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Number Plate Recognition without Segmentation

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Abstract

In real time number plate recognition, some vehicle number plates can not be recognized due to very poor illumination, motion blurred effect, fade characters and so on. The key problem is that number plate can not be segmented accurately and correctly. In this paper, we present a recognition method based on Support Vector Machines (SVMs). Firstly, some concepts of SVMs are briefly reviewed. Then a new number plate recognition algorithm is proposed. Unlike the traditional methods for number plate recognition, the innovation of the proposed algorithm is that it does not need a process for segmentation of input image of number plate but finds features in the whole number plate image. Multi-class SVMs are developed to classify the given number plate candidate. The experimental results show that our new method is of higher recognition accuracy and higher processing speed than using traditional SVM based multi-class classifier. This new approach provides a good direction for automatic number plate recognition.

Keywords: Number Plate Recognition, Segmentation, SVM

1 Introduction

A number plate is the unique identification of a vehicle. Automatic Number Plate Recognition (ANPR) is designed to locate and recognize the number plate of a moving vehicle automatically. The fundamental issues in number plate recognition are high accuracy and high recognition speed. There have been various commercial ANPR products around the world, which include Safe-T-Cam [1], SeeCar in Israel [2], VECON in Hongkong[3], LPR in USA [4], the ANPR in UK [5], IMPS in Singapore [6], and the CARINA in Hungary[7]. Among these systems, three types of classifiers are applied. They are OCR-based method, template matching method and learning-based method [8]. As a learning-based method, an algorithm on number plate recognition was proposed in [9] based on RULES-3 induction theory. One advantage of using this method is that the recognition speed is much quicker in number recognition and it is robust to image rotation and translation. But it is not robust to image scaling. Furthermore, it cannot distinguish digit 6 from digit 9 without additional observation. Kim [10] proposed another learning-based method called SVM-based character recognizer for license plate recognition. The recognition rate of Kim's module was about 97.2%. Zheng [11] compared several types of classifiers and found that SVM approach had the highest accuracy for printed text and handwriting identification in noisy document images. Zhao [12] made the same conclusion after comparing several classifiers for recognizing handwritten numbers. Hence, SVMs have considerable potential for classification.

Although SVM based number plate recognition [13] has achieved higher recognition accuracy, it does not work well still under some situations. For example, some number plates can not be recognized due to very poor illumination, motion blurred effect, fade characters and so forth. Furthermore, all the methods abovementioned performed license plate recognition after characters had been segmented. However, images taken in real-time may be difficult for character segmentation due to poor image quality. Improperly segmented characters will result in misrecognized characters.

In order to improve the recognition system performance, we propose a new SVM-based multi-class classifier to recognize number plates with poor quality. The number plates are recognized without going through character segmentation. This makes our method different from other methods as mentioned above. This new method is discussed in detail in Section 3.

The organization of this paper is as follows. We first introduce some basic knowledge of multi-class classifier model in Section 2. The algorithm of number plate recognition is presented in Section 3. The experiment results for number plate recognition are demonstrated in Section 4. We conclude in Section 5.

2 SVM based Multi-class Classifier

Since 1960s SVMs have become more and more important in the field of pattern recognition. SVM [14,15] is forcefully competing with many methods for classification. An SVM is a supervised learning technique first discussed by Vapnik [15]. SVM takes Statistical Learning Theory (SLT) as its theoretical foundation, and the structural risk minimization as its optimal object to realize the best generalization. They are based on some simple ideas and provide a clear intuition of what learning from examples is all about. More importantly, they possess the feature of high performance in practical applications. The SVMs use hyperplanes to separate the different classes. Many hyperplanes are fitted to separate the classes, but there is only one optimal separating hyperplane. The optimal one is expected to generalize well in comparison to the others. A new data sample is classified by the SVM according to the decision boundary defined by the hyperplane.

Among many classification methods, SVM has demonstrated superior performance. It has been successfully utilized in handwritten numeral recognition [11, 12]. However, SVM was originally designed for binary classification, and its extension to solve multi-class problems is not straightforward. Two main approaches have been suggested for applying SVMs for multi-class classification [16]. They are "one against all" and "one against one". In each approach, the underlying basis has been to reduce the multi-class problem to a set of binary problems to enable the use of basic SVM.

The first approach, called 'one against all' (OVA) [16, 17], uses a set of binary classifiers, each trained to separate one class from the rest. For a given input x_i, there are k decision functions. x_i is classified to be in the one of k classes that gives the largest decision value.

The second approach is called 'one against one' (OVO). In this approach, a series of classifiers are applied to each pair of classes, and only the label of the most commonly computed class is kept for each case. The application of this method requires $k(k-1)/2$ classifiers or machines be applied to each pair of classes, and a strategy to handle instances in which an equal number of votes are derived for more than one class for a case. Once all $k(k-1)/2$ classifiers have been undertaken, the max-win strategy is followed.

The multi-class model can be described as follows.

Given n training data

$$\Omega = \left\{ \begin{matrix} (x_1, y_1), (x_2, y_2), \cdots, (x_n, y_n) \mid x_i \in R^n, \\ y_i \in \{1,2,\cdots,k\}, i = 1,2,\ldots,n \end{matrix} \right\},$$

where k is number of classes, the classification function is as:

$$\begin{cases} \min\limits_{w_j^i, b^i, \xi_j^i} \quad \frac{1}{2} \| w^m \|^2 + C \sum\limits_{j=1}^{n} \xi_j^m \\ s.t. \quad (w^m)^T \phi(x_j) + b^m \geq 1 - \xi_j^m, if \quad y_j = m, \\ \quad\quad (w^m)^T \phi(x_j) + b^m \leq -1 + \xi_j^m, if \quad y_j \neq m, \\ \quad\quad \xi_j^m \geq 0, \quad j = 1,2,\cdots,n; \quad m = 1,\cdots,k, \end{cases} \quad (1)$$

where $\phi(x_i)$ is kernel function, w^m is a normal vector, b^m is a offset, ξ_j^m is a slack and nonnegative variable, and the term $\sum\limits_{j=1}^{n} \xi_j^m$ is an upper bound on the number of misclassification in the training set. C is the penalty term for misclassifications. $\sum\limits_{j=1}^{n} \xi_j^m$ indicates the distance that the training point from the optimal hyperplane and the amount of violation of the constraints. C controls the trade-off between maximizing the margin and minimizing the training error. It also controls the balance between a better generalization and an efficient computation.

The above formula implies the k decision functions for k different classes:

$$\begin{matrix} (w^1)^T \phi(x) + b^1, \\ \ldots \\ (w^m)^T \phi(x) + b^m \\ \ldots \\ (w^k)^T \phi(x) + b^k. \end{matrix} \quad (2)$$

An x is classified to be the class m $(m = 1, \ldots, k)$ if its decision function gives the maximum value in the SVM for a class, i.e.,

$$\text{Class of } x \equiv \arg \max_{m=1}^{k} ((w^m)^T \phi(x) + b^m) \quad (3)$$

3 Number Plate Classifier

The car number plate at the NSW state of Australia has up to six characters as shown in Figure. 1. Usually, the number plate consists of two main sections. The upper section contains main information of the number plate, and the lower part is for the name of the state. In order to speed up the process, we use histogram projection to separate number plate into two groups. The first group usually consists of three or four letters and three or two digits. The second group mainly includes the name of the state. Therefore, two sets of SVMs are designed according to these two groups of characters. One set of SVMs is designed for recognizing characters of number plates and the other one is designed for characters representing the state. In the experiments shown in [13], it is concluded that 'one against all' (OVA) could obtain higher accuracy than method of 'one against one' (OVO). In the following experiments, only OVA method is adopt.

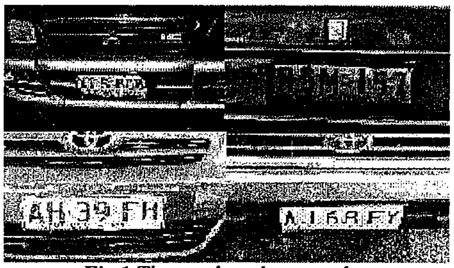

Fig.1 The number plate samples

For real time character recognition of number plates, there are many factors causing misrecognition. For example, the numbers may also appear slanted due to the orientation of the video system, the illumination condition may vary according to the time of day and the changing weather, and the characters in number plate may be obscured by rust, mud, peeling paint, and fading colour. In addition, the contrast between characters and number plate surfaces can be affected by their colors. Therefore, the recognition system must be robust to many changes in dealing real time images. Furthermore the recognition system must be fast and not too expensive in real-life application.

In order to solve these problems mentioned above, in our SVM-based recognition system, two kinds of SVMs are set up first. Each SVM has one type of number samples as one positive label and all or some of the other samples as another negative label. After training, each SVM gets its own values of parameters. The decision value of the testing sample will be calculated based on the values of parameters obtained. The final recognition result will be achieved according to the class that gives the maximum decision value.

We summarize the SVM based algorithm for number plate recognition in this paper as follows. In order to recognize a number plate, we go through the following steps.

Step1. Pre-process the image of number plate.
Step2. Segment and normalize the number plate.
Step3. Extract the feature vector of each normalized candidate.
Step4. Train SVMs based on saved sample database.
Step5. Recognize the number plate by the set of SVMs trained in advance.
Ste 6. If there are no more unclassified samples, then STOP. Otherwise, go to Step 5.
Step7. Add these test samples into their corresponding database for further training.

In traditional approaches, characters in a number plate were first segmented one by one so that each sub-image contains only one character of the number plate. However, as mentioned at the beginning of Section 3, number plates were often wrongly segmented because of poor image quality. Moreover, we may not find as many samples for certain characters as for others so that we may not have enough training samples for certain characters. For example, character "A" is seen much more often in a number plate than other characters. Our proposed method in this paper intends to resolve this problem. When a number plate region is located by using mean shift method [21] and extracted, the histogram projection method in horizontal direction is applied for a simple segmentation only. The number plate is segmented into two sub-images, of which one contains the name of NSW state of Australia, and the other one contains the characters of number plates. The top sub-image which contains the characters of a number plate is the most important information. Then it is normalized into size of 140x36. Then 315 dimensional feature vectors are obtained by averaging values in 4x4 window of the normalized sub-images. Same operation is done for bottom part of image. The high dimensional feature vectors are stored into two kinds of databases respectively. The feature vectors are used to train SVMs with RBF kernel (see Section 4). In our experiment, 315 dimensional feature vectors are input into SVMs that have been trained successfully. Then, which number plate matches a given candidate can be determined according to the decisions of SVMs. The process for recognition of number plate is then complete.

4 Experimental Results

Support vector machines in our experiments are trained using algorithm as shown in [18]. The training samples of these number plates are located and segmented from images of a real-time traffic flow.

Some number plates are motion blurred; some are overlapped by other vehicle's body. These cases are all failed recognized in our previous experiments. Examples are shown in Figure 2. The characters in these samples cannot be segmented correctly due to poor-quality images obtained for our research done previously. The final recognition accuracy has hence been downgraded for these number plates. Based on the algorithms that we proposed in this paper, we perform our experiments on segmented single characters and on 180 images of number plates under various conditions. They are poor contrast, characters cut-off, and blooming characters. Obviously, some information of these number plates should be known in advance.

The experimental results are based on RBF kernel function as shown in Table 1 below. Linear kernel and RBF kernel functions are given in Equation 4 and 5.

Linear: $$K(x, x_i) = \langle x \cdot x_i \rangle \quad (4)$$

RBF: $$K(x, x_i) = \exp\left(-\|x - x_i\|^2 / 2\sigma^2\right) \quad (5)$$

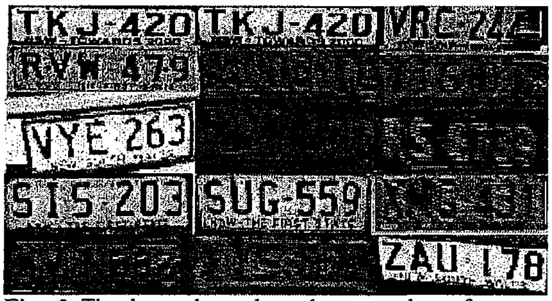

Fig. 2 The located number plate samples of poor quality

Table 1 gives a comparison of experiments using the two kernels. We estimate the matching rate using different kernel parameter values of s and C. The optimal parameters are determined by experiments. C's range is from 10^{-2} to 10^{10} and σ is from 0.1 to 1.0.

In the table, matching rate is defined as the proportion of number of correctly recognized characters to the number of all testing characters.

We also report the training time, testing time and the percentage of support vectors in the table. All the experiments are performed on a Pentium 4 PC with 2.0GHz CPU. The training time and testing time increase with the number of training samples. However, the classification accuracy does not change much. The results can be seen in Table 1. It is clear that recognition without segmentation obtains higher recognition accuracy than approach using segmentation.

Using the OCR software as shown in [20] for recognizing the same set of samples, we can only achieve 35% recognition accuracy on average.

We also demonstrate the experimental results of this SVM based method as shown in Table 2 using data from the well-known databases, Iris and UCI [19]. The recognition accuracies obtained are 97.8% for Iris and 89.86% for UCI dataset respectively.

5 Discussion and Conclusions

According to the experimental results, it is obvious that SVMs based on RBF kernel function perform better due to its properties described in previous section. Even when heavy noise is contained in the image of real number plate, the recognition rate of the method without segmentation is still higher than recognition results which obtained in some commercial products in [1] to [7]. Among these applications, the highest recognition rate was close to 100% as shown in [6, 7], about 95% in [3, 4], and is 80% in [1]. Compared with accuracy rate of average 35% using the OCR approach as shown in [20], accuracy rate (100%) obtained using SVM as shown in this paper is competitive and better. Furthermore, 'one against all' method always shows better performance.

The method proposed in this paper is suitable for poor quality images in real time applications. It gives a total different view in number plate recognition. It can achieve faster recognition in complex conditions especially in dark and poor weather conditions. It works well for broken or dirty images of number plates. In these special cases, we do not need to go through image preprocessing such as image denoising, image enhancement, image segmentation and so forth. Hence, the overall processing/recognition speed has been improved a lot while higher accuracy is obtained. Although it has the drawback that every number plate needs a corresponding classifier to be recognized, this method has suggested a new approach for high accurate and real time recognition of poor quality number plates. Furthermore, it can be used for toll charge supervision of highway and in other applications.

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Table 1. The Experimental Results of SVM s based Number Plate Recognition

	Segmented Number Plate		Unsegmented Number Plate
	RBF kernel	Linear Kernel	RBF Kernel
Matching Rate	82.3%	70.5%	100%
Percentage of SV	98.4%	13.4%	100%
Training Time (s)	3.04	3.4	0.1
Testing Time (s)	0.45	1.22	0.01

Table 2. The Experimental Results of Iris and UCI Database (RBF)

Cases	Test Matching Rate	Percentage of SV	Training Time(s)	Testing Time (s)
Iris	97.8%	16%	0.1	0.01
UCI	89.86%	29.3%	63.8	0.4