AUTOMATIC NUMBER PLATE DETECTION OF VEHICLE IMAGES BASED ON EDGE DETECTION AND MORPHOLOGICAL APPROACH

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ABSTRACT

A vehicle number plate (NP) is a metal or plastic plate in rectangular shape that contains unique numeric or alphanumeric identifier. In this paper, an algorithm for number plate localization is proposed. The proposed number plate localization algorithm has taken the combination of edge detection, morphological approach and connected component labelling (CCL) method to identify the location of the NP. The proposed algorithm includes image pre-processing stage and number plate localization stage. In image pre-processing stage, after some essential pre-processing and image enhancement, the Canny edge detector is employed to extract the edges from the image with Otsu's thresholding method. The edges in the binary image which generated by Canny edge detector is further thinning with skeletonization approach. Then, morphological approach with different combination of morphological operators is employed to strengthen the structural characteristics of the image including the rectangular shape and remove the small object in the image. The proposed algorithm utilizes the CCL method to label the connected component in the image and using some criteria to identify the rectangular shape of number plate. The proposed algorithm is tested on the total of 48 digital images from Ondrej Martinsky number plate dataset to evaluate and validate its performance. Experimental results show that this approach achieves localization rate around 91.67%.

Keywords: Number Plate, Edge Detection, Morphological Process, Connected Component Labelling, Localization.

1. INTRODUCTION

In the era of the Fourth Industrial Revolution (4IR), registered vehicles are massively increasing every year due to the rapid growth of economic and the improvement of living standards. This led to desperately needed of an intelligent transportation management system which can monitoring vehicles and managing the traffic activity (such as pay toll) in a very short time. Automatic number plate recognition (ANPR) is a mass surveillance method that can identify and read the vehicle's number plate (NP). It is a program which can implemented in the vision systems such as closed-circuit television (CCTV), or any related devices. Since the NP number is unique for every vehicle, ANPR can identify the target vehicle's NP quickly by locating the NP and recognizing the NP number automatically. It works more efficiency than the manual methods when dealing with massive number of vehicles.

One of the crucial parts in ANPR is the NP localization which also mean the detection of NP area. It will significantly affect the result of recognizing the NP number. Due to the mentioned statement, an effective NP localization method need to be carried out to increase the efficiency of ANPR. This project will only focus on NP localization. Thus, it is important to know the terminology of NP. A vehicle number plate (NP) is a metal or plastic plate in rectangular shape attached to a vehicle for official identification purposes. The numeric or alphanumeric identifier on NP are unique for every vehicle owner within the issuing country. The background color of the NP are vary according to the country. Human can define a NP easily, but machines do not understand what NP is. Hence, detect the vehicle NP automatically is not an easy task but a very challenging task. In point of view from machine vision, NP contains two parallel vertical lines and two parallel horizontal lines. The width of the NP is more than the height of NP. It required different technique and skill to identify the rectangular shape of NP in image. In addition, there are many rectangular shape items may appear in the image. It is very hard to determine which rectangular shape is NP accurately.

The purpose of this project is to propose a number plate localization algorithm which is based on the combination of edge detection and morphological processes approach for detecting the number plate in the image. There are two main objectives in this project in order to achieve the purpose mentioned:

i. Identify the rectangular shape of number plate in image.
ii. Able to extract and localize the number plate in image.

The most common techniques in NP localization in digital images are edge extraction, morphological operators, and Hough Transform. Among them, an edge approach is normally fast and simple. However, this approach is sensitive towards noise. In contrast, morphological based approaches is not sensitive to noise but it is very slow. On the other hand, Hough Transform for line detection requires an obvious outline of the NP for NP localization.

Despite the ANPR had been introduced since so many year ago, many researches are still being actively conducted to enhance the NP localization method. For example, S. Kim, et [1] proposed an edge extraction-based approaches for license plate localization under complex image conditions. This approach consists of two steps. The approach is using gradient information to search the candidate areas from the input image in first step and determining the plate area among candidates and adjusting the boundary of the area by introducing a plate template in second step. Moreover, Lee, W, et [2] implemented the morphological method for NP recognition. This approach involves Sobel edge detection method to find the plate edge and find the NP with the final morphological location. In [3], P. Kulkarni, et al proposed a method to find the probable number plate locations with the features of number plates. It needs to find the row and column thresholds. However, the performance is influence by the luminance on the NP. Sarfraz M. et al [4] utilized vertical edge detection and filtering followed by the vertical edge matching in the localization of Saudi Arabian NP. Additional edge extraction-based approaches are proposed in [5] and [6]

For morphological based approaches, Ganapathy and Lui [7] combined the morphological processes with a modified Hough Transform approach in their NP localization algorithm. This approach implements morphological processes to remove the irrelevant objects and find the NP and then apply the Hough Transform to obtain the peaks to determine the NP area. On the other hand, H. Lan and S. Gyanendra [8] proposed a NP localization algorithm based on morphological and image projection technology. This approach uses morphological operator to removes connected components that have fewer than 2000 pixels of binary image and using horizontal and vertical projection locate the NP area. Alternatively, Wu, C. et al [9] proposed an approach that combine morphological operations and a projection searching algorithm for localization of Macao NP.

This project aims to introduce a NP localization method; which mainly consist of the following stages: (1) image pre-processing, which includes color conversion, image enhancement with histogram equalization, Canny edge detection, skeletonize, (2) A method to find the location of rectangle shape NP in the image, based on morphological processes, fill holes, eight neighbourhood connected component labelling (CCL) method.

After the NP localization, a rectangle bounding box will be drawn on the area that contains the NP in the original image. The size of the bounding box is equal to the NP's height with one extra pixel and the image's width.

2. METHODS

The general process for the proposed method is shown in Figure 2.1.

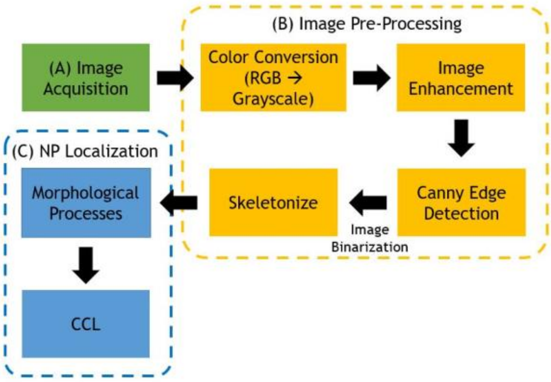

Figure 2.1: General process for the proposed method

2.1 IMAGE ACQUISITION

Image acquisition is an important stage to collect and prepare image dataset for NP localization. In this project, we will use Ondrej Martinsky number plate dataset [10]. This dataset contains 97 images of the front and rear views of various vehicles. The design and pattern of number plates in the dataset are commonly used in the European Union (EU). The background color of number plate in the image is white while the color of the characters on the number plate are black. The dataset is split into training set and test set with the portion 50:50 respectively.

2.2 IMAGE PRE-PROCESSING

Image pre-processing is prerequisite step to prepare the digital image for further processing. In our case, it is required before we perform NP localization. This stage consists of the following steps:

2.2.1 Color Conversion

First of all, the RGB color images will be converted into grayscale (gs) (illustrated in Figure 2.2) by using the standard NTSC or weighted method. This method is eliminating the hue and saturation information while retaining the luminance of the image. Most importantly, this step converts the three color channels – red, green, and blue channel, into a single grayscale channel which is more convenient for subsequent image processing steps. The formula that use in RGB color to grayscale conversion is as follows:

$$gs = 0.299 * R + 0.587 * G + 0.114 * B \qquad (1)$$

where R is red channel, G is green channel and B is blue channel.

Figure 2.2: Outcome of Color Conversion

2.2.2 Image Enhancement

Next, we use the grayscale image as input for image enhancement. Image enhancement is the process to adjust the digital images so that the results are more suitable for further image analysis. In this project, histogram equalization is applied to enhance the image contrast by adjusting the image histogram. In other words, histogram equalization increases the utilized intensity level range. With histogram equalization, the image is somehow sharpening to have a better edge detection result (illustrated in Figure 2.3). In histogram equalization, we constructed a uniform cumulative histogram on the cumulative histogram of input image and find a point of operation that shifts the histogram lines of image to the constructed histogram with linear approximation. The point of operation, $f_{eq()}$ is obtained from the cumulative histogram of image by the formula as follow:

$$f_{eq()} = \left\lfloor H(a) \times \frac{K-1}{WH} \right\rfloor \tag{2}$$

where a is cumulative position, K = 256 or the number of intensity value, W is image width and H is image height.

Figure 2.3: Outcome of Image Enhancement

2.2.3 Canny Edge Detection

Canny edge detection is a process to detect a wide range of edges in images (illustrated in Figure 2.5) with an edge detection operator that uses a multi-stage algorithm and output a binary image with the edges. Canny edge detector is being used in this work because it can minimize the number of false edge points and achieve good localization of edges. There are five algorithm runs separately as shown in Figure 2.4:

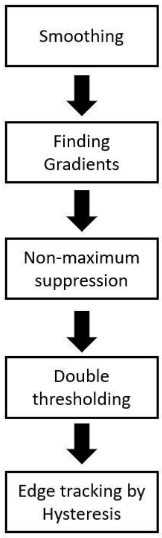

Figure 2.4: The flow of Canny Edge Detector

Figure 2.5: Outcome of Canny Edge Detection

I. Smoothing

Canny edge operator using Gaussian filter to remove the noise by blurring the enhanced grayscale image. Image noise is mainly composed of high-frequency component. Gaussian filter is very powerful in removing high-frequency components from the image. Hence, Gaussian filter is applied on the input images to reduce the noise and blurring the image by a Gaussian function. In our work, we are using 15x15 kernel size and standard deviation of Gaussian distribution, σ = 1.5, for the gaussian filter. Gaussian function is defined as:

$$G_\sigma = \frac{1}{2\pi\sigma^2} e^{-\frac{r^2}{2\sigma^2}} \tag{3}$$

where σ is the standard deviation of Gaussian distribution, and r is the distance (radius) from the center of kernel.

II. Finding Gradients

In this step, Canny edge detector using sobel filter to compute the magnitude, G and orientation, θ, of the edges in the image. Two 3x3 convolution kernels in sobel filter are used to compute the derivatives G_x (4) and G_y (5) of the images in the horizontal and vertical directions. The gradient magnitude for each pixel is computed with the formula as shown in (6) while the orientation for each pixel is computed with the formula as shown in (7). The edge direction or orientation is rounded to one of four angles representing vertical, horizontal and diagonals, [0°, 45°, 90°, and 135°].

$$G_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \quad (4)$$

$$G_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} \quad (5)$$

$$G = \sqrt{{G_x}^2 + {G_y}^2} \quad (6)$$

$$\theta = \arctan\left(\frac{|G_y|}{|G_x|}\right) \quad (7)$$

III Non-Maximum Suppression

Non-maximum suppression is applied to find the local maxima for thinning the edge. The pixels which are not part of the local maxima will be set to zero. This can suppress all image information that is not part of local maxima. This algorithm compares each pixel in the gradient image with the edge strength of the pixel in the positive and negative gradient directions. If the edge strength of the current pixel is larger than the neighbour pixels in the 3 x 3 mask with the same direction, then the edge strength of the current pixel will be retained. Otherwise, the value will be suppressed and set to zero. In short, only local maxima will be marked as edges.

IV Double Thresholding

This step is to determine the potential edges with double threshold value namely T_{low} and T_{high}. Different from the original thresholding algorithm in Canny edge detector, we are using Otsu's thresholding method to generate high threshold, T_{high}. In this work, we use the grayscale image after blurring with Gaussian filter as input for Otsu's thresholding method. Otsu's thresholding method involves iteration through all the possible threshold values which is also pixel values from 0 – 255 and calculating a measure of spread for the pixel levels each side of the threshold or class. There are only two side of the threshold or class: foreground and background.

For Otsu's thresholding method, we calculate what is called the *between class variance*, σ_B^2. It is faster to calculate compared to *within class variance*. In order to calculate *between class variance* (10), it is compulsory to calculate the *weight, W* (8) and *mean, μ* (9) for each side of the threshold. After that, the threshold value with the highest *between class variance* will be selected as the T_{high}. Subsequently, we set the $T_{low} = 0.5T_{high}$.

$$W = \frac{Total\ number\ of\ pixel\ for\ the\ class\ (foreground\ or\ background)}{Total\ number\ of\ pixel\ for\ input\ image} \quad (8)$$

$$\mu = \frac{\sum number\ of\ pixel\ i \times value\ of\ pixel\ i}{Total\ number\ of\ pixel\ for\ the\ class\ (foreground\ or\ background)} \quad (9)$$

where i is threshold value within the minimum and maximum threshold value for the class (foreground or background).

$$\sigma_B^2 = W_b W_f\ (\mu_b - \mu_f)^2 \quad (10)$$

where *f* represents foreground and *b* represents background.

V. Edge Tracking by Hysteresis

Hysteresis step is to determine the edges in the final edge image with the double thresholding from the previous step. There are 3 categories for the edge pixels:

a. Stronger: Edge pixels higher than T_{high}.
b. Suppressed: Edge pixels lower than T_{low}.
c. Weak: Edge pixels between two thresholds.

With hysteresis algorithm, the strong edges and the weak edges that connected to strong edges will be considered in the final edge image and set the value to 255. Otherwise, the edge pixel will be set to 0. In order to determine whether the weak edges are connected to strong edges, edge tracking is implemented by BLOB-analysis (Binary large Object). The edge pixels are divided into connected BLOB's using 3x3 kernel. If there is at least one strong edge pixel in BLOB's, then the weak edge pixels will be preserved. Since there are only two-pixel values, 0 or 255, hence this algorithm will output a binary image.

2.2.4 Skeletonize

Skeletonize is a method to thinning the edges aggressively. Skeletonize is peeling the contour of the edges until reaches most medial one pixel width. The binary image from the Canny edge detector is acquisitioned into this method. The pixels having value 0 in the binary image are considered as background while the pixels with the value of 255 are considered as foreground. The thinning process in this work are depend on the pixel value in north, south, west and east position of a 3x3 kernel. We will perform thinning process in the four direction sequentially. If the center pixel having value 255 and the positional value is 0, then we will do thinning on the center pixel. The center pixel will determined depend on the eight neighbourhood pixel value. If there are two background pixels in north, south, west or east position at a time and less than four foreground pixels in the mask, then the center pixel will set to 255 which represent the foreground pixel. Otherwise, the center pixel will set to 0. After the thinning process, the pixel value in the image will be inverted. The pixels with the value 0 will inverted to 255 while the pixels with the value 255 will inverted to 0. The edges is now represented with black pixels. The outcome of skeletonize is as shown in Figure 2.6.

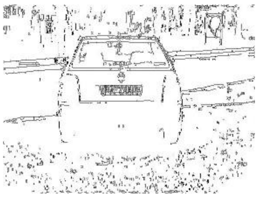

Figure 2.6: Outcome of Skeletonize

2.3 NUMBER PLATE (NP) LOCALIZATION

In this stage, all the necessary steps to find the accurate location of the NP in the digital image are carried out. All that is done throughout the following steps:

2.3.1 Morphological Processes

Morphology of the use of images to analyse and process the shape of the geometric structures in the binary image. It will strengthen the structural characteristics of the image and hence strengthen the rectangular shape of the NP. Morphology have four methods: Erosion, Dilation, Opening and Closing. Erosion will shrink the objects in the binary image while dilation will thicken object in the binary image. On the other hands, opening will smoothest the contours of an object, eliminates thin protrusions and breaks narrow isthmuses. Closing method tends to smooth sections of contours, fuse narrow breaks and long thin gulfs, eliminates small holes, and fills gaps in the contour. Hence, we conduct morphological processes to fill the gap between the edges, clear boundary objects and small objects in the binary image with the method mentioned. The formula of the methods is as follow:

$$\text{Erosion of A by B: } A \ominus B \tag{11}$$

$$\text{Dilation of A by B: } A \oplus B \tag{12}$$

$$\text{Opening of A by B: } (A \ominus B) \oplus B \tag{13}$$

$$\text{Closing of A by B: } (A \oplus B) \ominus B \tag{14}$$

In this work, there are 10 different combination of morphological methods with fill holes in order to remove the small object and strengthen the rectangular shape of the NP. The 10 combination is shown in Table 2.1.

Table 2.1: Combination of Morphological Processes with Fill Hole

1	Fill Hole Opening Closing Fill Hole Erosion (x 10) Dilation (x 10)	**6**	Fill Hole Dilation (x1) Closing Fill Hole Opening Erosion (x10) Dilation (x9)
2	Closing Dilation (x3) Erosion (x10) Dilation (x7)	**7**	Dilation (x1) Closing Erosion (x1) Opening Fill Hole Erosion (x10) Dilation (x10)
3	Closing Dilation (x3) Closing Erosion (x10) Dilation (x7)	**8**	Fill Hole Dilation (x3) Closing Erosion (3) Opening
4	Fill Hole Dilation (x1) Erosion (x10) Dilation (x7)	**9**	Fill Hole Opening Dilation (x3) Closing Fill Hole Erosion (x 10) Dilation (x 8)
5	Fill Hole Closing Fill Hole Erosion (x10) Dilation (x10)	**10**	Fill Hole Opening Erosion (x5) Dilation (x5)

Although we have 10 different combination, our proposed algorithm will stop earlier if it is successfully localized the NP in one of them. After the morphological processes, the pixel value in the image will be inverted. The pixels with the value 0 will inverted to 255 while the pixels with the value 255 will inverted to 0. The shape of the geometric structures in the binary image are filled with white pixel. The outcome of morphological processes is as shown in Figure 2.7.

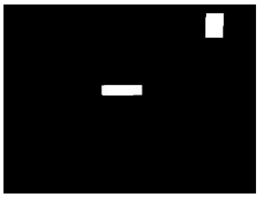

Figure 2.7: Outcome of Morphological Processes

2.3.2 Eight Neighbourhood Connected Components Labelling (CCL)

Eight neighbourhood CCL method is applied with the structure as shown in Table 2.2 to label the geometric structures in the binary image and find the location of the rectangular NP. With the CCL method, we can determine whether the object is connected around, and whether the object has done linked. This method scan each of the pixel in the image and then labels the connected region in the binary image. Only the pixels having the value 255 will be labelled.

Table 2.2: Eight Neighbourhood Connected Components Labelling

1	4	6
2		7
3	5	8

In this work, CCL consists of three passes in labelling the geometric structures. The first pass in CCL scan each of the pixel to find the connected pixel in north-west, north, north-east and west direction from top to bottom and left to right and labelled the connected region. The second pass scans each of the pixel to find the connected pixel in east, south-west, south and south-east direction from bottom to top and right to left. In first and second pass, there are union or overlapping between some labelling. Some of the pixel might belong to two or more labels. Hence, the third pass are used to re-labelling the union label to the smallest label among them. For example, if label 1and 2 are union, then all of them will re-labelling to 1 since there are connected.

Meanwhile, the third pass will also record the minimum location, x_{min}, y_{min}, and maximum location, x_{max}, y_{max}, and the number of pixels for each of the labelled connected region. Specifically, the location x and y represented the column and row of the pixel in the image respectively. These information are then used to compute the width with equation (15) and height with equation (16) of the geometric structures.

$$\text{width} = x_{max} - x_{min} + 1 \qquad (15)$$

$$\text{height} = y_{max} - y_{min} + 1 \qquad (16)$$

The height and width of the region will increase by one to make sure the complete rectangular shape of NP will be extracted. Next, only the labelled connected region that meet the following criteria (17 - 21) will be selected as NP. These criteria can eliminate the region that are too small or large and not in rectangular shape.

$$2.9 \leq \frac{width}{height} \leq 6 \qquad (17)$$

$$\frac{\text{Total number of pixels in the region}}{width \times height} \geq 0.6 \qquad (18)$$

$$20 \leq \text{ Total number of pixels in the region } \leq 15000 \qquad (19)$$

$$\text{height} \geq 20 \qquad (20)$$

$$\text{width} \geq 40 \qquad (21)$$

If there is no rectangular shape meets the criteria, the best result that meet the extra criteria (22) and (19 – 21) will be selected as NP. This is because some car plate might be too small in the image.

$$2 < \frac{width}{height} < 2.9 \qquad (22)$$

After NP area is selected, a red bounding box will be drawn in the original RGB images. The rectangle bounding box will be drawn on the area that contains the NP in the original image (illustrated in Figure 2.8). The size of the bounding box is equal to the NP's height with one extra pixel and the image's width.

Figure 2.8: Outcome of NP Localization

3. FINDINGS AND ARGUMENT

To facilitate in the validation of the robustness of the proposed algorithm, a simple Graphical User Interface (GUI) is needed. We modified the GUI from the Ondrej Martinsky *javaANPR* program in our work.

Our proposed algorithm is tested on the total of 48 digital images in the test set manually to evaluate and validate its performance. The result is recorded in Table 3.1, and the localization rate is calculated will the following formula:

$$Localization\ rate = \frac{\text{Number of successfully detected}}{Total\ number\ of\ tested\ image} \qquad (23)$$

Table 3.1: Experiment data.

Experiment	Successfully/All tested images	Localization rate
Result	44/48	91.67%

The 44 successfully detected images are made up of vehicles positioned in different orientation, different dirtiness of NP, and located in complex background. Figure 3.1: shows the results of 4 images selected from the test set with the NP successfully localized.

On the other hand, there is 8.33% unsuccessful localization in the test set. Our proposed algorithm is very dependent on the border or edges of the NP. If the border of the NP is not obvious, most probability it will fail to localize the NP. In morphological processes, there might have two and more region will combine together after the dilation. Some of the region do not have a clear separation after the erosion. Due to the problem, the NP region become larger and fail to meet the criteria. Hence, our proposed algorithm fails to localize the number plate. In addition, our proposed algorithm will wrongly localize the NP area if there is a rectangular shape or region meet the criteria since we lack analysis on the extracted region. Similarly, if there are multiple rectangular shape or region in the image after the morphological processes, our proposed method might fail to localize the NP. Figure 3.2 shows the results of 4 images selected from the test set which unsuccessfully localized.

Although the use of morphological processes with 10 different condition and CCL method are impose large memory and it might take amount of computing time to localize the NP, this may be worthwhile for its reliability. Moreover, the processors with high performance are more affordable nowadays.

Figure 3.1: Sample Images Successfully Localized

Figure 3.2: Sample Images Unsuccessfully Localized

4. CONCLUSIONS

From the experimental results, the proposed algorithm for the number plate localization able to localize the number plate that have a clear border and clear separation between others connected component. This algorithm is not a color based approach. It has taken a different approach which consists of edge detection and morphological approach to identify the location of the number plate in the digital image. This approach is possible to be used on the number plate from several countries worldwide that have the similar shape and ratio of width and height. Generally, the proposed algorithm consists of two main parts: Image pre-processing and number plate localization. In image pre-processing stage, the proposed algorithm enhanced the input image and extracted the edges from the image. These edges are important for morphological processes in subsequent stage. In number plate localization stage, the proposed algorithm using the morphological operator to further enhance the geometrical structure of the rectangular shape, remove the small object and implements the CCL method to label each of the connected component region. The labelled region that meets the criteria will be selected as number plate. However, there is still a lot of improvement can be done on the proposed algorithm. We might consider involving Hough Transform approach or Horizontal and Vertical projection to do analysis on the labelled connected component from CCL method to improve the localization rate. These approaches might help to filter the non-NP rectangular geometric structures in the image to further increase the reliability of the proposed algorithm.

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