The Location and Recognition of Chinese Vehicle License Plates under Complex Backgrounds

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***Abstract*—This paper presents the algorithms to locate license plate and recognize the characters on it. These algorithms have three advantages. First, they have strong robustness to against many noises and disturbances. Second, the methods can deal with license plates with different colors. Third, the recognition methods based on artificial neural network are suitable for Chinese characters.**

***Index Terms*—license plate location, character segmentation, character recognition, artificial neural network**

I. Introduction

With the development of transportation technology and universality of vehicles, automatic vehicle license plate management system has become a popular subject. This is a field that has been researched for decades and has many commercial systems in use, but few of them are designed for Chinese vehicles because the location and recognition algorithms for Chinese characters are quite different from English letters and numbers, especially when the license plate is shown in very complex backgrounds.

A method of location and recognition of Chinese vehicle license plates under complex backgrounds has been presented in the paper. The entire algorithm system can be divided into four sections: image preprocessing, license plate region location, character segmentation and character recognition, which has been shown in figure 1.

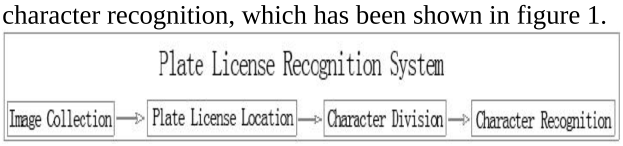

Figure 1. System structure

In image preprocessing section, the main task is to modify the luminance of the entire image and do some work for image enhancement according to the special features of the license plate. The location section is the most basic and important step in the system. If it can not give an accurate region of the license plate, then the character segmentation will fail, consequently, the entire work will become meaningless. Generally speaking, the more complex the algorithm is, the more accurate the location result is. The paper gives an effective method to locate the hot area. The character segmentation section is relatively easier than the others. Its purpose is to get all the characters on license plate and then output them to the next step, the character recognition. Therefore, it will influence the success probability of character recognition directly. The algorithm presented in this paper gives a way to judge the color type of license plate, and choose the right binary image for vertical projection. Furthermore, the new method improves the way to judge the characters stuck and gap, and increases the success probability of segmentation tremendously. The last section is the character recognition. Although the manuscript recognition system has been researched for decades and some have been used very successfully on PDA and mobile phone, their recognition principles are quite different. For manuscript recognition, it mainly depends on the stroke information. But for character recognition without stroke information, the system has to deal with the whole image without other help. When the luminance of the image changed, the shape of the characters will also be changed. In the paper we propose the method of the character recognition based on artificial neural networks. In traditional ways, researchers normally uses one type of ANN [3, 5], but we use BP and SVM together and get a better result.

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II. IMAGE PREPROCESSING

Image preprocessing consists of two tasks: luminance adjustment and image enhancement. These two goals can be achieved by changing luminance curve and top-hat transform.

A. Luminance Adjustment

For an image which contains x*y pixels, the first step is to calculate its luminance summation using the formula:

$$Sum = \sum_{i=1}^{n} l \tag{1}$$

where $n=x*y$, l represents the luminance of the hot pixel.

Then acquire the average hot value:

$$Ave = \mathrm{Sum}/(2*x*y*q) \tag{2}$$

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where q represents the quantization number.

After that, the image enhancement result has been shown as an example in figure 2.

Figure 2. The result of image enhancement

B. *Top-Hat Transform*

Gray scale top-hat transform is a mature algorithm using in digital image processing. Its advantage is to enhance the hot region where front and background have obvious differences while weakening the other regions at the same time. The result of this transform has been shown in figure 3.

Figure 3. The result of top-hat transform

III. THE LOCATION OF LICENSE PLATE

License plate location is the most important and hard link during the four main processing, so it can be divided into several steps.

A. *The Characteristics of License Plate*

According to the correlative regulations in China, there are some basic characteristics for license plates. Among them, there are two most useful and helpful ones. First, There are huge color differences between background and word, where exists many edge information. Second, there is a regulation for the length and width rate. These regulations can be used as the main special features.

B. *Rough Location*

The method that will be mentioned has strong robustness against noises and it can locate hot regions even without image preprocessing section, just like the example below. But we think that the image preprocessing is necessary because the system will work on complex backgrounds and the pretreatment will obviously weaken redundant information and reduce calculation sharply.

a. *Edge detection*

The edge detection of gray images is based on the changes of gradient. The gradient of function f(x, y) is defined as a vector:

$$\nabla f = \begin{pmatrix} G_x \\ G_y \end{pmatrix} = \begin{pmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{pmatrix} \tag{3}$$

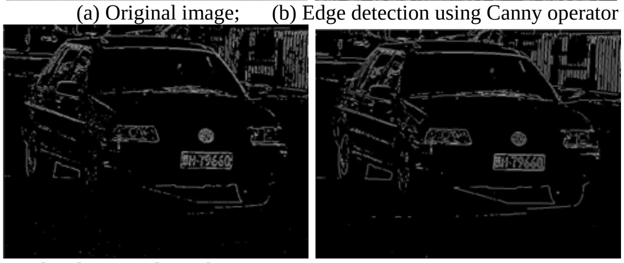
$$mag(\nabla f) = [G_x^2 + G_y^2]^{1/2} = [(\partial f / \partial x)^2 + (\partial f / \partial y)^2]^{1/2} \tag{4}$$

Edge detector used in digital image processing is replaced by a mask, which can represent differential coefficient of G_x and G_y. For example, the gradient in the centre of a neighborhood can be calculated by Sobel edge detector through this way:

$$g = [G_x^2 + G_y^2]^{1/2} = \{[(z_7+2z_8+z_9)-(z_1+2z_2+z_3)]^2 + [(z_3+2z_6+z_9)-(z_1+2z_4+z_7)]^2\}^{1/2} \tag{5}$$

It is vital to choose a proper operator. The judgment mainly depends on experience coming from experimental results, namely the edge information should not be too complex, such as Canny operator (Fig. 4 (b)), also it should not be too simple, such as Roberts operator (Fig. 4 (c)). After comparing, Sobel operator is the best choice to locate license plate region, which can both display characteristics of the license plate and eliminate other textures there.

(a) Original image; (b) Edge detection using Canny operator



(c)Edge detection by Roberts operator (d)Edge detection by Sobel operator

Figure 4. The results of edge detection using different methods

b. *The enhancement of textures of license plate*

Dilation operation is a mathematical morphology application in digital image processing. Mathematical morphology gets special image features through set operation between structuring element and image object. Within set $\boldsymbol{Z}$, dilation operation to set $\boldsymbol{A}$ by set $\boldsymbol{B}$ is defined as:

$$A \oplus B = \{ z \mid (\hat{B})_z \cap A \neq \varnothing \}, \tag{6}$$

where $\boldsymbol{B}$ is the structuring element.

This operation makes images expand both inside and outside, that is why it is called dilation (Figure 5).

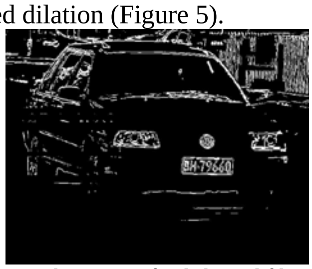


Figure 5 The result of dilation Figure 6 The output of red channel filter

But, dilation operation has a problem, namely not only are the areas inside the words dilated but also the areas around the words are also full of new elements. In that case, neighbor words will connect together, which disturbs the vertical texture characteristics. Therefore, the problem is how to delete redundant pixels between two words while not eliminate necessary pixels inside a word simultaneously. Figure 6 shows the result of logical AND operation using the image shown in figure 5 and the limited red channel mentioned above. The red channel works as a filter here.

c. Top-hat transform of binary image

It is popular to use top-hat transform to compensate background luminance or emphasize texture information in grayscale mathematical morphology [1-2]. Its first step is opening operation. If the structuring element is larger than the object that you want to pick up, then these objects will be deleted only leaving the background. The next step is to subtract the image processed by opening operation, using the original image. As the result, only the objects will be left. The algorithm in this paper presents the top-hat transform of binary image according to the theory above. Its first step is dilation, a different step from top-hat transform of grayscale image. The second step is to subtract the image processed by dilation using the original image. Furthermore, in order to emphasize vertical textures, another opening operation, with the structuring element larger than the height of words and shorter than the width of words, is needed.

The opening operation can be divided into two steps, erosion and dilation, which is shown in formula (7).

In set $\boldsymbol{Z}$, the erosion operation to set $\boldsymbol{A}$ by structuring element set $\boldsymbol{B}$ is defined as:

$$A\Theta B = \{z \mid (B)_z \subseteq A\} = \{z \mid (B)_z A^c \neq \varnothing\} \quad (7)$$

In set $\boldsymbol{Z}$, the opening operation to set $\boldsymbol{A}$ by structuring element $\boldsymbol{B}$ is defined as:

$$A \circ B = (A\Theta B) \oplus B = \bigcup\{(B)_z \mid (B)_z \subseteq A\}, \quad (8)$$

where $\bigcup\{\bullet\}$ denotes all of the sets inside the braces.

The results of these different steps are shown in figure 7.

(a) Horizontal dilation operation; (b) The result of opening operation

Figure 7. The results after using different processing methods

C. The Horizontal And Vertical Location

For horizontal location, the number of white pixels in license plate region should have a low threshold because the vertical stripes and lines standing for the texture characteristics of the license plate appear quite frequently. Therefore, the lines shorter than the low threshold should be deleted. Then, the entire image will be separated into several segments. Search these segments separately and find out the region which has the most similar characteristics with license plate. The structure of this process is shown in figure 8.

For vertical location, the first task is to emphasize the license plate region with dilation operation. Then, get the left and right borders using the same method in horizontal location. The result of location is shown in figure 9.

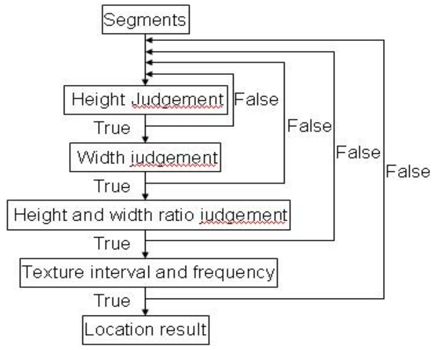
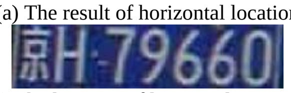


Figure 8 The structure of final location

(a) The result of horizontal location



(b) The location of license plate region

Figure 9. The result of vertical Locating

D. The Robustness Test and the Location Conclusion

For traditional algorithms, it is difficult to deal with some special kinds of license plates, such as license plates with different background colors, license plates with a bumper bar, license plates influenced by obvious head lights, tilt license plates, license plates sharing the same color with its vehicle, and license plates influenced by the vertical textures of the radiator. For these problems, we have got good results by using the algorithm in the paper. The result of location using the method in the paper is shown below in figure 10.

(a) The location result of the license plate whose background has the same color with the vehicle

(b) The location result of the license plate influenced by vertical textures of the radiator

(c) The location result of the license plate influenced heavily by headlights

(d) The location result of the license plate whose words are black

(e) The location result of the license plate protected by bumper bar

(f) The location result of the license plate influenced by fake license plate

Figure 10. The result of robustness test

The experimental result has proved that this new algorithm has great robustness.

The quantitative and comparative result using the method mentioned in this paper (method one) and the traditional wavelet transform method (method two) has been listed in table 1 (LP is the abbreviation of license plate):

TABLE I.
THE LOCATION CONCLUSION

Different images	Successful cases	
	Method one	Method two
100 blue LPs	98（98%）	92（92%）
40 yellow LPs	40（100%）	13（32.5%）
20 white LPs	18（90%）	3（15%）
20 black LPs	20（100%）	19（95%）
20 disturbed LPs	11（55%）	8（40%）
Total 200 LPs	187（94%）	135（68%）

As can be seen from this comparative result, the new method is good for locating license plate with difference colors, which is a greater improvement than the traditional methods.

IV. CHARACTER SEGMENTATION

Generally, there are three common segmentation algorithms: vertical projection, template matching and connected domain segmentation. Vertical projection is based on the binary image of the license plate region. It is a good method for images that are not heavily influenced by character stuck, but it has a weak robustness against “1”, “川” and noises.

Template matching is strong robust against many disturbs. But, everything is based on the presupposition that the left border of the license has been located absolutely exactly. Otherwise, the whole segmentation will be completely wrong. In addition, some different templates are needed for the character segmentation on military, police and embassy license plate.

Connected domain segmentation is based on the connectivity of character. There will be several domains left after this segmentation operation. Then, the next task is to screen out the real characters according to their size, proportion and texture. For letters and numbers, the effects of segmentation are perfect using this way, but for Chinese characters, especially the characters with left-right structure such as “鄂、琼、皖”, it always makes mistakes.

In order to overcome the disadvantages of these three methods, a modified method of projection segmentation is used in this paper. Before character segmentation, there are two tasks must be done: skew correction and color judgment.

A. Characteristics of Character

There are some basic regulations [6] for license plates in China.

a. The license plate region is a rectangle, with 44cm long and 14cm wide; all the characters are 90mm high and 45mm wide.

b. The interval distance, 34mm, between the second and third character is the biggest one among all the characters.

c. The first character must be a Chinese character. The second character is an English letter. The third one can be a letter or a number. Others are all numbers.

B. Skew Correction

For some reasons, the located license plate may be inclined and needed to be corrected. The main problem is to find the slope of the inclined license plate. This paper presents two methods.

a. Hough Transform

The Hough transform is a technique which can be used to isolate features of a particular shape within an image. In the image space, the straight line can be described as $y = m*x + b$ and can be graphically plotted for each pair of image points (x, y). In the Hough transform, a main idea is to consider the characteristics of the straight line not as image points x or y, but here the slope parameter m and the intercept parameter b. Based on that fact, the straight line $y = m*x + b$ can be represented as a point (b, m) in the parameter space. For computational reasons, it is better to parameterize the lines in the Hough transform with two other parameters, commonly referred to as r and θ (theta). The parameter r represents the distance between the line and the origin, while θ is the angle of the vector from the origin to this closest point (see coordinates). Using this parameterization, the equation of the line can be written as:

$$r = x\cos\theta + y\sin\theta \quad (9)$$

Therefore, each point stands for a sine curve in Hough domain. These sine curves have intersections. The more sine curves join in an intersection in Hough domain, the more pixels standing in a line in Cartesian coordinate system (Figure 11).

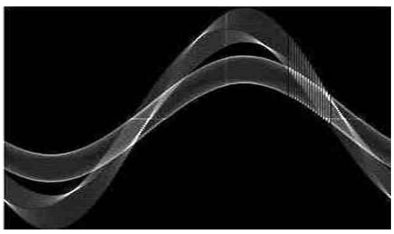


Figure 11. The curves in Hough domain

After finding the intersection that has been joined the most times by sine curves, many points in Cartesian coordinate system can be calculate according to formula (9). Two points can determine a line.

But Hough transform needs many calculations.

b. Morphology Method

The first step is to do a close operation. For an ideal license plate location result, the whole region will be covered, while for an inclined license plate, there will be a little space left in the corner. Then a dilation operation using a 3*3 square structure element is needed. The structure element makes sure that the original image will be dilated only one pixel. There will be only the contour left, which stands for the slope of the license plate, after subtracting the original image using the dilation result. The whole process can be seen in figure 12.

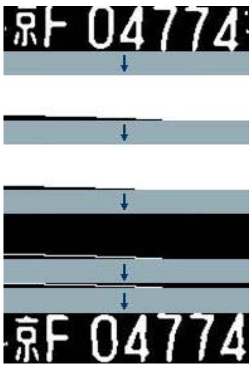


Figure 12 The skew correction using morphology method

After getting the slope of the license plate, it is easy for the skew correction processing.

C. Modified Projection Segmentation

For the character segmentation problems encountered above, the modified projection segmentation presented in this paper will mainly solve three difficulties. First, classify the color type of license plate and make the algorithm compatible with any color. Second, increase the robustness against car bumper, nails and other noises. Third, make the method compatible with not only civil license plate, but also military, police and embassy license plates.

a. The Judgment of License Plate Color Type

It is not difficult to get the binary image of a license plate and its logical NOT image. Whatever the license plate color type is, one of these binary images is suitable for projection segmentation. The problem is how to choose the right one. A new method is mentioned in this paper.

First, get a template which can stand for most information of license plate characters. Then, compare the template with the binary image of license plate and its logical NOT image. Finally, distinguish the license plate color type according to the similarity of the two images. The whole process is shown in figure 13.

A famous psychological formula to transform a color image to gray image was used in the first step:

$$\mathrm{Gray}(x,y)=0.229\mathrm{R}(x,y)+0.587\mathrm{G}(x,y)+0.114\mathrm{B}(x,y). \quad (10)$$

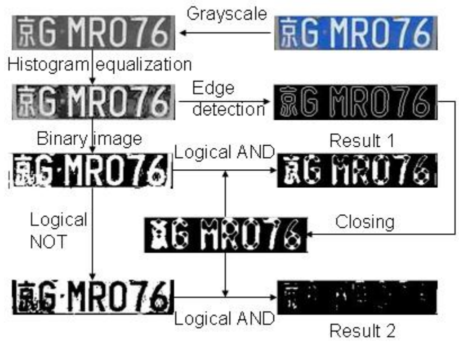


Figure 13 (a) The first type judgment process

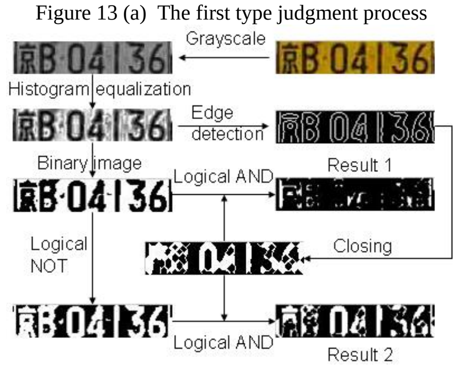


Figure 13 (b) The second type judgment process

In order to eliminate disturbs coming from the luminance, the best solution is histogram equalization. After that, it is easy to get the binary image and edge detection image of the license plate. For edge detection, the choice of the operator is the most important thing. Canny operator will bring too many redundant edge details. In contrast, Robert operator cannot get enough edge information. After iterative comparison, Sobel operator is the most appropriate one for the edge detection of license plate characters. Furthermore, its enhancement can make the edge texture much clearer.

$$\begin{pmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{pmatrix}\begin{pmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{pmatrix} \qquad \begin{pmatrix} -2 & -4 & -2 \\ 0 & 0 & 0 \\ 2 & 4 & 2 \end{pmatrix}\begin{pmatrix} -2 & 0 & 2 \\ -4 & 0 & 4 \\ -2 & 0 & 2 \end{pmatrix}$$

Figure 14 (a) Sobel operator (b) The enhancement of Sobel operator

The most significant task to transform a gray image to a binary image is to get an appropriate threshold. If the threshold is too high, the characters stuck will appear; if the threshold is too low, there will be gaps appearing within a single character. Therefore, it is wise to choose a threshold dynamically according to the characteristics of an image. Now Otsu algorithm [5] is considered the most appropriate way to get the threshold. Logical NOT operation on this image is needed to obtain another binary image. One of these images is the right choice for projection segmentation. This choice needs a template for comparison.

During the whole color judgment process, the choice of template is the most significant thing. In order to fill up the image of edge detection and represent the license plate characters, the result of edge detection needed a closing operation in mathematical morphology. Closing operation is based on dilation and erosion. With ***A*** and ***B*** as sets in $\boldsymbol{Z}^2$, the dilation operation to $\boldsymbol{A}$ by $\boldsymbol{B}$, denoted $A \oplus B$, is defined as

$$A \oplus B = \{z \mid (\hat{B})_z \cap A \neq \varnothing\}, \tag{11}$$

where $\boldsymbol{B}$ is the structuring element.

For sets $\boldsymbol{A}$ and $\boldsymbol{B}$ in $\boldsymbol{Z}^2$, the erosion operation to $\boldsymbol{A}$ by $\boldsymbol{B}$, denoted $A \Theta B$, is defined as

$$A \Theta B = \{z \mid (B)_z \subseteq A\} = \{z \mid (B)_z A^c \neq \varnothing\}, \tag{12}$$

where $\boldsymbol{B}$ is the structuring element.

Similarly, the closing operation to set $\boldsymbol{A}$ by structuring element $\boldsymbol{B}$, denoted $A \bullet B$, is defined as

$$A \bullet B = (A \oplus B) \Theta B. \tag{13}$$

After closing operation, the inside area of characters will be filled up with white pixels. Until now, the template standing for character information has been established. Then a logical AND operation should be made between the template and the binary image of license plate, and the same operation should also be made between the template and the logical NOT image of the license plate. Finally, two different results have been gotten, result 1 and result 2. For license plates with white characters, blue or black background, there will be more white pixels left in result 1 than result 2 after being processed by the steps above. In contrast, for license plates with black characters, yellow or white background, there will be more white pixels left in result 2 instead of result 1 after the same processes. So the color type of license plates can be distinguished clearly.

b. The Solution of Characters Stuck and Segmentation Mistake

The reason of characters stuck is that some characters are influenced by various disturbances, including car bumper, nails and noises. According to experimental experience, on the row where car bumper and nails exist, the number of white pixel is no more than one third of the number of white pixel on the row where characters exist. So the average number of white pixel in each row should be calculated first. Then, search the rows whose number of white pixel is less than one third of the average number. Among these rows, the nearest row from top to bottom should be the top of license plate, and the nearest row from bottom to top should be the bottom of license plate.

Generally speaking, the size of disturbance is small and it's easy to confuse with the width of number "1". But, number "1" is able to fill up most of the area where it exists, while disturbances are not able to do this. Therefore, the area ratio of white pixel and the whole projection region can be used as the judgment of number "1" and disturbances. If the area ratio is less than 0.5, this region is a disturbance or noise; if the area ratio is more than 0.5 and it is also not the first character of this license plate, this is number "1"; if it is the first character of this license plate, this is Chinese character "川". Not only can this method distinguish disturbances and characters, but also can recognize "1" and "川" without character recognition process. Therefore, it both decreases the complexity of algorithm and increases the success probability of recognition.

D. Experrimental Results of Character Segmentation

Figure 15 displays the segmentation results of four license plates, which can represent most color types on Chinese license plates. Among them, the last one is a police license plate, whose character order is different from the order on license plate for civil use, and there is clear characters stuck between "8" and "3", which is divided by the remedial measure. Experimental result shows that this modified projection segmentation is able to deal with different color types of license plates and improve the ability to judge and solve characters stuck and segmentation mistakes. The success probability reaches 94% on a database of plate images taken in Beijing.

Figure 15 The effect of segmentation

E. Segmentation Conclusion

Considering the characters stuck and segmentation mistakes, this paper presents the algorithm of character segmentation for license plates with different colors and gives some methods to deal with the problems of the characters stuck and segmentation mistakes. The methods make the performance of character segmentation improved and better than that of traditional methods [7, 8, 9]. They increase the success probability of segmentation obviously.

V. Character Recognition

There are many methods to recognize regular characters or print characters. But for a system working on complex backgrounds, the shapes of characters are always not as perfect as the printed ones. Sometime they may change a lot because of the influence of luminance. Therefore, the system needs a recognition algorithm that has strong associative memory ability. For this reason, artificial neural network becomes the best choice.

A. Back-Propagated Network

Back-Propagated Delta Rule Network is a development from the simple Delta rule in which extra *hidden layers* are added. The network topology is constrained to be feed-forward: i.e. loop-free - generally connections are allowed from the input layer to the hidden layers and then to the output layer.

The hidden layer learns to recode (or to provide a representation for) the inputs. More than one hidden layer can be used. The architecture is more powerful than single-layer networks. Their input/output relation, which shown in Figure 16, is defined as a function:

$$Y = 1 / (1 + \exp(-k.(\Sigma W_{in} * X_{in})) \tag{14}$$

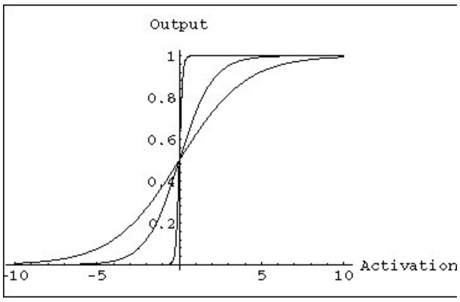


Figure 16 The input/output graph of the perception

The weight change rule of BP networks is a development of the perception learning rule. Weights are changed by an amount proportional to the error at that unit times the output of the unit feeding into the weight. Forward pass: the outputs are calculated and the error at the output units calculated. Backward pass: The output unit error is used to alter weights on the output units. Then the error at the hidden nodes is calculated (by back-propagating the error at the output units through the weights), and the weights on the hidden nodes altered using these values. For each data pair to be learned, a forward pass and backwards pass is performed. This is repeated over and over again until the error is at a low enough level (or we give up).

B. Support Vector Machine

Support vector machines (SVM) are a set of related supervised learning methods used for classification and regression. Viewing input data as two sets of vectors in an n-dimensional space, an SVM will construct a separating hyperplane in that space, one which maximizes the margin between the two data sets. To calculate the margin, two parallel hyper-planes are constructed, one on each side of the separating hyper-plane, which are "pushed up against" the two data sets. Intuitively, a good separation is achieved by the hyper-plane that has the largest distance to the neighboring data-points of both classes, since in general the larger the margin the better the generalization error of the classifier.

A set of points of the follow form are given as training data:

$$\mathcal{D} = \{(\mathbf{x}_i, c_i) | \mathbf{x}_i \in \mathbb{R}^p, c_i \in \{-1, 1\}\}_{i=1}^{n}, \quad (15)$$

where the c_i is either 1 or −1, indicating the class to which the point $\mathbf{X_i}$ belongs. Each $\mathbf{X_i}$ is a p-dimensional real vector. We want to give the maximum-margin hyperplane which divides the points having $c_i = 1$ from those having $c_i = -1$. Any hyperplane can be written as the set of points $\mathbf{X_i}$ satisfying

$$\mathbf{w} \cdot \mathbf{x} - b = 0. \quad (16)$$

The vector **W** is a normal vector: it is perpendicular to the hyperplane. The parameter $\frac{b}{\|w\|}$ determines the offset of the hyperplane from the origin along the normal vector **W**. The optimization problem presented in the preceding section is difficult to solve because it depends on $\|\mathbf{w}\|$, the norm of **w'**, which involves a square root. Fortunately it is possible to alter the equation by substituting $\|\mathbf{w}\|$ with $\frac{1}{2}\|W\|^2$ without changing the solution (the minimum of the original and the modified equation have the same w and b). This is a quadratic programming (QP) optimization problem. More clearly, minimize $\frac{1}{2}\|W\|^2$ subject to

$$c_i(\mathbf{w} \cdot \mathbf{x_i} - b) \geq 1, \quad 1 \leq i \leq n \quad (17)$$

The factor of 1/2 is used for mathematical convenience. This problem can now be solved by standard quadratic programming techniques and programs. Writing the classification rule in its unconstrained dual form reveals that the maximum margin hyperplane and therefore the classification task is only a function of the support vectors, the training data that lie on the margin. The dual of the SVM can be shown to be:

$$\max \sum_{i=1}^{n} \alpha_i - \frac{1}{2}\sum_{i,j} \alpha_i \alpha_j c_i c_j \mathbf{x}_i^T \mathbf{x}_j \text{ subject to } \alpha_i \geq 0, \text{ and } \sum_{i=1}^{n} \alpha_i c_i = 0 \quad (18)$$

where the α terms constitute a dual representation for the weight vector in terms of the training set:

$$\mathbf{w} = \sum_i \alpha_i c_i \mathbf{x}_i \quad (19)$$

The original optimal hyperplane algorithm was a linear classifier. However, in 1992, Bernhard Boser, Isabelle Guyon and Vapnik suggested a way to create non-linear classifiers by applying the kernel trick (originally proposed by Aizerman et al.. [10]) to maximum-margin hyperplanes[11]. The resulting algorithm is formally similar, except that every dot product is replaced by a non-linear kernel function. This allows the algorithm to fit the maximum-margin hyperplane in the transformed feature space. The transformation may be non-linear and the transformed space high dimensional; thus though the classifier is a hyperplane in the high-dimensional feature space it may be non-linear in the original input space.

If the kernel used is a Gaussian radial basis function, the corresponding feature space is a Hilbert space of infinite dimension. Maximum margin classifiers are well regularized, so the infinite dimension does not spoil the results. Some common kernels include:

Polynomial (homogeneous): $k(\mathbf{x}, \mathbf{x}') = (\mathbf{x} \cdot \mathbf{x}')^d$

Polynomial (inhomogeneous): $k(\mathbf{x}, \mathbf{x}') = (\mathbf{x} \cdot \mathbf{x}' + 1)^d$

Radial Basis Function: $k(\mathbf{x}, \mathbf{x}') = \exp(-\gamma\|\mathbf{x} - \mathbf{x}'\|^2)$, for $\gamma > 0$ (20)

Gaussian Radial basis function: $k(\mathbf{x}, \mathbf{x}') = \exp\left(-\frac{\|\mathbf{x} - \mathbf{x}'\|^2}{2\sigma^2}\right)$

Sigmoid: $k(\mathbf{x}, \mathbf{x}') = \tanh(\kappa \mathbf{x} \cdot \mathbf{x}' + c)$, for some (not every) $\kappa > 0$ and $c < 0$

C. BP and SVM based Recognition System

Although BP and SVM network can solve recognition problems, each of them has some disadvantages.

For BP network, it is a multi-classifier. That means the output of BP network will give a single result from the whole character samples. Therefore, the more characters you want to classify, the more choices BP network has. If the input image is influenced by some noises, then the output may give a wrong result.

For SVM network, it is an one-against-one classifier. If the system recognizes that they are the same type, the output will be 1 and the whole recognition process ends, otherwise the input image will be compared with the next output image until it meets the same element. If there is no same element with the input image, the system will refuse to recognize it. Therefore, the recognition of SVM network is more accurate than BP network. But, in some cases, SVM network may output 1 for several elements. The traditional ways [3], the researchers always choose the first element that can output 1.

D. Mixed Solution

After compared both the advantages and disadvantages of BP and SVM network, this paper gives a mixed solution.

The first step is to use the SVM network to recognize the input image. In the case, the disadvantage of BP network will be obviated. The only problem is the SVM network may give several classifiers sometime. Then, the second step is to use BP network to find the best solution in the few choices that have been selected by the SVM network. This mixed network can avoid their disadvantages and enhance their advantages and achieves better recognition success rate than each of them.

E. The Feature for the Character Recognition

After character segmentation, the seven characters have been divided clearly. But these characters may have different shapes because of the influence by the luminance, so they need to be thinned and become skeleton images. For skeleton image, one stroke consists of a line, and the width of the line is just one pixel. Through this way, the influence caused by the luminance has been reduced to the utmost extent.

In order to fit the input requirement of the network, any skeleton image of characters need to be normalized. Besides, the summation of the line and the row can be used as another input element. So the input nodes are 280. The experimental results have proved that the summation element improves the recognition success rate a lot.

TABLE II.
THE DIFFERENCES OF RECOGNITION SUCCESS RATE

	Recognition successful rate
BP network	87.9%
SVM network	91.4%
Mixed network	98.6%

VI. CONLUSION

This paper introduces the four sections in the license plate location and recognition system. The whole system has been realized in C++ languages. From the experimental results, the whole system and its algorithms have been proved very successful. The recognition success rate has a great improvement than before. The only problem is the location result may have a small migration sometime when the complex background heavily influences it. That is because the system has sacrificed a lot for the real time ability. The future work is to improve the location algorithm. The location algorithm can be more complex and powerful, while the real time ability will be reduced at the same time.

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