Vehicle License Plate Number Recognition Scheme Using Support Vector Machine Network

Chen-Chung Liu
National Chin-Yi University of Technology, Department of Electronic Engineering
ccl@ncut.edu.tw

Chen Lin
National Chin-Yi University of Technology, Department of Electronic Engineering
k1107327335@yahoo.com.tw

Abstract

At the present time, vehicle license plate (VLP) recognition system has become an important key of numerous traffic related applications, e. g. the road traffic monitoring, the traffic analysis, the parking lots access control etc. Accurately detecting the VLP from a vehicle image, extracting the VLP number from the detected VLPs, and quickly recognizing the VLP number are considered to be the most important stage of vehicle license plate recognition (VLPR) system. They greatly influence the overall recognition accuracy and processing speed of the whole system. This paper presents an algorithm to locate the VLPs of moving vehicles from a video traffic image sequence, adopts the projection scheme to extract the VLP number from the detected VLPs, and utilizes the radius based support vector machine network to recognize the VLP number. Moreover, the shifting of the VLP in the detected image is also studied and then a transformation based on relative position vector to correct the distorted plate image into a calibration standard image is developed. By means of the distortion calibration techniques, the VLP number in a distorted state can also be extracted more correctly. The experiment results show that the presented algorithm can correctly localize the VLPs even in overlapped vehicles situation, can effectively extract the VLP number from a distorted VLP caused by the shifting of relative position between the vehicle and the camera, and can recognize the VLP number quickly and accurately.

Keywords: VLP, localization, calibration.

1. Introduction

The flux and quantity of motor vehicles increase fast along with the rapidly development of the world's economy. The worsening of social order causes destruction and violence around the world. They have weighted the importance of security, and raised the growing demand for traffic data in regard of traffic flux and automatic identification of motor VLP. Among all the possible schemes, installation of video surveillance systems at streets to record suspected vehicles has become a main tool for police. Whenever criminals committed a crime, it is very possible that they would use vehicle. Hence, the police can get back all the videos recorded around the crime scene to find the possible suspects to follow the vehicle to track the owner. However, to check the enormous volume of video should easily wear down the spirit and efficiency of the pursuit. Therefore, methods that automatically extract the vehicles and recognize their VLPs for identification would be a great help for the police to solve the problem more quickly and efficiently. It leads researchers around the world to develop an automatic system called Intelligence Transportation system (IT system), to monitor motor vehicles and control traffic volume without human interruption [1-6]. So, Intelligence Transportation system is the major development direction of recent transportation management.

In IT system, Vehicle License Plate Recognition system (VLPR system) is one of the most important parts. VLPR system plays a central role in many applications in traffic monitoring; save time and lessen heavy traffic by allowing vehicles to pass crowed plazas or weigh stations, save money and time by collecting and managing vehicle data without human interposition, offer security control of restricted regions, and assist in traffic law enforcement [1-8].

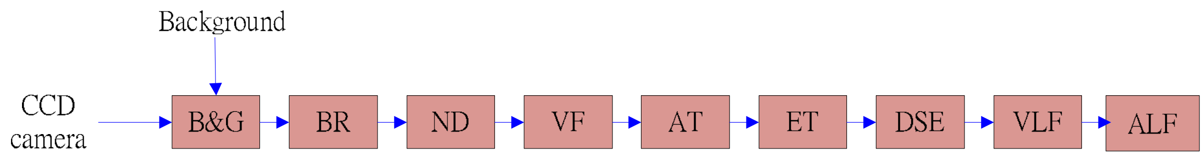
A VLPR system usually consists of four modules; that are the VLP extraction module, the distorted VLP image correction module, the VLP number segmentation module, and the VLP number recognition module. In order to recognize a VLP efficiently, however, the location of the VLP must be detected firstly. Detecting the accurate location of a VLP from a vehicle image is considered to be the most important stage of a VLPR system, which greatly influences the overall recognition accuracy and processing speed of the whole system. In the VLP extraction module, VLP location and extraction from images is always difficult to be located accurately and efficiently, due to following reasons: (i) The size, shape and pose of plate may vary. (ii) The lighting condition in the image may vary. (iii) The plate may be any color, and the background color may be very similar to that of plate. (iv) The image may contain a number of noises. The VLP candidates are decided based on the features of VLPs. Features are commonly derived from the VLP format and alphanumeric symbols constituting VLP number. The features deriving from the VLP format are shape, width to height ratio, color, spatial frequency, texture of grayness, and variance of intensity values [1-8]. Alphanumeric symbols are line, blob, the aspect ratio of alphanumeric symbols, and the sign change of gradient magnitude [1-5]. A set of effective and easy to detect features is adequate usually.

A number of techniques have been proposed. However, most of these techniques are based on conditions, such as fixed illumination, fixed the relative position between a camera and the VLP, limited car speed, designated routes, and stationary backgrounds [1-8]. The methods based on textures mainly take the aspect ratio, the contrast variations, the uniform distribution of the VLP numbers, and the ratio between background area and VLP number area [9-13]. They process the image as a grayscale image and employ the Sobel edge detection, projection, and seed-filling algorithm to remove the redundant regions. The result is then filtered by the aspect ratio and object connections. These methods are high efficiency, but they are easily undergone by the interference of the lighting effect. The methods based on the colors retrieve the color edge and then enhanced the edge. The object connection is applied to the classified regions separated by the edges and further locates the LP. Yang et al. [14] adopted textures and colors simultaneously to locate the LP, it has the high efficiency and good localization result and the disadvantage is the vulnerability in dealing with low contrast or poor color. The aim of this paper is to lessen many of these restrictions to detect VLPs whose sizes and orientations are slightly different from the original VLP caused by being not shot from exactly the same distance and orientation.

In the distorted VLP image correction module, the pose of VLP image extracted from car picture may distorted, due to the perspective effect of lens or the various combination of visual angles between the camera and the car. It becomes very difficult for segmenting out interior VLP numbers, and decreasing the recognition ability [15-20]. We must correct those distorted plate images before the VLP number segmentation. We propose a smart system using an automated VLP location and distortion calibration to overcome most of the problems with previous approaches. The system can deal with difficulties raised from noise distortion and complex background. In order to construct a high accurate and high performance VLP number recognition system, this paper uses the support vector machine network (SVMN) to achieve the goal. The presented algorithm recognizes the input segmented character image by selecting 10 segmented character images for each character to train the SVMN with supervision version. The remainder of this paper is organized as follows: Section 2 – Vehicle license plate localization. Section 3 –Vehicle license plate number recognition. Section 4 – Experiment results. Section 5 – Conclusion.

2. Vehicle License Plate Localization Algorithm

The first step of a VLP identification algorithm is to extract the VLP image correctly. Our system uses the video sequence images captured by a charge-coupled device digital video camera from a road in Taipein town in a sunny afternoon, in which there are many lighting effects, plate damage, dirties and complex backgrounds as the input. The overall VLPs localization of moving vehicles process of our proposed scheme is shown in Figure 1. The original input video color image sequence is divided into separated successive frames of color images $C(t_i), t = 1,2,...$ which are presented by RGB planes. A background removal processing discards the useless image part to increase object identification correctly. In addition, VLP extracting and its distortion adjustment (DA) are the most signification roles during the recognition process. However, get the correct VLP location is the condition of exactly identification. The details of our approach are described in the following.



B&G - Gray transformation and Binary transformation
BR - Background Removal
ND - Noises Deleting
VF - Vehicles Framing
AT - Adumbration Transformation
ET - Edges Thinning
SED - Sequence Edges Deleting
VLF - Vehicles License plates Framing
ALF - Adjust License plates Frame

Figure 1. The flow chart of license plate localization algorithm.

2.1. Color mapping RGB to YIQ

The red, green and blue (RGB) are three dimensions of illumination spectrum. They are enough to compose any color adequately, although the spectrum of illumination is infinite dimensional. A common alternation to the RGB representation of an image is the YIQ representation. The YIQ representation of an image is the standard model in the television transmission. The YIQ representation of an image obtained from the RGB representation of an image is given by equation,

$$\begin{bmatrix} Y \\ I \\ Q \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.144 \\ 0.596 & -0.274 & -0.322 \\ 0.212 & -0.523 & 0.311 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (1)$$

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \begin{bmatrix} 1.000 & 0.956 & 0.621 \\ 1.000 & -0.272 & -0.647 \\ 1.000 & -1.106 & 1.703 \end{bmatrix} \begin{bmatrix} Y \\ I \\ Q \end{bmatrix} \quad (2)$$

Where Y is the luminance or brightness which refers to color density, I is the hue which is the dominant such as orange, red or yellow, and Q is the saturation or depth which is the amount of white light mixed with a hue of color. The equation (1) is the inverse transformation of equation (2), to transfer the image in YIQ planes back into the RGB planes.

The image in RGB color space is not suitable for image processing applications, because the image in RGB color space is highly correlated. Other color models like as HIS, L*a*b*, YIQ, YUV, and YCbCr are suitable for image processing applications, they are the reducing redundancy models of the image in RGB color space, obtained by some color transform.

2.2. Background Removal

Figure 2 shows the flow chart of image processing procedures for obtaining a gray image of moving objects with background removal. The background averaging procedure is used to obtain a background image by averaging more than 30 pictures of a location. Background subtraction is a popular and effective method for detecting moving objects in a scene. Based on the concept of probability, the background image can be constructed from the modified histogram of individual pixel in image sequence. Figure 3(a) is an original input image (Y plane) and Figure 3(b) shows a constructed background image that is obtained from background averaging procedure. Figure 3(c) shows that the objects apart from the background in the scene are extracted by erasing the background from original image.

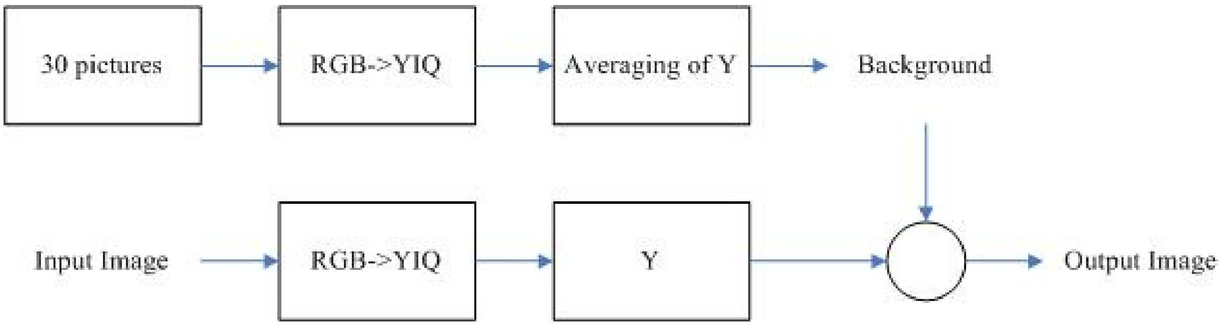


Figure 2. The background removal flow chart.

(a)	(b)	(c)

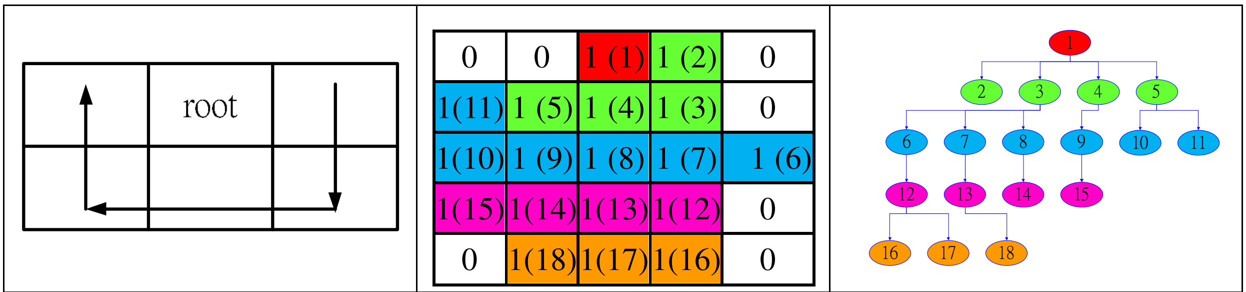
Figure 3. Moving objects extraction; (a) original input image, (b) constructed background image, (c) extracted moving objects.

2.3. Noises Deleting

There are many small noises in the gray image of moving objects with background removal. Most of these small noises are generated by the illuminant changes with time due to the input is video image sequence and they are photographed at different time. These noises can be exhibited more obviously on the binary domain. In this paper, we use the erosion of morphology to delete noises from the binary image of moving objects with background removal. In the binary image of moving objects with background removal and noises deleting, vehicles are colored in white (pixel value equals 255) and background is black colored in black (pixel value is zero). We frame the vehicles from the black-white image by finding the seed of vehicle and construct a vehicle by a tree with the seed as the root of the vehicle tree:

1) We find the first white pixel to take as a seed by starting at the left-upper pixel of the black-white image, and shifting from left-to-right and top-to-bottom in the black- white image.

2) A 2X3 window shown in Figure 4(a) is taken as the mask to filter other white pixels as the leaves of the vehicle hierarchical tree. Each vehicle hierarchical tree represented an object of the black- white image. Figure 4 shows an example of the construction of a vehicle hierarchical tree.

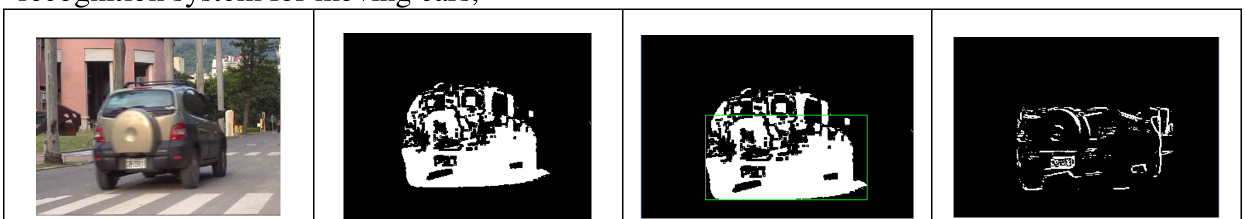


(a) (b) (c)

Figure 4. (a)The 2X3 window used to filter in other white pixels as the leaves of the vehicle hierarchical tree.(b)Black- white image with background removed (the number in parentheses represent the order of searching for tree constructing), (c) the corresponding vehicle hierarchical tree of (b).

2.4. License Plates Localization

The localization of VLPs from a traffic images sequence is considered to be the most important stage of VLP recognition system for moving cars, which greatly influences the overall recognition accuracy and processing speed of the whole system. The VLPs location is dealt with following six steps in this paper.



(a) (b) (c) (d)

Figure 5. Residual image extracting; (a) original color car image, (b) moving objects, (c) residual image of object, (d) edge map of (c).

1) For saving the processing time, we segment each object into 3 equal parts from the top to the bottom of the object. The upper part is removed due to the VLP never be placed in the upper part, the middle part and the bottom part are retained as the residual object image. Each residual object image is framed with a suitable outer- connected rectangle to become a residual image of the original image. Figure 5 shows an example of the framing of the residual image.

2) To take each residual color image of original image by extracting the object image from the residual image's corresponding position in the original color image. Then, we transform each residual color image of original image into gray image; the residual gray image is then transformed into binary image with the median filter. Edge features of the car image are very important, and edge density can be used to successfully detect a number plate location. Since most edges in the residual binary image are horizontal or vertical edges, and we want to avoid taking too much redundancy edges to extract license correctly, we find the 45 or -45 degree edges from the residual image with Sobel filter. An example of the edge image of a residual image is shown in Figure 5(d).

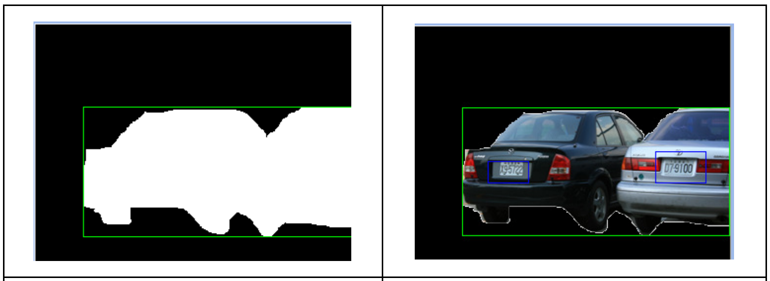
3) For extracting VLP correctly, the edges in the edge image are thinned to take the one pixel width skeleton of edge by ZS thinning method [21]. An example of the edge thinning is shown in Figure 6.

4) In the image of edge skeleton, we delete these over- size skeletons due to that the VLP number skeleton size of the VLP in skeleton image has its limitation. Then, the residual skeleton should concentrate in the VLP region. An example of the residual skeleton image is shown in Figure 6(c).

(a) **(b)** **(c)**

Figure 6. The residual edge image (a) before thinning, (b) after thinning, (c) after deleting over-size skeletons.

5) We use a plate- frame with height h equals the 1/8 height of the residual image and width w is (8/5)* h as the mask to extract the VLPs from the residual skeleton image, and shifting from left-to-right and top-to-bottom in the residual skeleton image to calculate the number of edge pixels in the mask. The first extracting VLP located at the frame that has the maximum number of edge pixels $N_M(e)$ in the mask. If the second large number of edge pixels of another masked region that does not overlapped with the first extracted VLP is not less than 80% of $N_M(e)$, then the second masked region is extracted as the second VLP (the object is composed by two overlapped vehicles). Figure 7 shows an example of the VLP localization.



(a) (b)

Figure 7. (a) The framed overlapped vehicles in background- removed black- white image, (b) the framed vehicle license plates in an overlapped vehicles color image with background- removed.

6) From Figure 7, we can see the plate-frame size framed in step 5) is much greater than real VLP size. We need to adjust the size of the frame rectangle to increase the framing precision. The size adjustment of the framing rectangle is the same as the method of locating VLP in residual image. We take a plate-frame as a residual image and take a rectangle with size equals to the size of plate-frame times 0.9 as a mask each time, and shifting the mask from left-to-right and top-to-bottom in the plate-frame to calculate the number of edge pixels $N_M(e)'$ in the mask. We find a rectangular region that has the maximum number of $N_M(e)'$, and then calculate the edge pixels density of the region. We stop the iteration and take the rectangular region as the final VLP region if density is greater than 0.6, we repeat step (6) otherwise.

3. VLP Number Recognition Algorithm

The presented algorithm of VLP number extracting consists of five major stages: color transformation and bright adjustment, edge detection and Hough transformation, distorted plate calibration and binarization, edges detection and shrinking, horizontal projection and horizontal Segmentation, and Vertical projection and Vertical Segmentation. Figure 8 shows the presented algorithm for VLP number extraction, and the detail description of the presented algorithm is illustrated in the following subsections. The first step is the same method as 2.1.

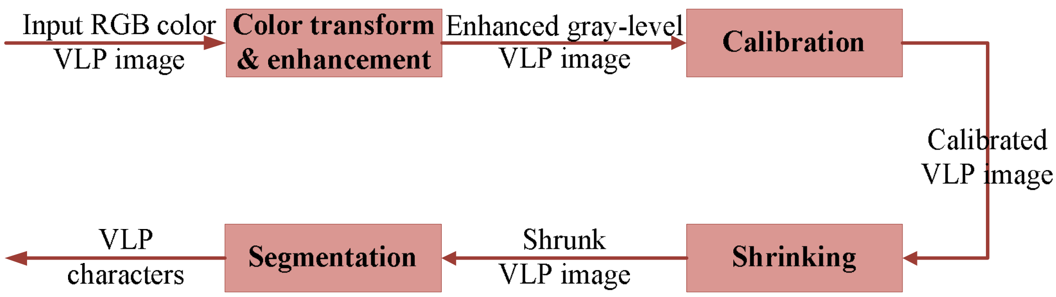


Figure 8. The flowchart of VLP number segmentation algorithm.

3.1. Distorted plate calibration

For calibrating distorted VLP images, the algorithm needs two non-parallel lines as the reference lines. The two reference lines are found in the

VLP edge image by utilizing the Sobel gradient mask and the Hough transform. The Sobel gradient mask is one of the popular edge detection methods [15]. In this paper, we use the Sobel filter to find out the contours of the object images in the scene. Figure 9(a) and Figure 9(b) are the masks used for detecting the horizontal and vertical edge, respectively. The presented algorithm uses the Sobel filter to construct the VLP edge image from the gray level VLP image.

-1	-2	-1
0	0	0
1	2	1

(a)

-1	0	1
-2	0	2
-1	0	1

(b)

Figure 9. Sobel gradient masks used for (a) detecting the horizontal edge, (b) detecting the vertical edge.

To extract the location and characteristics of geometric objects, such as lines, edges, and curves from an image is always a key in digital image processing. The Hough transform has been considered as the most popular technique for solving this problem, which was first introduced by Hough in 1962 [16]. The Hough transform is based on the fact that all points of a straight line placed in a digital image can be mapped to a single point in Hough space with using polar coordinate to describe a straight line, where a straight line is represented by the magnitude of the normal vector from the original to the straight line and the angle between the normal vector and the x-axis and the parameter, such that the line detection operation is converted into a peak seeking step. This property enables the Hough transform to detect straight lines stably and robustly in noised images [17].In the edge image, the presented algorithm uses the Hough transform to find the longest line segment first, and then to find the second line segment with absolute angle difference around 90 degree from the first detected line segment from the longest 4 line segments. These two line segments are used as reference lines for distorted VLP calibration.

For boosting the segment rate of VLP characters, the presented algorithm calibrates distorted VLP images to normalized pose. The VLP calibration includes rotating and translating operations. On the other hand, a rotation operation with respect to an axis can be decomposed into a sequence of one-dimensional translations. In this paper, the rotating operation is first decomposed into a sequence of one-dimensional translations, and they are then combined with the translating operation into shearing along x-axis and shearing along y-axis. In the calibration of gray-level VLP image, the two reference lines found in the edge image are first mapped to the gray-level VLP image. For the shearing along x-axis, the algorithm evaluates the angle between the first reference line and the x-axis, then determines the displacement of each pixel within the VLP image, and finally moves each pixel according to the evaluated displacement. For the shearing along y-axis, the algorithm evaluates the angle between the second reference line and the y-axis, and the subsequent steps are similar to the shearing along x-axis. Figure 10 shows the calibration of distorted VLP.

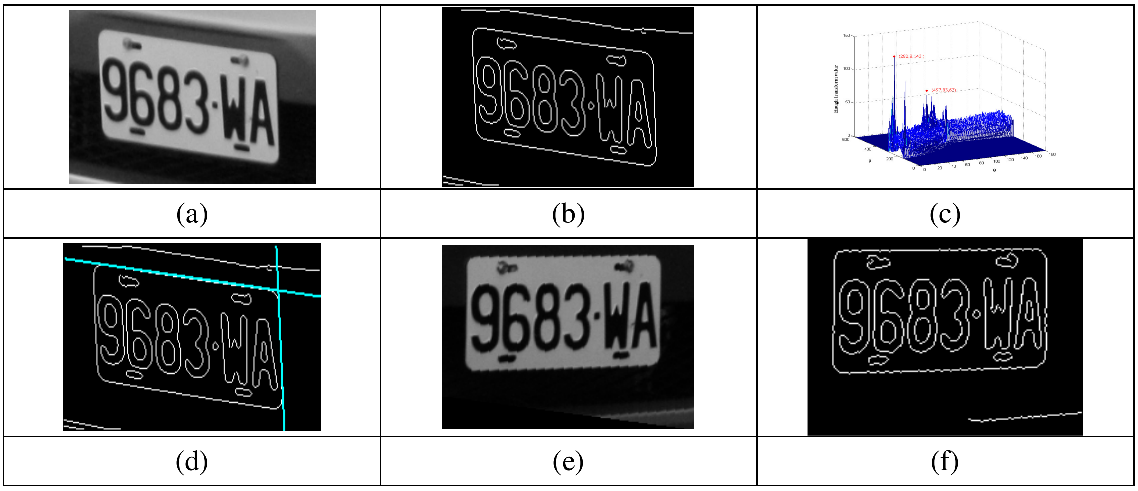


Figure 10. Calibration of distorted VLP, (a) gray-level distorted VLP image, (b) edge image of (a), (c) the longest 4 line segments of Hough transform, (d) selected two reference lines, (e) calibrated VLP image, (f) edge image of calibrated VLP.

3.2. Shrinking

Due to many noises exist around the boundary of a VLP image. For accurately extracting the VLP number, the redundancy areas around the boundary of a VLP image have to be removed. In this paper, the Sobel filter is again introduced on the calibrated gray-level VLP image to construct the calibrated edge image. On the calibrated edge image, the number of pixels of edges is counted for each row. The number of pixels of edges in a row in the upper half image is checked. The row that its number of pixels of edges is less than the threshold and is position is most close to the center row is taken as the upper boundary of the VLP image. Similarly, the lower boundary of the VLP image is also determined in the lower half image by the same way. The rows between the upper boundary and the lower boundary are reserved as the horizontal shrunk image. The left boundary of the shrunk image is defined as the column that the most left edge pixel placed in it and, the right boundary of the shrunk image is defined as the column that the most right edge pixels placed in it. The final shrunk image is obtained by deleting the outside parts of the four boundaries. Figure 11 shows the procedure of VLP image shrinking.

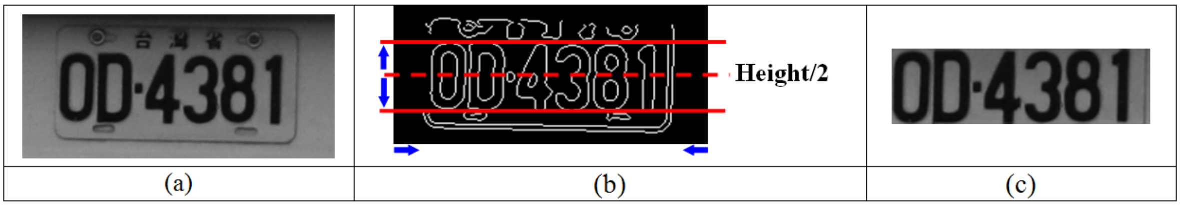


Figure 11. VLP image shrinking, (a) calibrated VLP image, (b) upper bound and lower bound on calibrated edge image, (c) shrunk VLP image.

3.3. Characters Segmentation

After the gray VLP image has been calibrated and shrunk, the binarization stage will be started. In the binarization stage, the average pixel value of the calibrated gray VLP is timed with a no more than one positive real number as the threshold. The algorithm uses the threshold to filter the pixels of the calibrated gray VLP into black regions consist of darker pixels and white regions consist of brighter pixels. The presented algorithm uses the weighted threshold to overcome the problems caused by too dark images or too bright images. After obtaining the shrunk VLP image, the presented algorithm uses the vertical projection scheme to accumulate the pixel values in each column. The accumulation of pixel values of each VLP number of VLP is larger than zero and the accumulation of pixel value of each gap between two adjacent VLP numbers of VLP is zero. And thus, the VLP number will be extracted by extracted the region between two zero accumulation pixel values. An example of the vertical projection for a VLP image is shown in Figure 12.

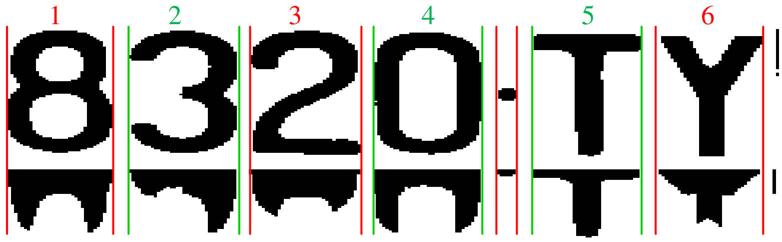


Figure 12. The algorithm of character extracted by vertical projection.

3.4 Character Recognition

In order to construct a high accurate and high performance VLP number recognition system, this paper uses the support vector machine network (SVMN) to achieve the goal. The presented algorithm recognizes the input segmented character image by selecting 10 segmented character images for each character to train the SVMN with supervision version. The structure of the SVMN is showed in figure 13. The SVMN possesses outstanding advantages; (i) the strong theoretical basis provides a high generalization capability and avoids over fitting, (ii) the global model can deal with high-dimensional input vectors efficiently, (iii) the solution is light and only a subset of training samples contributes to this solution, thus reducing the workload [22].

Consider a training data set $T = \{(\vec{x}^{(i)}, y_i)\}_{i=1}^{N}, \vec{x}^{(i)} \in R^n, y_i \in R$, where $\vec{x}^{(i)}$ is a vector of input variables and y_i is the corresponding scalar output (target) value. The objective over here is to construct a SVM model such that it can accurately predict the outputs, $\{y_i\}_{i=1}^{N}$ corresponding to the input vectors $\{\vec{x}^{(i)}\}_{i=1}^{N}$. With this objective, the linear SVM formula can be given as

$$f(x) = w \cdot \Phi(x) + b, \qquad (3)$$

where f is the SVM formula to be built, w the weight vector in feature space, Φ is the transformation function that transfer input vectors into the high dimension feature space, $w \cdot \Phi(\vec{x})$ is the inner product of w and $\Phi(\vec{x})$, and b is the bias (constant). In this paper, the chosen kernel of the SVM is exponential radial based function (RBF) kernel which is expressed as $K(\vec{x}^{(i)}, \vec{x}^{(j)}) = -\exp\left(\|\vec{x}^{(i)} - \vec{x}^{(j)}\| / (2\sigma^2)\right)$, where the kernel width σ is taken to be one, the penalty parameter C is taken as infinity, and the insensitivity value ε is set to 0.01.

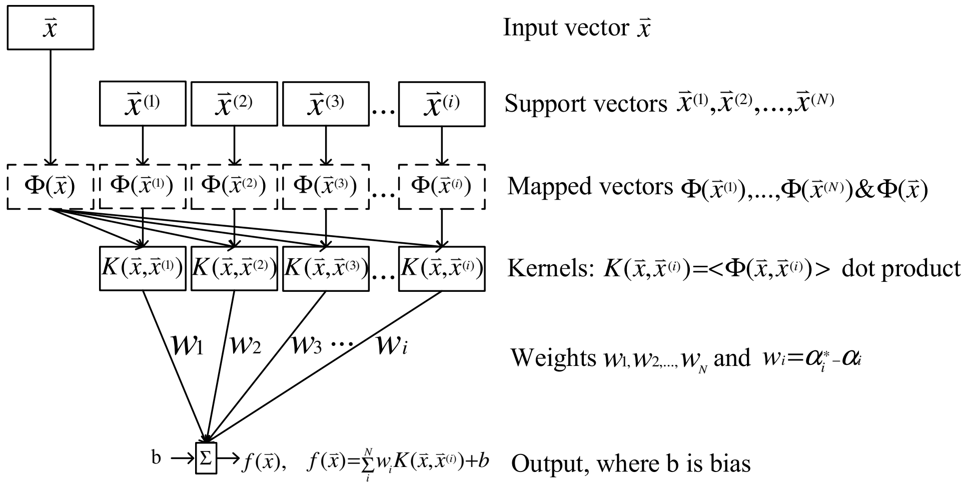


Figure 13. The structure of support vector machine.

The overall procedure for vehicle license plate recognition comprises the following steps:

Step 1: The normalized segmented character images (32×16 pixels) are manually pre-classified into 35 character groups(number 0~ 9, English characters (A~ Z except O)).

Step 2: Transform all pixels values of individual character images (2 dimensional image) to form the one dimensional sample vectors.

Step 3: For each character group of the 35 VLP characters, variance of each image is evaluated, and the top 10 ones' images are selected as the character's training data.

Step 4: Iteratively train all the training data with supervision version to find a set of optimal parameters.

Step 5: Recognize all of the other data using the trained SVMN.

4. Experiment Results

In order to demonstrate the performance of the proposed scheme, a series video sequence images of traffic scene captured by a charge- coupled device digital video camera from a road in Taipein town in a sunny afternoon, in which there are many lighting effects, plate damage, dirties and complex backgrounds were used in simulation. There are 258 cars in the video series; there 252 VLPs are located successfully and 6 cars driving too fast to locate them successfully, 248 VLPs are successfully segmented, and 243 VLPs are correctly recognized. The results images were obtained by through several processes and describing as following. The proposed algorithm can accurately locate VLPs for those vehicle images whatever the background color of VLP is different from that of the vehicle body or not and whatever the background complexity. Figure 14 shows our real experiment results on the road. This experiment results show that our scheme can locate the VLP precisely of moving vehicle from the image sequence captured by a CCD digital video camera wherever the VLP is adhered on the head or on the tail of a car. In addition, a graphical user interface (GUI) of the proposed vehicle license plate recognition system is also offered for experimental convince. Figure 15 shows a test example of the GUI. Figure 16 shows a test example of the VLP characters segmentation and the recognition for an overexposed VLP.

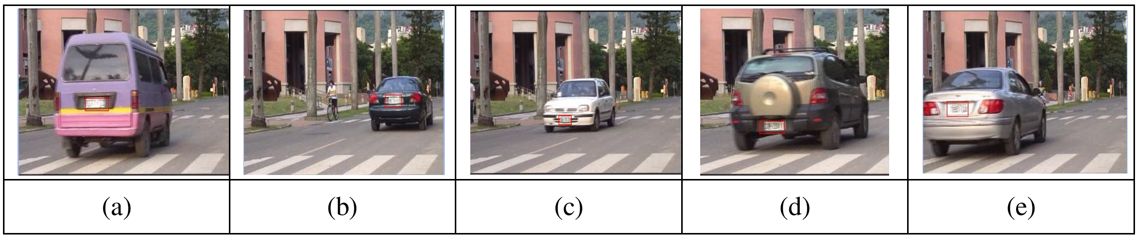


Figure 14. Experiment results of VLP location for moving vehicle; (a) successive locating the back VLP of a pink car; (b) successive locating the back VLP of a black car; (c) successive locating the front VLP of a white car; (d) successive locating the back VLP of a green car; (e) successive locating the back VLP of a car colored in silver.

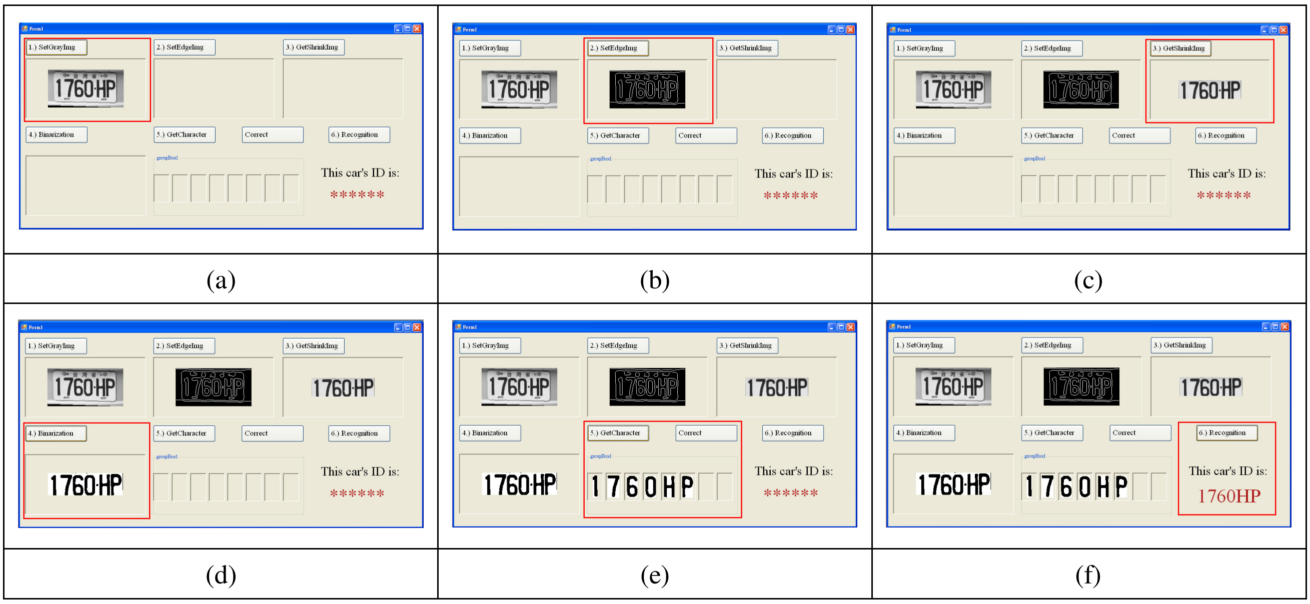


Figure 15. Execution results; (a) button 1,(b) button 2,(c) button 3,(d) button 4,(e) button 5,(f) button 6.

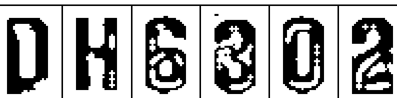
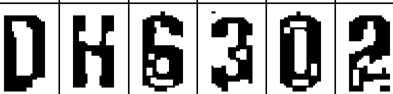
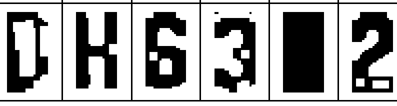
VLP	Morphological Operations	After Mathematic Morphological Operations	Recognition Results					
	Erosion then Dilation		D	H	6	0	0	X
	Closing then Opening		D	H	X	3	X	X
	Binarization then Opening		D	H	X	3	X	2

Figure 16. An example of the VLP characters segmentation and the recognition for an overexposed VLP.

5.Conclusion

At the present time, vehicle license plate (VLP) recognition system has become an important key of numerous traffic related applications, e. g. the road traffic monitoring, the traffic analysis, the parking lots access control etc. Accurately detecting the VLP from a vehicle image, extracting the VLP number from the detected VLPs, and quickly recognizing the VLP number are considered to be the most important stage of vehicle license plate recognition (VLPR) system. They greatly influence the overall recognition accuracy and processing speed of the whole system. This paper presents an algorithm to locate the VLPs of moving vehicles from a video traffic image sequence, adopts the projection scheme to extract the VLP number from the detected VLPs, and utilizes the radius based support vector machine network to recognize the VLP number. Moreover, the shifting of the VLP in the detected image is also studied and then a transformation based on relative position vector to correct the distorted plate image into a calibration standard image is developed. By means of the distortion calibration techniques, the VLP number in a distorted state can also be extracted more correctly. The experiment results show that the presented algorithm can correctly localize the VLPs even in overlapped vehicles situation, can effectively extract the VLP number from a distorted VLP caused by the shifting of relative position between the vehicle and the camera, and can recognize the VLP number quickly and accurately.

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