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Automatic License Plate Recognition Using Neural Network and Signal Processing

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Automatic License Plate Recognition Using Neural Network and Signal Processing

A Thesis submitted in partial satisfaction
of the requirements for the degree of

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in

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by

Yuanxi Fu

March 2019

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ABSTRACT OF THE THESIS

Automatic License Plate Recognition Using
Neural Network and Signal Processing

by

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Master of Science, Graduate Program in Electrical Engineering
University of California, Riverside, March 2019
Dr. Yingbo Hua, Chairperson

Automatic license plate recognition (ALPR) plays an important role in intelligent transportation systems which would not only save labor but also improve efficiency. However, many license plate recognition methods work under restricted conditions like slow speed and good illumination. In this thesis, the constraints are relaxed by the reviewed effective method for ALRP, which consists of three major steps: 1) pre-processing of images, 2) location of license plates, and 3) recognition of license numbers and characters. The goal of step 1 is to remove noise from images and highlight edges in images. Step 2 is to extract the license plate from an image. Step 3 is to segment and recognize the numbers and characters.

Step 1 of the above ALPR method involves a Gaussian filter, the Sobel operator, the image intensification, a closed operator, and a grayscale transformation. Step 2 involves the wavelet edge detection and a contour extraction. Step 3 consists of a vertical projection based character segmentation and a convolution neural network based character recognition. With the first two steps, the ALPR method can handle images of vehicles moving at a high speed, under poor illumination and from bad imaging angles.

The thesis also presents an application of the ALPR method to 500 images for training and another 300 images for testing. A successful rate of 97 percent was achieved for recognizing the characters and numbers in these test images.

Contents

List of Figures

Chapter 1

Introduction

Automatic plate recognition plays an important roll in daily life in situations like unattended parking lot and security control area with the rapid growth of urbanization. Technical support can help alleviate the city congestion issues and save manpower resource. The goal of License Plate Recognition is to extract and recognize the license plate without any human involvement. License plate recognition acts as key in traffic management department and plate numbers act like ID for identification. The variations in license plate and environment causes problem in detection of vehicle license plate such as size, font style, color, location of plate on vehicle and plates may have different intensity due to headlight or due to environment. The recognition method varies in different locations. There are several constraints such as different backgrounds, fixed illumination [1], moving speed, etc.

License plate recognition method has changed dramatically with the development of computer vision. In the 1963, the first object detection method with perceptron[2] is invented by David Hubel and Torsten Wiesel. They have studied biology related recognition and confirms that edge describes key information. In 1970s, image modeling such as 3D modeling and stereoscopic vision has maintained great popularity and artificial intelligent has been first applied to computer vision. Computer vision has vigorous achievement since 1980s. Mathematical methods such as canny edge detection[3] and pattern recognition have been invented. In 1990s, machine learning[4] has been widely applied to recognition, detection, segmentation, etc. Since then computer vision is not only processed through signal processing but also machine learning. In this thesis, signal processing methods such as sobel operator, close operation are constructed together with machine learning method like convolution neural network. The two methods are combined for gathering the efficiency of traditional signal processing and the accuracy of machine learning. In this thesis, there are three steps in the license plate recognition process, which are image pre-processing, license plate location and character recognition. The first step is image pre-processing. Image pre-processing [5] makes the image to contain less noise points and easier to extract plate border. A gaussian blur is first constructed to denoise the image. The image is then transformed into gray-scale image for simplifying the whole process because colored images takes far more steps and there are operators do not suit color images. Sobel operator is applied for getting the horizontal first-order derivative for making the plate characters more obvious. Binarization turns the gray images pixels into just 0 or 1 for simplification.

During the edge detection process, close operation makes the characters on plate connecting to each other and forming a rectangle. Sobel Operator is applied for better location comparing with Roberts Operator and Laplace Operator. Edges are located by wavelet or morphological method. After that the rotation and distortion condition should be checked for further recovery. The pre-processing and edge detection process can be combined as license plate location. It is shown as Fig.1.1.

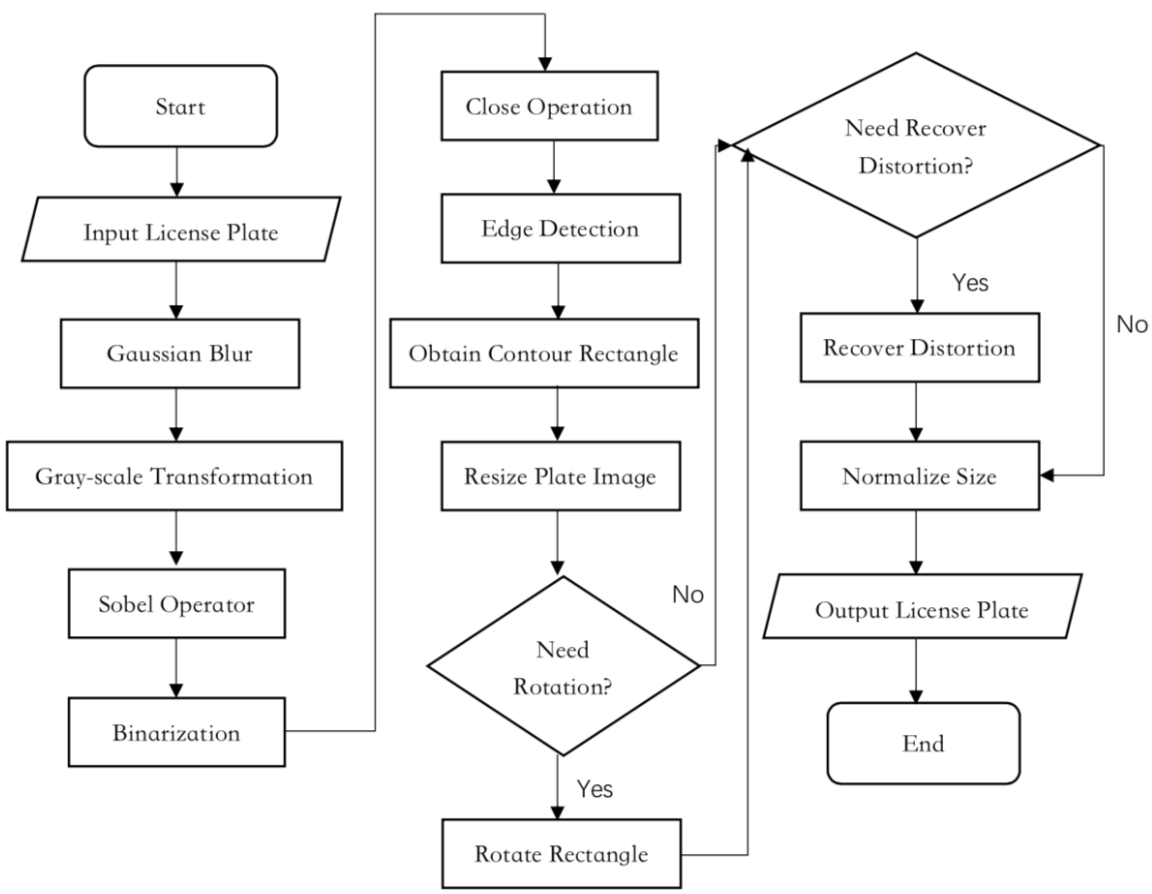

Figure 1.1: License Plate Location Process

The character recognition process begins with character segmentation by constructing a horizontal projection to the plate for detecting the characters' position and gap. Then the character are segmented and built for database. The character database contains 26 characters(from a to z) and 10 numbers(from 0 to 9), but zero and O are taken as the same so there would be only 35 classes. Convolution neural network model is trained by the 35 classes for recognizing. Then we use the trained CNN model to detect more license plate characters. The process of character recognition can be summarized as block diagram as Fig. 1.2.

The result is tested within the license plate image database and the overall performance of the method is good in most conditions.

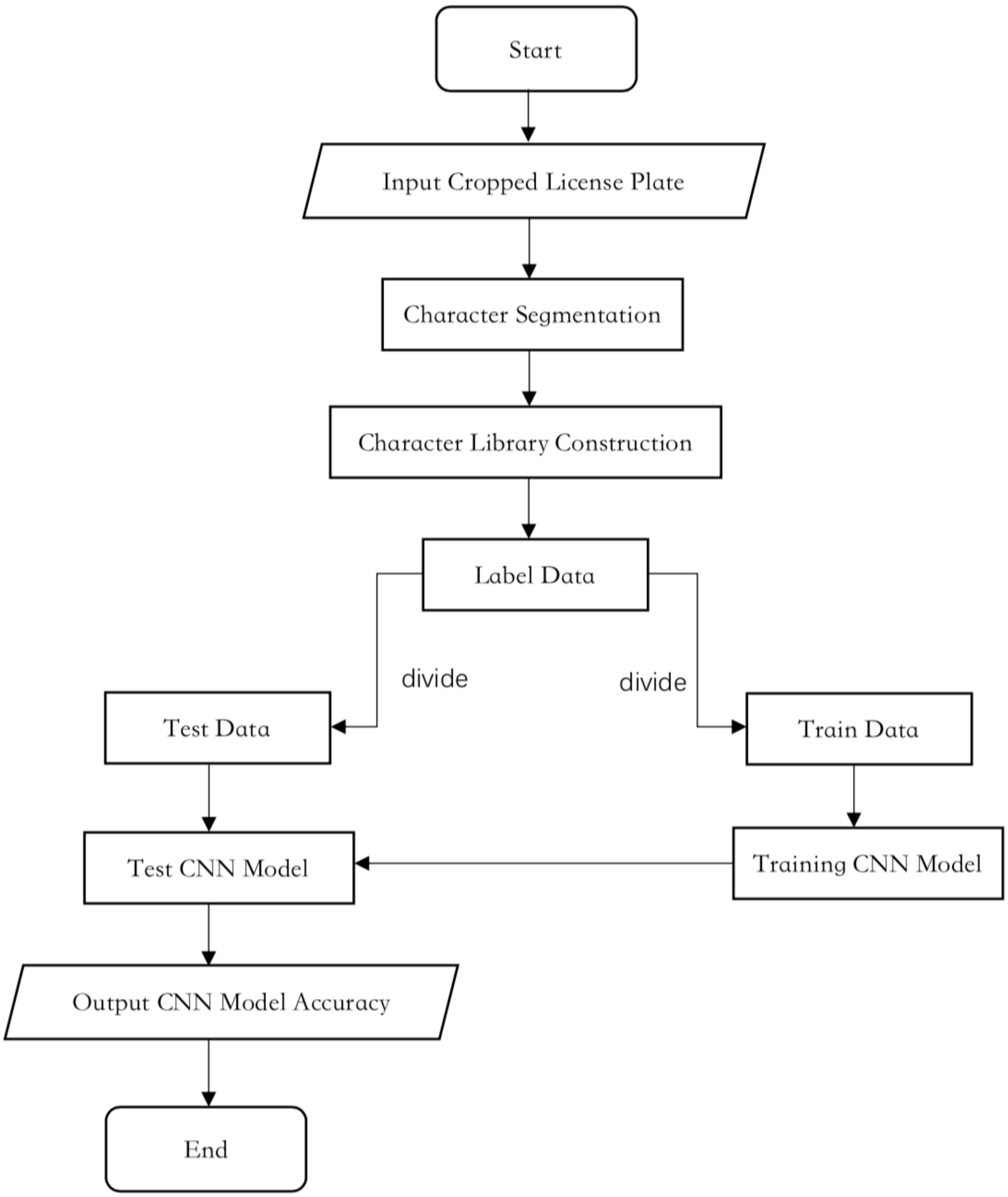

Figure 1.2: License Plate Recognition Process

Chapter 2

License Plate Recognition

2.1 License Plate Pre-processing Module

2.1.1 Basic Concepts

Image pre-processing provides solid foundation for plate recognition and makes it more adaptive for recognition. Pre-processing can ignore effects like light, movement, shooting position and sharpness of the image. When the light does not irradiate evenly, the contrast of the image is low and requires equilibrium. This thesis aims at relaxing the constraints by several optimization methods.

- SHAPE CHARACTERISTICS The height and width of the license plate is set. The plate edge is rectangle consists of lines and varies in a certain range. The finished plate size for digital license plates is 12 inches * 6 inches and allows up to 7.5 characters (a space counted as 0.5 characters). The actual width and height can vary due to shooting angle.

- Character Characteristic This part is produced by Yuanxi Fu. The license plate contains numbers and characters. There are 26 characters and 10 numbers.

- GRAY SCALE VARIATION [6] The license plate contains different colors which have different gray scale values. The color edge of plate leads to mutation. The plate edge tend to act as roof shape. The edge gray-scale of the plate from horizontal direction and perpendicular direction shows continuous downtrend and then uptrend. The histogram of the edge gray-scale has two separate center. These characteristics are used for plate recognition and character segmentation.

2.1.2 Gaussian Blur [7]

There are always some noises on images. Gaussian filter can remove the noise from the license plate. Gaussian blur contains the convolution of Gaussian function with the image pixels. The convolution in discrete case is:

$$f * g[n] = \sum_{m=-\infty}^{\infty} f[m] \cdot g[n-m] \tag{2.1}$$

In two dimension as dealing with images, the function can be described as:

$$f(x,y) = M \cdot e^{-(\frac{(x-x_0)^2}{2\sigma x^2} + \frac{(x-y_0)^2}{2\sigma y^2})} \tag{2.2}$$

where M is the amplitude, (x_O, y_O) is the pixel center and $\sigma x, \sigma y$ is the standard deviation. The variance of the Gaussian distribution significantly affects the filtering results.

2.1.3 Gray-scale Transformation [8]

Gray-scale transformation could speed up the subsequent steps and transform various kinds of images to gray images to simplify the process. Color image is of three basic colors, red, green and blue. Gray-scale transformation simply transforms images from color to gray and the weight of those three colors equal. Gray-scale transformation is usually applied by achieving gray-scale invariance. The gray-scale transformation is by calculating the red, green and blue component with respective weight as equation 2.3.

$$Gray = (R * 299 + G * 587 + B * 114 + 500)/1000 \tag{2.3}$$

Where Gray is every pixel's final gray-scale value. R,G,B is the pixel's red, green and blue component value. The result of gray-scale transformation is shown as figure 2.1 and 2.2.

Figure 2.1: Original Plate

Figure 2.2: Gray-scale Plate

2.1.4 Image Intensification

The image edges blur after gray-scale transformation and is hard to detect. Intensification helps increase the contrast of image for better obtain license plate. Gray-scale transformation, image smoothing and linear filter are frequently used intensification methods. In this paper, we apply object detection open operator for removing the edges of small objects and smoothing big objects.

- Open operator [9] is applied to the original image for background image. Opening operation is defined as erosion first and following a dilation by the same structured element. The two inputs for opening are an image and a structuring element serves as a filter template. Gray-scale opening consists simply of gray-level erosion followed by gray-scale dilation. Then the background image is deducted from the original gray image for image intensification.

- The background image is deducted from the original gray image for image intensification.

2.1.5 Edge Detection

Edge detection focuses on three kinds of edges, object to object, background to object and region to region(including different color). Edge detection precisely locates the edges and restrains noises. The differential operator has significant effect on gray-scale transformation and makes edges get high value in results. These can be applied for edge classification. Sobel operator, Roberts operator and Laplace operator are frequently applied edge detection operators and in this thesis a comparison between the three operators are constructed for better edge detection results.

Roberts Operator [10]

Roberts Operator locates edges very precisely but cannot remove noise. Edges appear when brightness varies and has complex forms. Edges can be detected most precisely with gradient detection method. Suppose f(x,y) is the distribution function of image gray scale, s(x,y) is the gradient value of image edges, and p(x,y) is the gradient direction, then

$$s(x,y) = \sqrt{[f(x+n,y) - f(x,y)]^2 + [f(x,y+n) - f(x,y)]^2} \tag{2.4}$$

$$p(x,y) = tan \frac{f(x+n,y - f(x,y)}{f(x,y+n) - f(x,y)} \tag{2.5}$$

And equation(1) can be rewritten as gradient value and direction at (x,y),

$$g(x,y) = \sqrt{[\sqrt{f(x,y)} - \sqrt{f(x+1,y+1)}]^2 + [\sqrt{f(x+1,y)} - \sqrt{f(x,y+1)}]^2} \tag{2.6}$$

where g(x,y) is the Robert edge detection operator. The square calculation of f(x,y) makes the process like vision system. In fact, Robert edge detection searches for edges by partial differentiation by calculating the diagonal difference of adjacent pixels. The expressions can be written in gradient forms as in equation 2.12 and 2.13.

$$\Delta_x f(x,y) = f(x,y) - f(x-1,y-1) \tag{2.7}$$

$$\Delta_y f(x-1,y) = f(x,y) - f(x,y-1) \tag{2.8}$$

Sobel Operator [11]

Sobel Operator is directional and forms the strongest edge from horizontal direction and vertical direction. Sobel Operator is expert in both detecting edges and controlling noises. The operator is the convolution of $g_1(x,y)$ and $g_2(x,y)$ and the original f(x,y). The operator can be expressed as equation 2.14.

$$s(x,y) = \max\,[\sum_{m=1}^{M}\sum_{n=1}^{N} f(m,n)g_1(i-m,j-n), \sum_{m=1}^{M}\sum_{n=1}^{N} f(m,n)g_2(i-m,j-n)] \tag{2.9}$$

In fact, Sobel Operator first measures the weighted average and then measures the differential operation. The gradient is as equation 2.15.

$$\Delta_x f(x,y) = [f(x-1,y+1)+2f(x,y+1)+f(x+1,y+1)]-[f(x-1,y-1)+2f(x,y-1)+f(x+1,y-1)] \tag{2.10}$$

$$\Delta_y f(x,y) = [f(x-1,y-1)+2f(x-1,y)+f(x-1,y+1)]-[f(x-1,y-1)+2f(x+1,y)+f(x+1,y+1)] \tag{2.11}$$

Sobel Operator detects edges from horizontal and perpendicular direction of an image and measures the maximum convolution of the two convolutions. The result is an image with obvious edges.

Laplacian Operator [12]

Laplacian Operator measures edges from all directions and is sensitive to fine lines and independent points. However, it has negative effect on noise and produces dual pixel edges. Laplacian edge detector measures the derivative of 2D function. The definition is as equation 2.17.

$$\nabla^2 f(x,y) = \frac{d^2 f(x,y)}{dx^2} + \frac{d^2 f(x,y)}{dy^2} \tag{2.12}$$

If replacing derivative by differential equation, it can be expressed as equation 2.18 and 2.19.

$$\Delta^2 f(x,y) = f(x+1,y) + f(x-1,y) + f(x,y+1) + f(x,y-1) - 4f(x,y) \tag{2.13}$$

$$\begin{aligned}\Delta^2 f(x,y) = f(x-1,y-1) + f(x,y-1) + f(x+1,y-1) + f(x-1,y) + \\ f(x+1,y) + f(x-1,y+1) + f(x,y+1) + f(x+1,y+1) - 8f(x,y)\end{aligned} \tag{2.14}$$

The character of Laplacian edge detector is that the central coefficient is positive and the rest are negative. The coefficients sum up to be zero. The Laplacian operator is sensitive to lines, points and noises but not directions. So it is not usually applied for edge detection.

Comparison

We can obtain the three edge detector results from figure 2.3, figure 2.4 and figure 2.5. We could learn from the figures that sobel operator performs best in connecting parts within license plate.

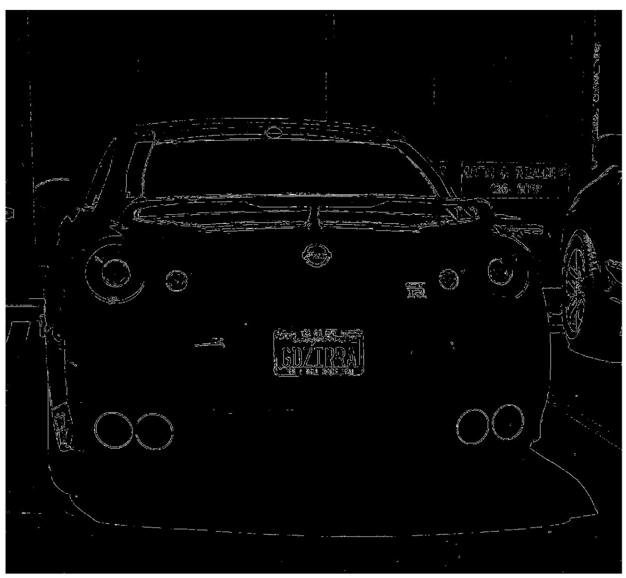

Figure 2.3: Roberts Operator

Also we could learn from the above edge detection, Roberts operator is good at

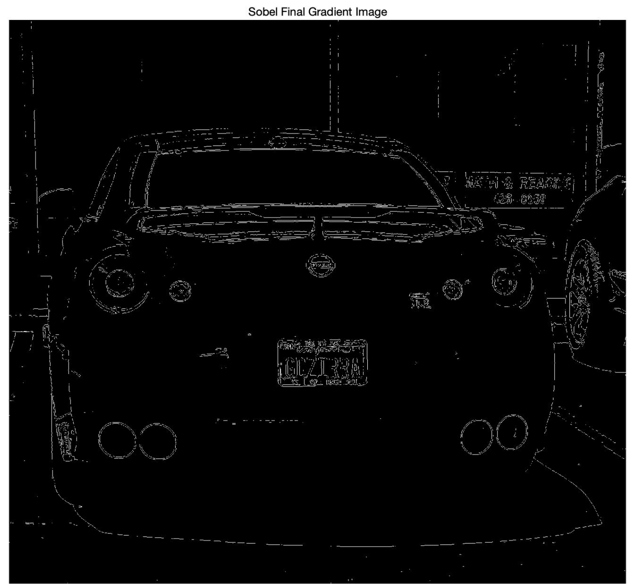

Figure 2.4: Sobel Operator

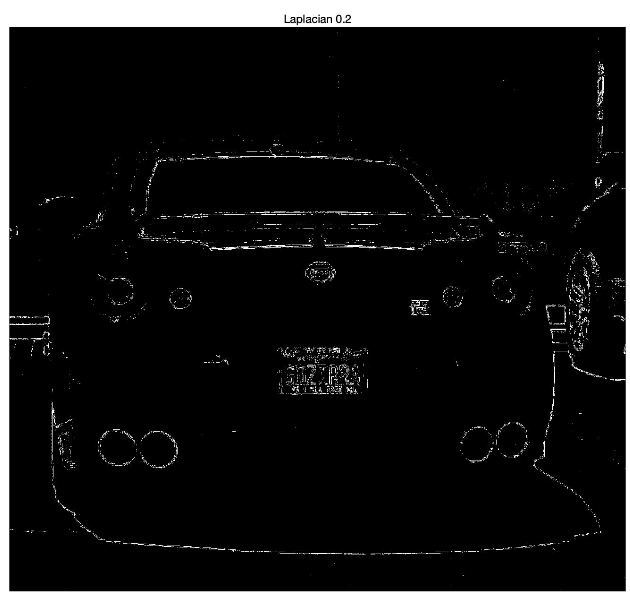

Figure 2.5: Laplace Operator

locating but is not sensitive to noise. Sobel operator is an average filter and can control noise. Laplace operator is good at detecting step edges but not sensitive to noise. In this paper we choose Sobel operator for better denoising.

2.2 Gray-level Image Binarization [13]

Gray-level image binarization is for setting the image to gray condition that has gray-level value of 0 or 255. Adjusting the threshold of 256 luminous level can get the binary image of the original image. The image features are only influenced by the pixel between 0 to 255. This would simplifies the process and decrease the data processing workload. Closed and continuous but not overlapping boundary region is usually applied for ideal binary image. Any image which gray-scale value greater than threshold would be classified as particular object and the gray-level value is 255, or it would be excluded from object region. If a specific object has same gray-scale value inside and is under the background where other gray scale value is even , threshold method can do well in segmentation. Different features can be turned into gray scale value if a object background difference is not in gray-level value. Dynamic adjustment for image binarizaion gets segmentation observable results. The threshold value is calculated by equation 2.20.

$$Level = f_{max} - (f_{max} - f_{min})/3 \tag{2.15}$$

where Level is the best threshold value, f_{max} is the maximum gray scale value and f_{min} is the minimum gray scale value.

2.3 License Plate Location Method

Traditional textural feature extraction method most bases on gray-level images. So the image is pre-processed and transformed from color to gray-scale condition. Textural feature method first scans the image and finds every line contains license plate and records the start point and length. If there is more than one row contains more than one license plate line and the row numbers is greater than threshold, it is confirmed that a possible license plate region is found in the horizontal direction. The possible region's start point and height are recorded. Then scan the possible license plate region and confirm the start point and height for a real license plate region.

2.3.1 Mathematical Morphology Location Method [14]

The basic principal of mathematical morphology location method is compiling the image by a structural element to see if the element could fill perfectly inside the image. The method is also valued for efficiency in filling elements. Erosion, dilation, open and closed is the basic mathematical operations. Erosion can be defined as:

$$F \Theta B = x : B + x \subset F \tag{2.16}$$

Dilation can be defined as:

$$F \oplus B = YF + b : b \subset B \tag{2.17}$$

Open and close operation is composed of erosion and dilation algebraic operation and set operation. Open operation can be defined as:

$$F \circ B = (F \Theta B) \oplus B \tag{2.18}$$

Close operation can be defined as:

$$F \bullet B = (F \oplus B)\Theta B \tag{2.19}$$

Based on the morphological characteristics of computing, the operation of erosion and dilation meets:

$$F\Theta B \subseteq F \subseteq F \oplus B \tag{2.20}$$

the operation of open and close meets:

$$F \circ B \subseteq F \subseteq F \bullet B \tag{2.21}$$

If Ed(F) represents dilation residue edge detector, it can be defined as the difference between the result of image F which is dilated by structure element B and the original image.

$$Ed(F) = (F \oplus B) - F \tag{2.22}$$

If Ee(F) is the erosion residue edge detector, it can be defined similarly to the original image and the results of image F which was eroded by the structure element B.

$$Ee(F) = F - (F\Theta B) \tag{2.23}$$

If G(F) is the morphology gradient of image F, it can be calculated by dilation and erosion:

$$G(F) = (F \oplus B) - (F\Theta B) \tag{2.24}$$

The processing of dilation and erosion makes the image minishing or enlarging, while the difference between original image and the changed image is the image edge. We can see the close-operated figure as figure 2.6 and 2.7.

Figure 2.6: Binarized Plate

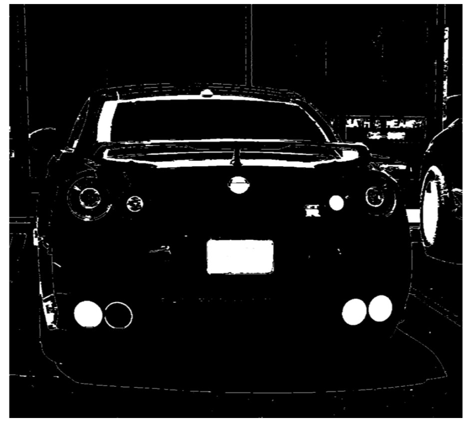

Figure 2.7: Close-operated Plate

2.3.2 Wavelet Analysis Location Method [15]

Wavelet analysis is an important application for image processing and has the microscope feature. It has the multi-resolution character and acts different on high frequency wavelet with different direction. Directional wavelet can show image variation on different resolution. It matches more with human vision. The continuous wavelet transform of a function $f(t) \in L^2$ with respect to an analyzing wavelet ψ is defined as equation 2.25.

$$WT_f(a,b) = \int_{-\infty}^{+\infty} f(t)\psi_{a,b}dt, \tag{2.25}$$

where $\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi(\frac{t-b}{a})$, $a > 0$, and $\psi(t)$ satisfies equation 2.26.

$$\int_{-\infty}^{+\infty} \psi(t)dt = 0. \tag{2.26}$$

Wavelet transforms can be computed by convolving the signal with a wavelet, so the wavelet transform of f(t) at the scale a and position b is represented as equation 2.27.

$$WT_f(a,b) = \sqrt{a}f * \psi_a(b), \tag{2.27}$$

where

$$\psi_a(t) = a^{-1}\psi(-t/a). \tag{2.28}$$

$\psi_a(t)$ can be considered as a high-pass filter.

We can obtain the wavelet edge detection image as figure 2.8 and 2.9. As we could

Figure 2.8: Binarized Plate

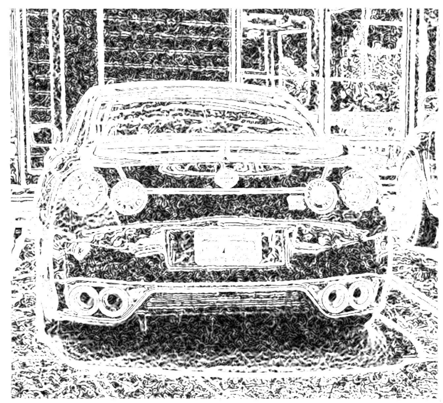

Figure 2.9: Wavelet Edge Detection

obtain from the result images that, wavelet operator is good at locating whole regions like license plate. However, it is bad at dealing with noises.

2.4 License Plate Recognition by Traditional Method

2.4.1 License Plate Region Segmentation

This paper applied an effective segmentation method[16]. It is different from neural network model recognition but more sufficient than traditional methods. The method has the following steps.

Vertical Projection

Vertical edge detection on the license plate performs as Sobel operator as we mentioned before. We can obtain the histogram as below figure 2.11. After finding the area

Figure 2.10: Binarized Plate

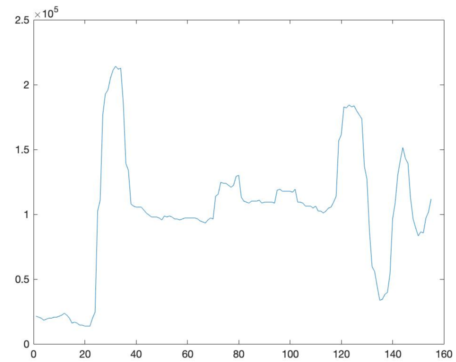

Figure 2.11: Horizontal Projection Histogram

bounded by the upper and lower bounds of a number plate, the area above the upper bound and below the lower bound are removed. The remaining area without the upper and lower boundaries of the number plate is considered for character segmentation on the number plate. An array is used for collecting the white pixel numbers in each column.

Gray-scale Projection Histogram

We performs a projection histogram to find the gaps between characters on a license plate. The value of a histogram bin is the sum of the white pixels along a line in vertical direction. As we could learn from figure 2.11, there are obvious drop in the figure which represents the gap between characters. So the gap can be easily obtained.

2.4.2 License Plate Further Process

There are still noises exists after the segmentation. A threshold value t is set for separating the data into two parts: pixels bigger than t and pixels smaller than t. Median filter constructs the median pixel to replace the original pixel.

2.4.3 Character Segmentation and Normalization

In this thesis, I examine the pixels one by one and confirm there is no other pixel. If there is other pixel then unnecessary image parts are cut. A threshold is set by image size and detect the x-axis of the image. If the width is greater than the threshold, the image is cut. The normalized character image size is 20*10 and matches the template.

Character Segmentation

In the automatic license plate process, character segmentation serves as a link between previous and next process. Segmentation bases on the previous process of license plate location and take advantage of segmentation for character recognition. In this thesis, a character searching method of searching continuous character module is implemented. If the width of the character is greater than the threshold, there is more than two characters and requires second segmentation.

Character Normalization

Segmented character usually requires further process for character recognition. However, for license plate recognition no further process is needed for accurate recognition.

2.4.4 Character Recognition

There are two character recognition(OCR)[17] method in license plate recognition: template based OCR method and convolution neural network based method. Template based OCR first recognizes character and binarizes it to template size. Then it matches it with the template and selects the best results. This method is easily realized and efficient when the image has defects. So we use this method as comparison in this paper. It first extracts some characteristic from image region $f(i, j)$ and compares it with the template according region $T(i, j)$ for standardization cross correlation. The highest value correlation has the most similarity. It can also be measured by calculating the characteristic distance between object and model. Normally the images applied for matching have different forming conditions and much noises. Or they are pre-processed or standardized so the gray level and pixel location changed. When designing the real model, the intrinsic shape characteristics of the region, noise and image displacement are taken into consideration. The template is constructed with image intrinsic characteristics to avoid other impacts. This method applies subtraction to search for the most similar character and output the most similarity. The license plate has seven characters and each character can be number or letter. So in this paper we constructed a template of 26 letters and 10 numbers. But the total classes should be taken as 35 because zero and O are treated the same. The image is compared with the template and is being subtracted with the template. More zeros are produced then the characters match with more characters.

2.5 License Plate Recognition by Neural Network Method

In this thesis, convolution neural network method[18] is used for license plate recognition. This contains the following processes.

2.5.1 Image Pre-processing

The license plate image is first transformed to gray level image for simplifying the process. Then the image is binarized for contours extraction. Different coefficients are applied as threshold for binarization.

2.5.2 Contour Extraction

The interconnect periphery is connected to form a circumscribed rectangle. This process takes all the independent but not correlated with background parts out. Then the minimum bounding rectangle is calculated for further character segmentation.

2.5.3 Rotation

The image may have some slope between standard requirements and therefore rotation is needed. This thesis applies randon transformation[19] to the license plate. Randon transformation projects x-y axis to another space. When recording the points on another space, I know the existance in x-y axis. Suppose a function f(x,y), so the integration of a line going through it should be $\int_L f(x,y)ds$, while ds is the line differential. So given a ρ or θ, we could obtain the integration of ρ or θ in the direction of L. If we integrate each line with $f(x,y)$, we would get N specific randon integration values, and each integration value has a coordinate. Randon transformation projects the original space line to $\rho\theta$ space points. The high gray-scale-value lines would becomes light spot in $\rho\theta$ space and the low gray-scale-value lines would becomes dark spot. We can see the results as Fig. 2.12.

Figure 2.12: Rotated Plate

2.5.4 Distortion [20]

Distortion can be recovered by vanished points recovery method. A pair of parallel lines forms vanished points after image tomography as shown in Fig. 2.13, where ABCD is a rectangular license plate and abcd is a uneven trapezoid projection. It generates two vanished points $F_u and F_v$. The camera focal distance equation is as equation 2.29.

$$f = OP = \sqrt{OP_{uv}^2 - PP_{uv}^2} = \sqrt{F_u P_{uv} \times F_v - P_{uv} - PP_{uv}^2} = \sqrt{-(F_u^x \times F_v^x + F_u^y \times F_v^y)} \tag{2.29}$$

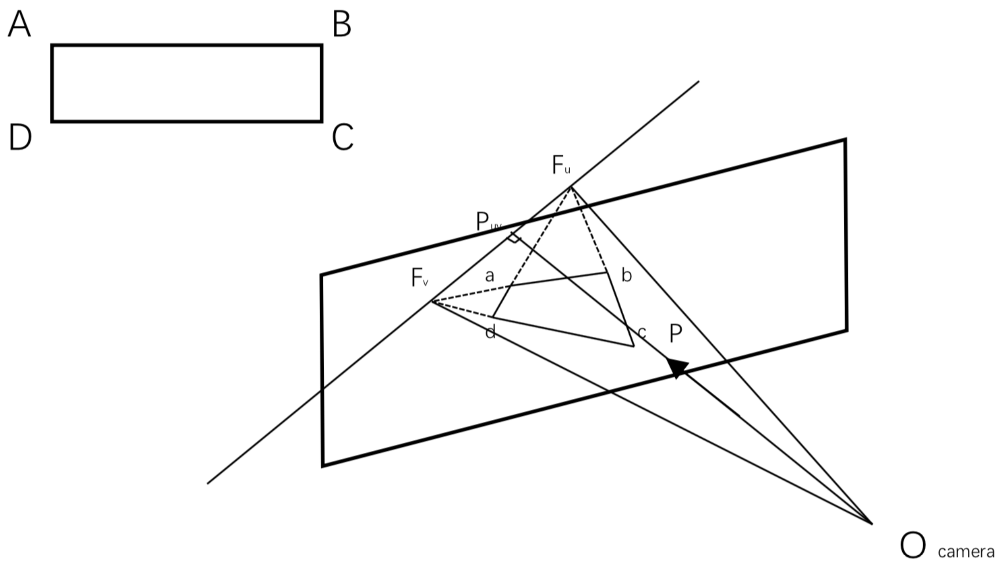

Figure 2.13: License Plate Tomography

where as P_{uv} is the vertical projection of P on (F_u, F_v). F_{xu},F_{xv},F_{yu},F_{yv} are the vanished points F_u and F_v's coordinate on x-axis and y-axis. Usually suppose the real world z-axis coordinate is zero, so

$$S\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = K[r_1 r_2 r_3 t]\begin{bmatrix} X \\ Y \\ 0 \\ 1 \end{bmatrix} = K[r_1 r_2 t]\begin{bmatrix} X \\ Y \\ 1 \end{bmatrix} \tag{2.30}$$

Every point $X' = [X, Y, 1]^T$ and its relation between its projection point $x = [u, v, 1]^T$ can be described as a homography matrix H:

$$x = HX'; H = K[r_1 r_2 t] \tag{2.31}$$

The homographic relation between space plane and projected graph is independent from background. Matrix H is a nonsingular matrix and can be applied to projection image to recover the license plate's original shape. The homographic matrix H can be decomposed as equation 2.32.

$$H = EH_eH_p; H_e = \begin{bmatrix} 1/\beta & -\alpha/\beta & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}; H_p = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ l_1 & l_2 & 1 \end{bmatrix}; \tag{2.32}$$

Where E is a similar transformation matrix, H_P is reconstruction matrix and H_e is measurement matrix. H_P projects the distorted shape to be parallelogram and projects L_∞ to infinite distance. H_e projects the parallelogram to a rectangle. The line can be calculated as equation 2.33.

$$L_\infty = [l_1 l_2 1]^T = F_u \times F_v \tag{2.33}$$

The reconstruction matrix H_e can be calculated by absolute quadratic curve ω and line L_∞ as equation 2.34.

$$\omega = (KK^T)^{-1} = K^{-T}K^l I^T \omega I = 0; I = \begin{bmatrix} \alpha - i\beta \\ l \\ -l_2 - \alpha l_1 + i l_1 \beta \end{bmatrix} \tag{2.34}$$

Where l is absolute quadratic curve ω and L_∞'s cross point, we can obtain the last equation as:

$$(1 + l_1^2 f^2)x^2 + 2l_1 l_2 f^2 x + (1 + l_2^2 f^2) = 0 \tag{2.35}$$

where α and β respectively gets its real part and imaginary part. The gray-scale value of a point can be estimated by adjacent pixel's gray-scale as equation 2.36.

$$f(x,y) = [f(1,0)-f(0,0)]x+[f(0,1)-f(0,0)]y+[f(0,0)+f(1,1)-f(0,1)-f(1,0)]xy+f(0,0) \tag{2.36}$$

where (x,y) is P's coordinate and (0,0),(0,1),(1,0),(1,1) are P's adjacent coordinates, whose gray-scale value is f(0,0),f(0,1),f(1,0),f(1,1). We could obtain the effect of matrix H_e and H_p as figure 2.14.

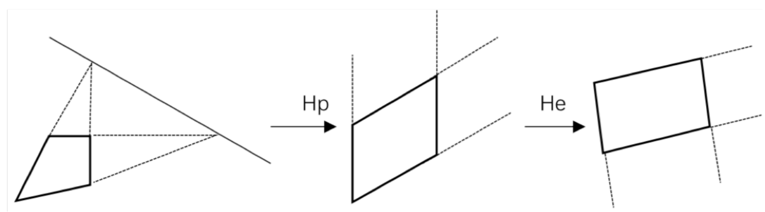

Figure 2.14: Reconstruction Process

The final results of distortion recovery is as figure 2.14 and 2.15.

Figure 2.15: Distorted Plate

Figure 2.16: Recovery Plate

2.5.5 Character Segmentation

After finding the out bounding rectangle of the characters, it is easy to cut the rectangle regions each with a character as traditional segmentation method. Normalization is applied for standard character format.

2.5.6 Feature Extraction for Training Image

The image should be put into Artificial Neural Network Model for training. Before that features should be extracted for training. There are three kinds of features. Histogram of Oriented Gradient is a kind of object detection feature by calculating image regional gradient distribution. Local Binary Pattern is a kind of partial binarized model and is image regional textural features operator and rotational invariant and gray-level invariant. Haar features has edge feature, linearity feature, central feature and diagonal feature. The extracted features are brought for training.

2.5.7 Training

The extracted features are brought to OpenCV for training. In this paper we applied RBF core for training. RBF core property is classified by penalty coefficient and gamma. We need to find the best match of these factors and the easiest way is exhaustion method.

2.5.8 Convolution Neural Network

The pre-trained images are input into the convolution neural network model to train the model to recognize the characters. A convolution neural network[21] is a computational model inspired by networks of biological neurons. It learns from its past experience and errors in a non-linear parallel processing manner. The neuron is the basic calculating entities which computes from a number of inputs and deliver output comparing with threshold value and turned on. The computational processing is done by internal structural arrangement consists of hidden layers which utilizes the back propagation and feed forward mechanism to deliver output close to accuracy. The learning is based on reinforcement and unsupervised type. The unsupervised mimics the biological neuron pattern of learning. In this paper we applied artificial neural network model to be trained by characters and predict characters later. The settings of the convolution neural network is as Tabel 2.1.

Layer Type	**Parameters**
Softmax	35 classes
Fully connected	35 neurons
Dropout	0.5
ReLU	
Fully connected	1024 neurons
Maxpooling	P:2x2, stride:2
ReLU	
Convolution	filtres 256 kernel :3 x3 , stride :1
ReLU	
Convolution	filtres 128 kernel :3 x3 , stride :1
ReLU	
Convolution	filtres : 64 kernel :3 x3 , stride :1
Maxpooling	P :2 x 2 , stride :2
ReLU	
Convolution	filtres : 32, kernel :5x5, stride :1, p :0
Input	32 x 32 binary image

Table 2.1: Neural Network Settings

Chapter 3

Discussion and Conclusion

3.1 Discussion

In this thesis, 300 images are applied for testing. The accuracy is calculated by the division of the numbers of characters and numbers recognized to the numbers of total characters and number. The images are collected manually on Google and license plate database. Each picture is labeled manually by changing the file name as the license plate number to check the accuracy. The total character accuracy achieves 97.05% where the accuracy for normal condition license plate recognition is 100%. The accuracy may be restricted by the distortion recovery limitations. When the license plate is extremely distorted, the plate cannot be recovered. Also when there is additional marks between license plate character like "· ", it influences the accuracy. The recognition accuracy can be improved by changing the neural network models to better accuracy but slower models like fast R-CNN. We could learn from the accuracy curve that the CNN model performs well after around 10 times of performance. The accuracy and loss curve is shown as figure 3.1

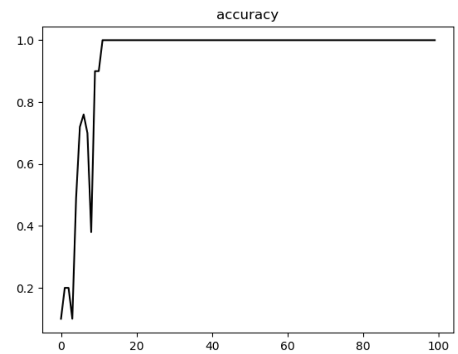

Figure 3.1: Accuracy Curve

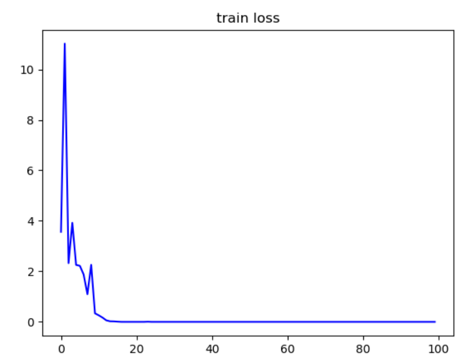

Figure 3.2: Training Loss Curve

and figure 3.2. The model is trained well and with acceptable loss and the accuracy is almost 100with good enough license plate images.

3.2 Conclusion

The thesis conducts a license plate detection and recognition method. The license plate is firstly pre-processed for better obtaining the edges and removing noise. Wavelet edge detection and close operation are applied for plate location. Horizontal and vertical projection are applied for character segmentation. Optical character recognition and convolutional network methods are used for character recognition. The total accuracy is 97.05% from 300 tested pictures. The results can still be improved by adjusting parameters of neural network and conducting rotation and distortion recovery.

Bibliography

[1] P. Davies, N. Emmott, and N. Ayland, ”License plate recognition technology for toll violation enforcement”, Inst. Elect. Eng. Colloquium Image Analysis for Transport Applications, pp. 7/17/5, 1990.

[2] Lienhard, Dina A., ”David H. Hubel and Torsten N. Wiesels Research on Optical Development in Kittens”, Embryo Project Encyclopedia (2017-10-11). ISSN: 1940-5030 http://embryo.asu.edu/handle/10776/12995.

[3] John Canny, ”A Computational Approach to Edge Detection”, IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE, VOL. PAMI-8, NO. 6, NOVEMBER 1986.

[4] Sayanan Sivaraman, Mohan Manubhai Trivedi, ”Looking at Vehicles on the Road: A Survey of Vision-Based Vehicle Detection, Tracking, and Behavior Analysis”, IEEE Transactions on Intelligent Transportation Systems Volume: 14 , Issue: 4 , Dec. 2013.

[5] M Sonka, V Hlavac, R Boyle, ”Image processing, analysis, and machine vision,” 2014.

[6] Keun-Chung Kim, Doo-Young Kim, J. K. Aggarwal, ”Feature Extraction of Edge by Directional Computation of Gray-scale Variation”, Proceedings. Fourteenth International Conference on Pattern Recognition (Cat. No.98EX170), 1998.

[7] Estevo S. Gedraite, Murielle Hadad, ”Investigation on the Effect of a Gaussian Blur in Image Filtering and Segmentation”, Proceedings ELMAR-2011 14-16, Sept. 2011.

[8] Timo Ojala, Matti Pietikinen, Topi Menp, ”Gray Scale and Rotation Invariant Texture Classification with Local Binary Patterns”, European Conference on Computer Vision ECCV 2000: Computer Vision - ECCV 2000 pp 404-420, 2000.

[9] A.M.Raid, W.M.Khedr, M.A.El-dosuky, and Mona Aoud, ”Image Restoration Based on Morphological Operations”, International Journal of Computer Science, Engineering and Information Technology (IJCSEIT), Vol. 4, No.3, June 2014.

[10] Aili Wang, Xusheng Liu, ”Vehicle License Plate Location Based on Improved Roberts Operator and Mathematical Morphology”, 2012 Second International Conference on Instrumentation Measurement, Computer, Communication and Control, 2012.

[11] Girish N. Chaple, R. D. Daruwala, Manoj S. Gofane, ”Comparisions of Robert, Prewitt, Sobel Operator Based Edge Detection Methods for Real Time Uses on FPGA”, 2015 International Conference on Technologies for Sustainable Development (ICTSD-2015), Feb. 04 06, 2015, Mumbai, India.

[12] ”Blur Image Detection using Laplacian Operator and Open-CV”, Proceedings of the SMART -2016, 5th International Conference on System Modeling Advancement in Research Trends, 25th November, 2016 College of Computing Sciences Information Technology, 2016.

[13] Haijun Lei, Lingmin Li, Panpan Zhang, Ming Wang, Xianyi Li, ”A Binarization Algorithm for Digital Meter Image”, 2010 3rd International Congress on Image and Signal Processing (CISP2010), 2010. Based on Gray-scale Morphology

[14] Chun-rong X., Tie-jun C., Jie L. (2012) ”Algorithm of License Plate Location Based on Morphological Multi-Structural Elements”. In: Zhang Y. (eds) Future Communication, Computing, Control and Management. Lecture Notes in Electrical Engineering, vol 141. Springer, Berlin, Heidelberg.

[15] Zhen Zhang, Siliang M, Hui Liu, Yuexin Gong, ”An edge detection approach based on directional wavelet transform”, Computers and Mathematics with Applications 57 (2009) 12651271,2009.

[16] Xiangjian He, Lihong Zheng, Qiang Wu, Wenjing Jia, Bijan Samali, Marimuthu Palaniswami,”Segmentation of Characters on Car License Plates”, 2007.

[17] Prashengit Dhar, Sunanda Guha, Tonoy Biswas, Md. Zainal Abedin, ”A System Design for License Plate Recognition by Using Edge Detection and Convolution Neural Network”,2018 International Conference on Computer, Communication, Chemical, Material and Electronic Engineering (IC4ME2), 2018.

[18] Muhammad Tahir Qadri, Muhammad Asif, ”Automatic Number Plate Recognition System for Vehicle Identification Using Optical Character Recognition”, 2009 International Conference on Education Technology and Computer, 2019.

[19] Cang Yan, Zhang Rubo,”Study on Time-Frequency Distribution based on Randon Transformation”, 2011 Cross Strait Quad-Regional Radio Science and Wireless Technology Conference , 2011.

[20] Xu Xiaowei, Wang Zhiyan, Cao xiaoye, Liang Yinghong, ”Rapid Skew Distortion Rectificaion for Vehicle Lisence Plate Images Based on Vanished Points”, Application Research of Computers Vol.25 No.8, 2008.

[21] Shoji Kido, Yasusi Hirano, Noriaki Hashimoto, ”Detection and Classification of Lung Abnormalities by Use of Convolutional Neural Network (CNN) and Regions with CNN Features (R-CNN)”, 2018 International Workshop on Advanced Image Technology (IWAIT), 2018.