C has 100% data in training set and 100% data in testing set. Feature-wise experimental results of testing are depicted in Fig. 7. Also in the table 2, our method is compared with normal factoring method represented in (R., Azad, B., Kazeroni, 2013) and template matching mentioned in (Parikh, D., Polikar, 2007)that both of them used this dataset for evaluation of their works.

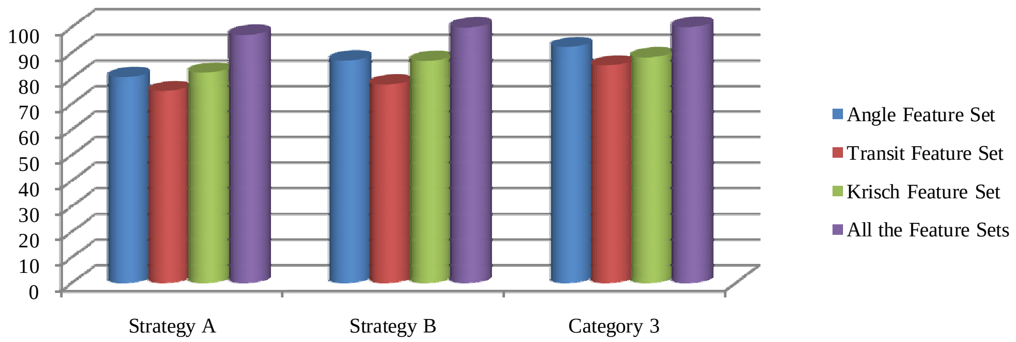

Fig. 7. Recognition accuracy using each feature set and proposed classifier

TABLE II

PERFORMANCE OF THE PROPOSED METHOD ON THE PERSIAN LICENSE PLATE CHARACTERS

Total Image	Method	Technique	Correct character recognition	Percent Efficiency
1200	S.H.M Kasaei and etc.	Template Matching	1104	92%
	R. Azad and etc.	Normal Factoring	1164	97%
	Proposed Method	Feature Extraction and classification ensemble	1188	99.85%

From the comparison, we could conclude that our algorithm, license plate recognition based on extracted features, has some sort of advantage over Normal factor method and template matching algorithm. Since the algorithm with extracted features could increase single character recognition accuracy and decrease the complex environment disturbance to a certain extent.

V. Conclusions

In this paper, we presented a model based on classification ensemble of SVMs for recognition of Iranian license plate characters. In the mentioned method for LPR character recognition process, firstly, a set of robust features are calculated from license plate characters based on angle, transit and Kirsch edge detector, and then classified using SVMs. In the result part the proposed recognition method is applied on a database of Iranian license plate characters consisting of 10,000 binary images, and the recognition rate of 99.68% is achieved. Further, we obtained 99.75% accuracy using four-fold cross validation technique on 10,000 dataset. Also for further evaluation we applied the proposed method on another Persian license plate character database and we achieved 99.85 accuracy rate. In addition, experimental results have demonstrated our method robust in successful recognition of license plate character with high accuracy.

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