Vehicle Number Plate Recognition Using Mathematical Morphology and Neural Networks

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Abstract: - This paper presents a method for recognition of the vehicle number plate from the image using neural nets and mathematical morphology. The main theme is to use different morphological operations in such a way so that the number plate of the vehicle can be extracted efficiently. The method makes the extraction of the plate independent of color, size and location of number plate. The proposed approach can be divided into simple processes, which are, image enhancement, morphing transformation, morphological gradient, combination of resultant images and extracting the number plate from the objects that are left in the image. Then segmentation is applied to recognize the plate using neural network. This algorithm can quickly and correctly recognize the number plate from the vehicle image.

Key-Words: - Mathematical morphology, morphological gradient, vehicle number plate, morphing transformations, image enhancement.

1 Introduction

In the current information technology era, the use of automations and intelligent systems is becoming more and more widespread. The Intelligent Transport System (ITS) technology has gotten so much attention that many systems are being developed and applied all over the world. Vehicle number plate recognition (VNPR) has turned out to be an important research issue. VNPR has many applications in traffic monitoring system, including controlling the traffic volume, ticketing vehicles without the human control, vehicle tracking, policing, security, and so on. Malaysians [14] are reportedly considering using RFID chip embedded in the license plates to prevent car thieves from stealing vehicles on road.

The most vital and the most difficult part of any VNPR system [8] is the detection and extraction of the vehicle Number plate, which directly affects the systems overall accuracy. The presence of noise, blurring in the image, uneven illumination, dim light and foggy conditions make the task even more difficult. In this paper we propose a detailed and novel method for accurately detecting the location and later recognition of the vehicle number plates. The proposed system can work very accurately in almost any environment, time of day, and conditions.

There are some international, national or local standards for vehicles. One sample is presented in the Appendix to this text. In China, the basic norms for the number plate are presented. Some regional co-operations such as European Union [15] (EU), have plates that define the country, the place of registration, etc. In this text, Chinese, Pakistani, and Kuwaiti plates are represented.

2 Related Work

The problem of automatic VNP recognition is being studied since the mid 90's [6]. The early approaches were based on characteristics of boundary lines. The input image being first processed to enrich and enhance boundary line-information by using such algorithms as the gradient filter, and resulting in an image formed of edges. The image thus processed was converted to its binary counterpart and then processed by certain algorithms, such as Hough transform, to detect lines. Eventually, couples of 2-parallel lines were considered as a plate-designate [2].

Another approach was based on the morphology of objects in an image [3]. This approach focuses on some salient properties of vehicle plate images such as their brightness, contrast, symmetry, angles, etc. Due to these features, this method could be used to detect the similar properties in a certain image and locate the position of number plate regions. The third approach was based on statistical properties of text [1]. In this approach, text regions were discovered using statistical properties of text like the variance of gray level, number of edges, edge densities in the region, etc. This approach was commonly used in finding text in images, and could well be used for discovering and designating candidate number plate areas as they include alphabets and numerals. Another approach uses color image processing [5] for the detection of the number plates. In this approach a color histogram and a fixed horizontal to vertical ratio is used to extract the number plates.

In addition, there have been a number of other methods relating to this problem focusing on detecting VNP using artificial intelligence and genetic algorithms [7], [16]. These systems used edge detection and edge statistics and then AI techniques to detect the location of the number plate-designate area. All of the systems discussed above have some kind of limitations for example they are plate size dependent, color dependent, work only in certain conditions or environment like indoor images etc. The method that we are proposing is independent of color, size, location and angle of the number plate of the vehicle. Post-processing can be done to check the validity of the plate.

The organization of rest of the paper is as follows: Section 3 describes the proposed technique adopted for recognition of the number plates of vehicles, Sections 4 & 5 discuss the processes of extraction of number plates from images and processes of segmentation and recognition, while in section 6 we describe the experiments performed on the images and analyze the results in next section. Section 8 concludes our work.

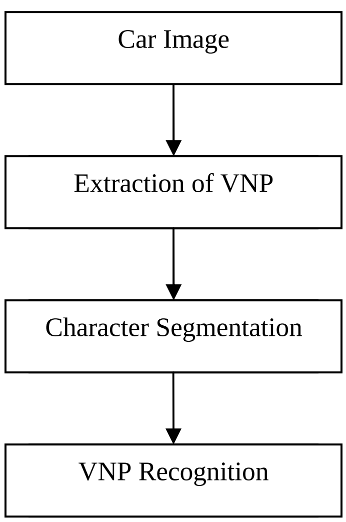


Figure 1. The proposed system

3 Proposed Technique

The proposed technique [11] for the recognition involves extraction of vehicle number plates using mathematical morphology techniques, character segmentation, use of neural network for recognition of characters, Fig. 1. The word "morphology" commonly [3] denotes a branch of biology that deals with the form and structure of animals and plants. We use the same word here in the context of "mathematical morphology (MM)" as a tool for extracting image components that are useful in the representation and description of region shape, such as boundaries, skeletons, and the convex hull.

We are interested also in morphological techniques for pre- and post-processing, such as morphological filtering, thinning, and pruning. The language of mathematical morphology is set theory. Approaches based on the morphology of objects in an image are presented in [3]. This approach focuses on some salient properties of remotely sensed images such as their brightness, symmetry, angles, etc. Due to these features, this method could be used to detect the similar properties in a certain image and locate the position of the desired objects.

In Fig. 1 we have not presented the image enhancement or pre-processing part, because for most of the number plates we follow the processes step by step. For already extracted plates we may or may not use pre-processing and go to character segmentation process. We consider the different processes in the next two sections.

4 Extraction of Vehicle Number Plates

This process [10] consists of the following five processes, as shown in Fig. 2. Image enhancement, morphological transformation, morphological gradient, combination of the two images obtained from the top or bottom hat transformations and morphological operations, resulting in the vehicle number plate designate confirmation. The two steps, that is, morphological transformation and morphological gradient may be performed in parallel using the parallel processing software or hardware.

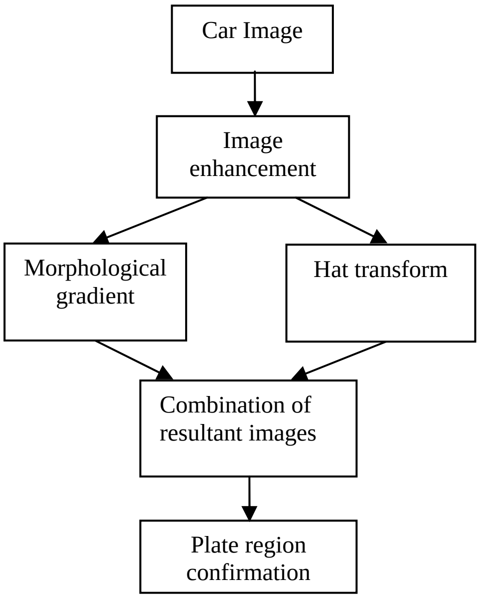


Figure 2. The proposed process for VNP extraction
We now discuss the above mentioned steps in detail:

4.1 Image Enhancement

Image enhancement is used for pre-processing in the image before any morphological operations are performed. In this process, we use methods that include adjusting the intensity of the image and reducing the contrast in the image. The technique used for intensity adjustment is known as histogram equalization. The contrast in the image can be reduced by several methods that are normally used for contrast enhancement. Secondly many images contain noise and are blurred that may be due to image capturing equipment. The noise removal algorithms and the de-blurring algorithms were also used in this process where required.

In addition, techniques are used for color enhancement in case of images that need color correction. Fig. 3 provides the contrast between original and enhanced images.

3a 3b

Figure 3a Original image and 3b shows the result of intensity and contrast adjustments.

4.2 Structuring Elements

The specific manner and extent of thickening is controlled by a shape referred to as a structuring element (SE). Computationally, SEs are typically represented by a matrix of 1s and 0s. As an example from PCB manufacturing industry [18] consider the inspection of PCBs, which is usually done manually. In this example, the acquired original image in Figure 4 (a) contains a short between two adjacent wires that should not be there.

Figure 4. PCB image processing to remove not needed artifact

To correct the image error, the image was first eroded using an SE that is smaller than the wire lengths but larger than the short wire. In Figure 4 (b), the resulting image is present with the short wire removed and the wires have thinned. To restore the image to its original state without error, the eroded image is dilated using the same SE and the result is presented in Figure 4 (c). This is a gray-scale morphological image processing example, which is presented in next section.

Depending on the SE complexity we can increase the accuracy of the system further. Generally, we choose structuring elements which are small and symmetric, with the origin in the center. Schonfeld [9] provides some suggestions, but generally, these are only guidelines. Figure 5 illustrates some useful structuring elements.

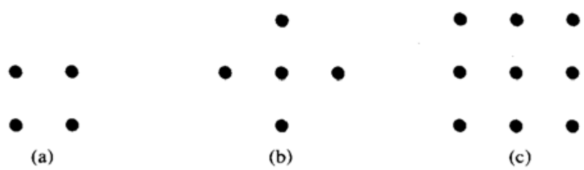


Figure 5. Structuring elements: (a) Box, (b) Rhombus, and (c) Square

4.3 Hat Transformations

Hat transformations can be used for contrast enhancement. There are two hat operations and are known as the top hat and bottom hat transformations [3]. Tophat operation is actually the result of subtraction of an opened image from the original one, mathematically,

$$th = f - (f \circ b) \qquad (1)$$

where, f is the input image and b is the structuring element.

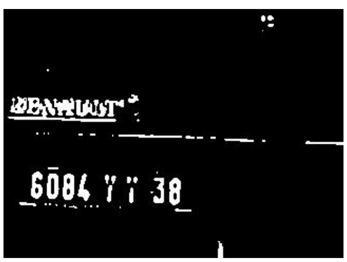


Figure 6 Resultant binary image after hat transformation and removing small features from the resultant hat image.

Whereas in the case of bottomhat operation, it is defined as the closing of the image minus the image, mathematically,

$$bh = (f \bullet b) - f \qquad (2)$$

The Bottomhat transformation may be used where the image is the complement. The tophat operation suppresses the dark background and highlights the foreground objects. Fig. 6 represents the image after hat transformations (top or bottom as the case maybe, mostly tophat transform is performed).

We see that no matter of what color the number plate is, the characters (i.e., text and numerals) on the vehicle plate are usually bright colored and contrast the color of the plate. So this operation highlights the characters and suppresses the irrelevant background. If we obtain the binary of the resulting image and remove very small scale features or components, we see that only a few plate designate foreground areas are been left and most of the irrelevant objects have been removed.

4.4 Morphological Operations

Mathematical morphology commonly refers to a broad set of image processing operations that process images based on shapes. There are several morphological operations but we use only dilation and erosion for the purpose of number plate extraction. The subtraction of an eroded image from its dilated version produces a morphological gradient, which is a measure of local gray level variation in the image. Mathematically,

$$g = (f \oplus b) - (f \,\theta\, b) \qquad (3)$$

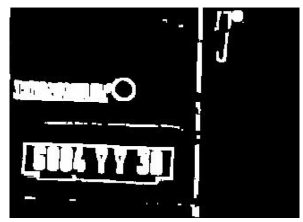


Figure 7 Binary image after morphological gradient and noise removal.

Fig. 7 gives us the result after the morphological gradient is performed on the enhanced image. We have used the morphological gradient for the detection of plate designated area. First the image was eroded by a disk shaped structuring element. Then the original image was again eroded using the same structuring element. After that the eroded image was subtracted from the dilated version. This produces an image with very less designated areas for the probable vehicle plate. After this step change the resulting image into binary and remove the smaller components which are categorized as noise.

4.5 Combination of resultant images from hat transform and morphological operations

There were some extra designated objects or regions that were present in the result of hat transformation and there were different designated areas produced in the morphological gradient, other than the probable number plate object. So to combine the results of both and remove the extra objects we intersected the both images,

Fig. 8 illustrates the combination results. This gave us even fewer designated areas which were present in both of the resulting images. i.e. the hat transformation and the morphological gradient.

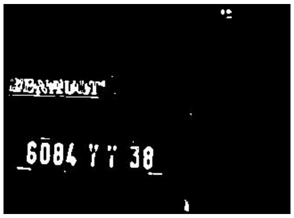


Figure 8 Result of combining the resultant images.

4.6 Plate region confirmation

We observed that there were many horizontal and vertical lines which are present in the resultant combined image and which could possibly bring some error in the final results. So to remove those horizontal lines we opened the image with a horizontal line shaped structuring element and subtracted that image from the intersected image. This considerably removed some false designate areas such as the bumper lines or the horizontal lines of the front or rear lights. After that we dilated the image with a rectangular structuring element so as to combine the objects on the number plate into one object.

9a 9b

Figure 9a Result of applying conditions like area, bounding box and aspect ratio. 9b shows the final plate area detected in the image within a green rectangle.

Next, we applied some checks and conditions which are based on the properties of the vehicle plate, for example the area of the plate, aspect ratio and the density of the region of the number plate were checked for all the remaining objects in the image. The result by using these features was that components other than the probable number plate designate are deleted, and we are left only with the number plate area. Lastly we calculate the bounding box around that object and get the coordinates of that bounding box, which are the actual coordinates of the vehicle number plate. Fig. 9 presents the extracted number plate.

5 Character Segmentation and Recognition

After vehicle features have been extracted from the input images, feature segmentation is performed to separate individual elements according to the type of part or feature. In the case of vehicle number plates, the Chinese and English characters, numbers are separated to form a single character, alphabet or number. Fig. 12 in appendix shows the sample plate with its measurements.

Based on the standard dimensions of characters, numerals and alphabet on the plate, we can isolate them. In most cases, this is the template we can use to extract characters. Fig. 9 above shows the result of extracting the characters, alphabets and numbers. Now this set is ready to be presented to the neural network recognizing the characters, alphabets, and numbers.

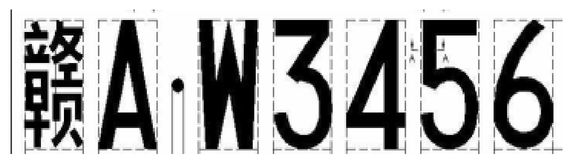


Figure 10 Characters extracted from number plate

An HNN [16] is based on the following parameters:

- McCulloch-Pitts neuron-this is the most commonly used neuron model.
- Sigmoid activation function-an S-shaped curve that reduces to a threshold function for digital case.
- Linear net function-this means that there is a summation operation which is linear.
- Hebbian learning rule-an outer product rule which multiplies a vector (input) to a matrix (weight matrix) to get the output.
- Rule of the thumb regarding the capacity-that is capacity equal to 0.13 N where N is the number of neurons.
- Partially parallel mode-as the net performs asynchronous updation.

Hopfield net may be used as a CAM [4] with the following specifications.

N = 120, so $N^2 - N = 14{,}280$ synaptic weights. 8 digit like patterns with 120 pixels. The network designed specially to produce good performances, that is, using the rule of the thumb for capacity of the network. According to rule of the thumb the capacity is

$0.13 \times N = 15.6$ or 15 rounding off.

So we can store 7 more memories. Eight patterns were used as fundamental memories in the storage (learning) phase of the HNN to create weight matrix **W**. The retrieval (recall) phase of the net's operation was performed asynchronously, as described in the Table 2 for 25% error. The Mean number of iterations is 30. Tables 3 - 6 present the recall at other error percentages.

When we perform the recognition of numerals, alphabet or characters, we are recognizing the parts of a number plate, thus we can recognize the vehicle number plates.

5.1 Post-processing

We can also perform post-processing to know the Chinese character, so that the region can be identified. Conversion of Character to Pin Yin [12]. The procedure of automatic converting characters into Pinyin are as follows:

* For single-Pinyin characters, directly convert the character to Pinyin
* For multi-Pinyin characters, search the word- base. If the character is a part of a multi-character-word, select the corresponding Pinyin syllable among the words
* If a character is described in a Pinyin syllable bi-gram or tri-gram data, select the corresponding Pinyin syllable.
* For a character which cannot be processed in above three steps, select the Pinyin syllable with the high frequency.

For Korean number plates [5], there are 15 geographical names, and some characters are often confused. But this kind of problem is solved by using post-processing, which may involve using a character dictionary.

For Japanese plates a method similar to [5] or [12] can be adopted to get the characters.

Further, this system can be modeled for implementation on FPGA hardware. The FPGAs [17] offer the most promising approach to emulation of NN models. An FPGA chip has a very large number of combinational logic blocks (CLBs) and generic interconnect. Chip level functionality is determined by the connectivity pattern that is specified in a vector of configuration bits. The configuration bit vector is downloaded onto the chip through proper hardware and software that permits high level logic to be expressed in an HDL and finally into a configuration bit vector. In order to emulate NNs, the memory requirements demand that an off-chip memory be accessible. This is necessary to store neuron parameters and state information.

As we have seen, MOSTs provide a natural way to implement functional requirements of simple neurons in analog VLSI. These have been used in the design of silicon retinas. Bio-inspired VLSI systems that employ analog components lie well beyond the arena of conventional digital computing, and have found widespread applications. For example, various applications such as the silicon retina and NM systems are based on the design of a diode-capacitor integrator. Carver Mead's not so recent book was the first comprehensive reference on this subject [83].

A number of pulsed neuron implementation models have been presented nicely in. In this context, returning to conductance based model, a 112 compartment VLSI NM neuron has been designed by Elias and Northmore. Dendrites in the model use integrate and fire (IF) neurons. Boahen used an extension of an IF neuron in a NM retina. The use of digital amplitude signal such as that employed in an action potential model are robust to noise and have been used in VLSI NNs. Other digital encoding techniques that use broadcast of action potential events include address-event representation (AER) and virtual wires. Even closer to neurobiology, excitatory and inhibitory shunting synapses have been approximated in silicon by Douglas and Mahowald.

6 Experiments

Experiments were performed to test the efficiency and accuracy of the proposed technique. 250 color images were used for testing the technique. All the images being normalized to just about 640 x 480 because some images were double this size and also it is normal to use the size. For improving the complexity and generality of the test databases, the images were acquired from the highways, car parks, at different lighting condition (cloudy, sunny, daytime, night time) and different kinds of vehicle (van, truck, car).

The images were taken of different color and variable sized number plates, also the images were irrespective of the angle and orientation of the camera. Some images contain Chinese and Arabic characters as in Fig. 11. Also many images were acquired using the worldwide web. These results report a high accuracy rate of above 95%.

11a 

11b 

11c 

Figure 11 The vehicle number plates in the images as well as an extracted vehicle plate.

7 Analysis

Comparison of the results derived from proposed method with other techniques. The other methods were 1. Feed-Forward Neural Network [7], 2. Hough Transform [2], 3. Back-Propagation Network [6], and 4. Maximum Entropy method [8], respectively. Comparison of results has been tabulated in Table 1, with these methods and our proposed method, where the new method corresponds well to the other methods of extraction. In our case, there were some cars that had no number plates attached to them.

Table 1 Comparison of results for extraction

Method	Correct	Reject	Other	No plate
1	90.00 %	8.00 %	2.0 %	
2	92.85 %	7.15 %		
3	95.0 %	5.00 %		
4	93.00 %	7.00 %		
PM	94.00 %	2.00 %		4.00 %

Table 2 Results of the recall process for HNN.

Pattern	No. of iterations
0	34
1	32
2	26
3	35
4	25
6	37
	32
9	26

Table 3 Results of the recall at 5% error.

Pattern	No. of iterations
0	7
1	8
2	10
3	7
4	7
6	7
	6
9	4

Table 4 Results of the recall at 10% error.

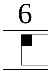
Pattern	No. of iterations
0	11
1	10
2	17
3	16
4	17
6	11
	10
9	17

Table 5 Results of the recall at 15% error.

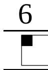
Pattern	No. of iterations
0	19
1	22
2	14
3	19
4	16
6	22
	25
9	17

Table 6 Results of the recall at 20% error.

Pattern	No. of iterations
0	25
1	25
2	20
3	25
4	18
6	25
	31
9	31

8 Conclusions

This paper describes an algorithm that allows the recognition of vehicles' number plates using hybrid morphological techniques including hat transformations and morphological gradients and neural networks. The main advantage of the technique that we propose is the high accuracy of the technique that works irrespective of the color, size, location, and angle of the number plates.

Although the technique is quite efficient enough to work very well in the real time environment but currently the technique proposed lays more emphasis on the accuracy of the overall system, while the some more work is to be done to make the technique more efficient. The authors are developing a vehicle detection system in which the VNP is a main part, we want to use vehicle noise signature for detection of vehicle through its engine sound. Also, future work is intended to implement this system on FPGAs.

Figure 12 Sample number plate.

Figure 13 Alphabets and numerals used on German plates.

Appendix:
Fig. 12 shows the sample plate with its measurements. This is a sample of number plate that is used on Chinese vehicles [13]. In this plate, first there is a Chinese character that represents one of the provinces, municipalities, autonomous regions of China. The second is the Roman letter to represent the city. The third and fourth can be a letter or a number, while all remaining are numbers.

Also, this figure shows that the numbers are embossed on a metallic sheet. The background is blue, the character or numerals are white. For buses and other vehicles, the typical background colors can be white, yellow, and black. In buses, motorcycles, the front and rear number plates are different in dimensions.

"Flschungserschwerende Schrift", used [15] on German plates to hinder falsification. Note that normally similar glyphs (e.g. O and Q) are distinct in shape. This is illustrated in Fig. 13, and is an example of adapting characters to simplify the pattern recognition task.

Japanese [15] use two types of plates yellow and white depending on the vehicle engine.

Complex operations of Mathematical Morphology are based on some simple operations such as opening and closing, erosion and dilation.

Dilation and Erosion

The gray-scale dilation of f by SE b, denoted $f \oplus b$, is defined as

$$(f \oplus b)(x, y) = \max\{ f(x - x', y - y') + b(x', y') \mid (x', y') \in D_b \} \quad (4)$$

where D_b is the domain of b, and f(x, y) is assumed to equal $-\infty$ outside the domain of f.

The gray-scale erosion of f by SE b, denoted f θ b, is defined as

$$(f \ \theta \ b)(x, y) = \min\{ f(x+x', y+y') - b(x', y') \mid (x', y') \in D_b \} \quad (5)$$

where D_b is the domain of b, and f(x, y) is assumed to equal $+\infty$ outside the domain of f.

Opening and Closing

The opening of image f by SE b, denoted f $\circ$ b, is defined as

$$f \circ b = (f \ \theta \ b) \oplus b \quad (6)$$

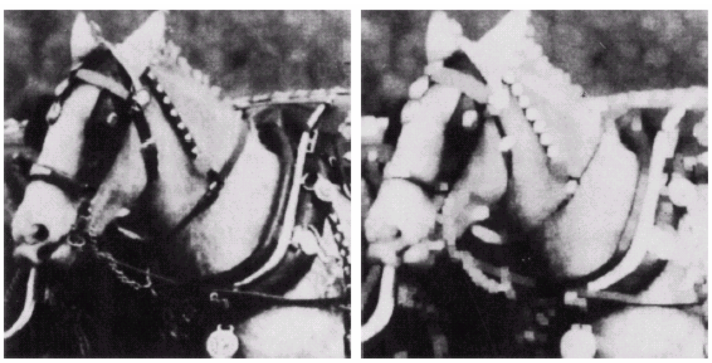
As before, this is simply the erosion of f by b, and followed by the dilation of the result by b. Similarly, the closing of f by b, denoted f $\bullet$ b, is defined as

$$f \bullet b = (f \oplus b) \ \theta \ b \quad (7)$$

Both operations have simple geometric interpretations.

Morphological Smoothing

One way to achieve smoothing is to perform a morphological opening followed by a closing. The net result of these two operations is to remove or attenuate both bright and dark artifacts or noise.



(a) (b)

Figure 14 (a) Original image and (b) its dilated version

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References:

[1] Clark, P., Mirmehdi, M.. Combining Statistical Measures to Find Image Text Regions. *Proceedings of the 15th International Conference on Pattern Recognition*, 2000, pp. 450-453.

[2] Duan, T.D., Duc, D.A., Du, T.L.H.. Combining Hough Transform and Contour Algorithm for detecting Vehicles License-Plates. *Proceedings of 2004 International Symposium on Intelligent Multimedia, Video and Speech Processing*, 2004, pp. 747-750.

[3] Gonzalez, R.C., Woods, R.E.. *Digital Image Processing*. 2d ed., Prentice Hall, Englewood Cliffs, NY, 2002.

[4] Haykin, S.. *Neural Networks—A Comprehensive Foundation*. 2d ed. Singapore: Pearson Education, 1999.

[5] Lee, E.R., Kim, P.K., Kim H.J.. Automatic Recognition of a Car License Plate Using Color Image Processing. *IEEE*, 1994, pp. 301-305.

[6] Lee, J.C.M., Wong, W.K., Fong, H.S.. Automatic Character Recognition for Moving and Stationary Vehicles and Containers in Real-life Images. *IEEE*, 1999, pp. 2824-2828.

[7] Parisi, R., Di Claudio, E.D., Lucarelli, G., Orlandi, G.. Car Plate Recognition by Neural Networks and Image Processing. *Procs of the 1998 IEEE International Symposium on Circuits and Systems*, 1998, pp. 195-198.

[8] Remus, B.. License Plate Recognition System. *Proceedings of the 3rd International Conference in Information, Communications and Signal Processing*, 2001, pp. 203-206.

[9] Schonfeld, D.. Optimal Structuring Elements for the Morphological Pattern Restoration of Binary Images. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 16, No. 6, 1994.

[10] Sulehria, H.K., Zhang, Y. & Irfan, D.. Mathematical Morphology Methodology for Extraction of Vehicle Number Plates. *International Journal of Computers*, Vol. 1, Issue 3, WSEAS, 2007.

[11] Sulehria, H.K., Zhang, Y., Irfan, D. & Sulehria, A.K. Vehicle Number Plate Recognition Using Hybrid Mathematical Morphological Techniques. *WSEAS International Conference on (SIP'08) Istanbul,* Turkey, May 27-29, 2008.

[12] Xuan Wang, Lu Li, Lin Yao & Anwar, W.. A Maximum Entropy Approach to Chinese Pin Yin-To-Character Conversion. *2006 IEEE International Conference on Systems, Man, and Cybernetics*, Oct 8-11, 2006, Taipei, Taiwan.

[13] GA666-2006. *People's Republic of China regulations for vehicles number plates* (in Chinese). Nov, 2006

[14] Malaysia to embed car license plates with microchips to combat theft. *International Herald Tribune*, Dec. 8, 2006.

[15] Web page of http://thefreedictionary.com for number plates regulations of many countries.

[16] Sulehria, H.K., Zhang, Y.. Hopfield Neural Networks: Model, Applications, and Implementations. *WSEAS Transactions on Computer Research*. February 2007, pp. 156-159.

[17] Kumar, S.. *Neural Networks*, McGraw-Hill, China, 2006.

[18] Snyder, W.E., Qi, H.R.. *Machine Vision*. Cambridge University Press, Cambridge, UK. 2004.