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A Systematic Review of Vehicle License Plate Recognition Algorithms Based on Image Segmentation

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ABSTRACT

Recently, vehicle license plate recognition (VLPR) is a very significant topic in smart transportation. License plate (LP) has become an important and difficult research problem in recent years due to its difficulties such as detection speed, noise, effects, various lighting, and others. In the same context, most VLPR algorithms include should have many methods to be able to identify LP images based on different letters, colors, languages, complex backgrounds, distortions, hazardous situations, obstructions, vehicle speeds, vertical or horizontal lines, horizontal slopes, and lighting. Therefore, this study provides a comprehensive review of current VLPR algorithms in the context of detection, and segmentation. Where, available VLPR algorithms are classified according to image segmentation methods (characteristics, and features) and are compared in terms of simplicity, complexity, uptime, problems, and obstacles.

Keywords: License plate detection, License plate Recognition, Segmentation, Threshold.

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INTRODUCTION

Vehicle and license plate tracking and identification systems play an important role in smart transportation and are frequently used in areas such as automated driving, antitheft vehicles, security management, and service efficiency. Most of these systems are based on vehicle image analysis, often using computer vision techniques [1]. Therefore, accuracy and speed are the key requirements for the quality of the image [2]. In fact, license plate recognition has three basic functions: image detection, image Segmentation, and image enhancement [3].

Therefore, these three functions focus on the image processing technique used to detect licensed vehicles by many algorithms that play an important role in controlling in detection and recognition of the license plate from the original car image. Since each vehicle has a different license plate number (color and letters) [4, 5]. However, the process of recognition largely depends on the technology of image processing such as segmentation image [6]. So far, many algorithms are established in the process of plate recognition. Thus each algorithm has a different method in terms of detection and recognition speed based on image segmentation. This study is intended to represent an update, highlight, and general review of the VLPR algorithms by the search method for established LPs is analyzed and the

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methods are classified according to each model algorithm used with focusing on the advantages and disadvantages.

LITERATURE REVIEW

A. Sliding Concentric Window Algorithm

This algorithm is used for storing the pixels that have the same characteristics to pixels in the licensed domain and then determine the master domain after using the appropriate binaryization and link analysis process. This system cannot divide the license plate with the white characters in the background [7]. This method was developed to identify "large" irregularities in images using statistics of image like the values of standard deviation and mean. This algorithm is established by implementing these steps [8].

Step 1: Create two concentric windows A and B with dimensions (2X1) × (2Y1) pixels and (2X2) × (2Y2) for the first pixel of the image (top left)

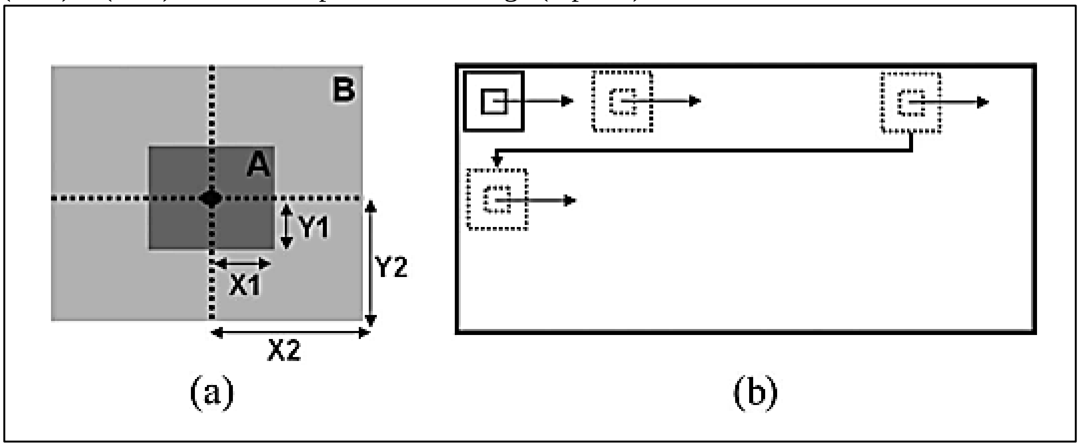

Figure 1. Sliding Concentric Window

Step 2: Save the measurements in windows A and B. Interpretation of partitioning rules: If the ratio of statistics in the two windows exceeds the threshold set by the user, the base A pixel of the window is considered a RoI. So let the coordinates of the analysis pixel in screenshot I be x,y. The values of the pixels in the x, y coordinates of the resulting image IAND are 0 (no RoI) or 1 (ROI), respectively.

$$in\, I_1(x,y) \Rightarrow \begin{cases} I_{\mathrm{AND}}(x,y) = 0, & \text{if } \frac{M_B}{M_A} \le T \\ I_{\mathrm{AND}}(x,y) = 1, & \text{if } \frac{M_B}{M_A} > T \end{cases} \qquad (1)$$

Figure 2. The pixel value equation

where M is the measured parameter (mean or standard deviation). Both windows scroll until t he whole image is produced, as presented in Figure 1(b). No. X1, X2, Y1, Y2 and T can be ad juste in accordance
with the specific application. However, after testing in the first SCW method, it is intere sting to see that the partitioning result will be better if the scale of the concentric window is cl ose to the scale of the object to be partitioned. Therefore, the parameters X1, X2, Y1 and Y2 were chosen from the above analysis. The algorithm phases are showed Section IV-A and

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Section B. In contrast, no evidence for the presence of a best possible method to select the initial T value, so this would be a matter of trial and error depending on the application.

B. Optical Characters Recognition Algorithm

OCR is an electronic process that converts images into computer data. This is a general system for replacing paper documents with digital documents and allows documents to be edited, stored and viewed online [18]. All characters derived from the license number have the same size as the characters stored in the file. OCR technology uses a pattern matching algorithm to recognize each character. The character image is then compared with a database template in memory and the similarity of the data is evaluated [7, 8].

Tesseract is an OCR (Optical Character Recognition) engine for automatic recognition ofcharacters in various document types: printed, typed and typewritten [7]. Before this device came along, the only way to digitize text was to manually rewrite all the text. This process is time consuming and can lead to inconsistencies and typos. Figure 3 shows the results obtained with optical resolution (OCR) technology. Five of the seven pictures are from the license attached to the body, and the other two are from the license only. Due to the dark image, the system processed the characters except for the fifth image, which made the characters unknown. On license plates, the system cannot recognize all the characters as the characters may not match the pattern. Therefore, recognition depends on image quality [7].

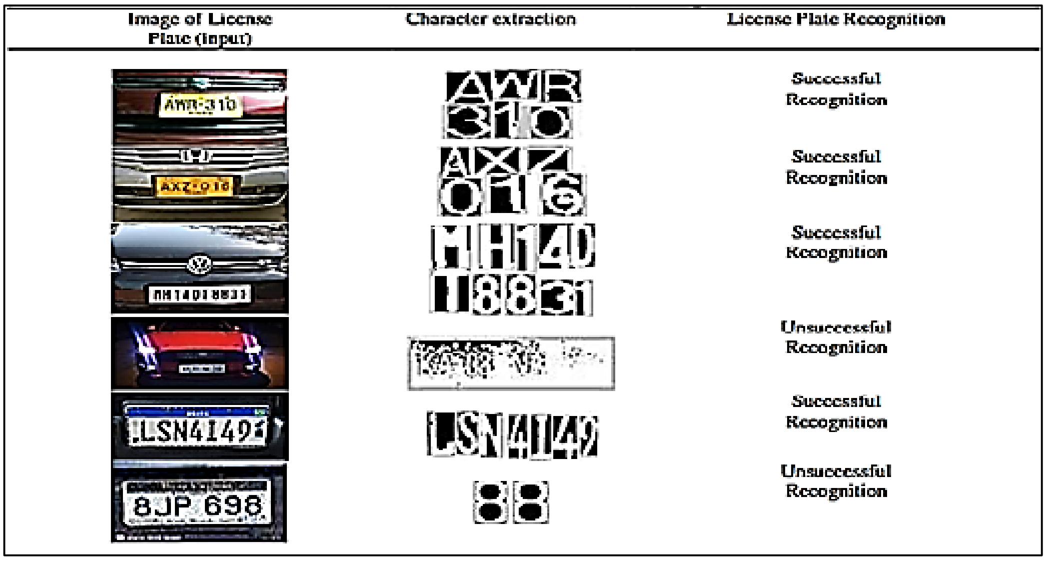

Figure 3. Optical Characters Recognition

C. Region convolution neural network Algorithm

RCNN is the most advanced deep learning model due to its success in imaging. The RCNN contains neurons that adjust the weight and bias. Input data can be images and RCNN layers hav 3 dimensions (width, height and depth). RCNN is widely used in car and license plate detection. Vehicle level RCNNs are the most difficult because vehicles are often in heavy traffic, which interacts with intelligent monitoring of vehicles. Identifying vehicles with the correct credentials is critical to overall performance. In this layer, a 15-layer RCNN is used as shown in Figure 4.

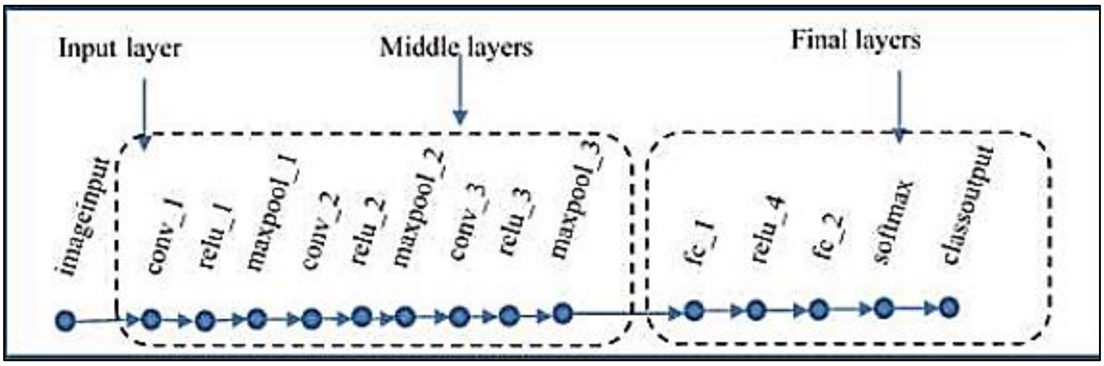

Figure 4. Region convolution neural network

In the same context, RCNN has 3 pretrained layers of convolutional pooling layers. The locati on of the vehicle can be obtained after the vehicle is detected by the vehicle level RCNN. L icense level RCNNs focus only on this region rather than the entire image [9].

D. license Plate Recognition Algorithm

It plays an important role in many applications and many processes are demanded. However, most work under limited conditions such as constant lighting, limited vehicle speed, path selection and constant history. In this study, some limitations of the working environment are discussed. The ANPRR plan has two components: the license plate module and the license plate module. The first, characterized by disciplinary lines, tries to extract the license from the entry image, while the second, conceptualized in terms of neural mediators, aims to recognize numbers now found on license plates. Tests are done for individual modules.

1088 photos were taken from different events and under different conditions to obtain licenses. Among these, there are 23 photographs that could not find a license; The success rate of the license site is 97.9%. 1065 licensed images were used in the barcode recognition test. Of these, 47 photographs could not recognize the license number in the photograph; detection rate is 95%. 6% Combining the two examples above, the overall success rate of our ANPRR algorithm is 93.7%. [7, 10].

E. Automated Detection of License Plate Algorithm

Automatic License Plate Recognition (ADANPR) uses Optical Character Recognition (OCR) and divide-and join segmentation techniques to identify individual characters of license plates that are illegally parked. Generally, the ADANPR system uses a camera to get input from the license plate number and uses an image processing technique to recognize the Chinese number of aANPR. This technology is mainly used in transportation to increase safety and mobility, as well as advanced technology production [8,9,10].

F. Hough transform Algorithm

Transform is among the most useful transforms applied to binary images for extracting lines from object images. Then, there are (2) parallel lines whose areas are considered as parallel graphs. Nevertheless, this method has disadvantage Hough transform requires more time when applied to multi pixel binary images requires a lot of computation. In particular, the larger the image, the slow er the algorithm. The improvement of algorithm speed could be achieved through thinning image before the application of Hough transform. However, this algorithm of refinement is relatively slow; however, this does not make the method suitable for managing real-time traffic [11].

G. YOLO Algorithm

Meet the YOLO (You See Only One) algorithm. It makes it possible to detect and recognize objects in images 103 times faster than R-CNN and 102 times faster than RCNN, but with lower accuracy. The algorithm applies a grid to the input image and splits it into cells. By estimating the fact and probability of each cell belonging to the class around it, the algorithm determines a bounding box of the area where the object is likely to be found. The correct prediction for each area is then divided by the class probability and we get the final value of the detection probability. The algorithm analyzes several thousand to tens of thousands of parts of an image with frames of different sizes [12].

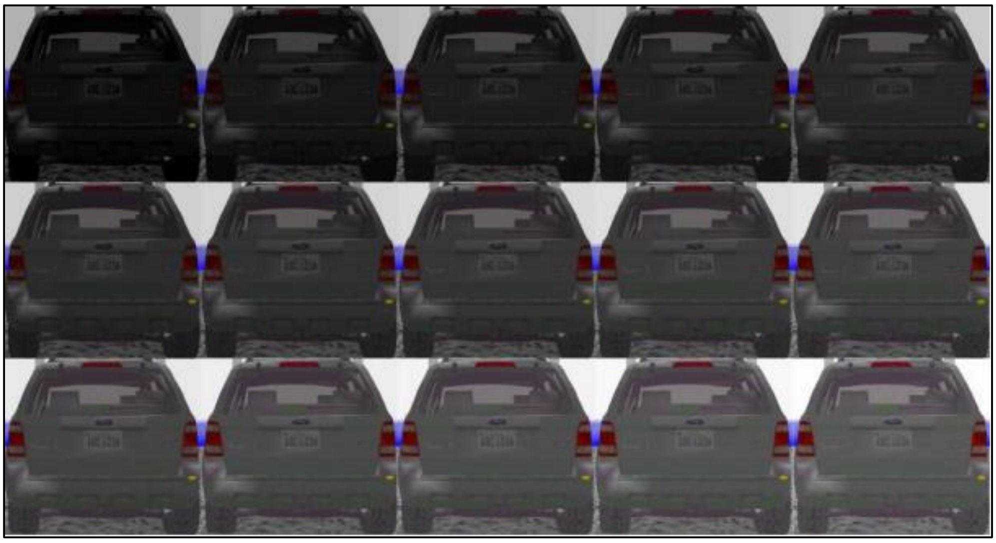

Figure 5 . Effect of brightness on a collected image

After the luminance has been applied, a negative masking, also known as a negative filter, is required to show the edges and thus improve signal licensing. The main idea is to add a useful image by dividing the value of the edges of the image by a constant that determines the level of enhancement (FISHER et al., 2003). If the original image is defined as f(x,y), the edge of the image as g(x,y) and constant k, then the mask is not good can be defined as:

$$f_{sharp}(x, y) = f(x, y) + k \cdot g(x, y)$$

Figure 6. Luminance Equation

The key is to find a good set of edges, for example g(x,y). For this function, the Gaussian high pass filter provides the best results. Therefore, it is explained accordingly work properly.

$$GH(x, y) = 1 - e^{U}$$

Figure 7. High-Pass Filter equation

Since the open source AANPRR library has its own prefilters, there is no need to modify the i mage further [13].

Figure 8. Preprocessing filters

H. K-means Algorithm

According to [13, 14], the better the box before selection, the better. This means that the boxes quality is significant for the current model. The boxes defined in the original YOLO are not suitable for the current model. This K-means as the clustering algorithm, which helps finding selections more than achieved. Therefore the clustering of cells , indirect clustering is done through calculating similarities samples, typically by using Euclidean distance or Manhattan distance as a measure. Therefore, there will be more errors in yolo with large bounding boxes than small bounding boxes. In Yolo, IOU is used reflecting the error between the opponent's frame and the actual value. The distance model is: d (box , centroid) = 1 - IOU (box , centroid).
The intersectionjoin (IoU) between a box and k clusters is calculated using IOU (box, centroid). The algorithm of k-means is run with different values of K. Figure 2 illustrates the outcomes of the K and the average IOU.

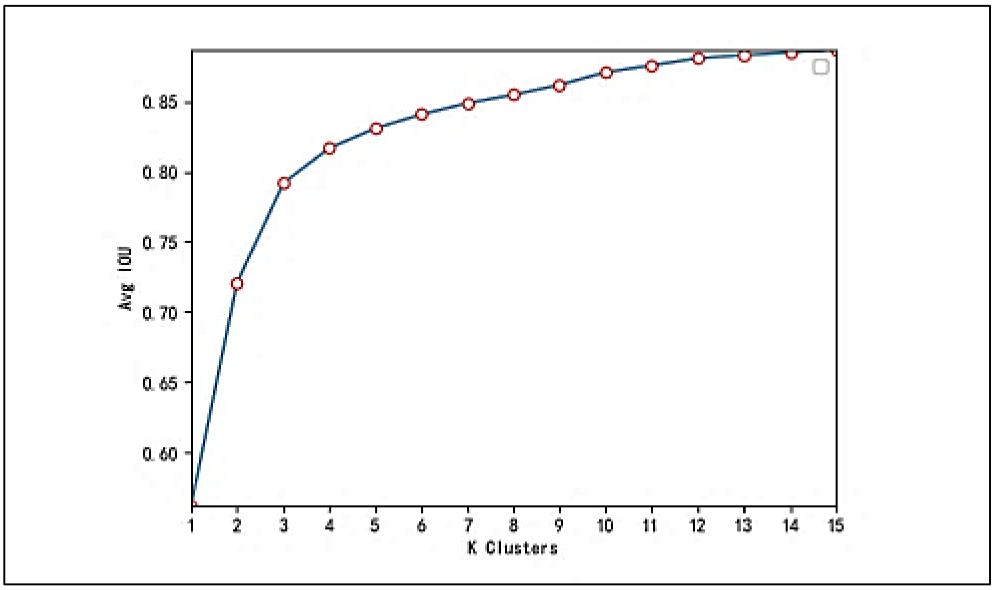

Figure 9. Analysis result of K-means clustering

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This K=10 as the K. Based on Figure 2, when K <10, the average IOU is not very good; however, when K>10, this average becomes higher, complicating the model more. When K=10 is selected [14].

METHODOLOGY

The segmentation level depends on the successful extract of plat from an image. A separate license may have a different problem, change of lighting, etc., or point out from different angles. In this case, preprocessing techniques, skew correction, or other methods should be used before segmenting the marks depending on the conditions of the plate. This step is performed during extraction or after receiving the recommended isolation, depending on the processing method. For oblique license images, preprocessing techniques such as bilinear transformation are used to map individual plates to right-angled rectangles.

Therefore, the study method focuses on the comparison of current findings of algorithms based on image segmentation to determine the accuracy and processing time in recognition on the car plate as in Table 1.

Table 1: License Plate Recognition Comparison Models

Algorithm No.	Segmentation Method	Algorithm Features	Process (Weaknesses)	Sources	Accuracy
1	texture	deformed boundaries to frequent colour transitions of LPR	time long and complex for multiple edges	[2]	93.5%
2	character	rotation of characters LPR	binary objects. error image with other letters style	[15]	99%
3	boundary information or edge	faster and easier for the rectangular boundary for LPR	Sensitive edges. complex images	[16]	96.75%
4	colour	LPR with deformities and skew	long time	[9]	97%
5	global image	independent of LP position and straightforward approach	broken letters	[17]	96.62%
6	Diverse	robust and implementation of attributes	computationally complex, long time	[18]	97.3%
7	vertical and horizontal projection	Independent and robust in slightly rotation	noise; character dimension prior	[19]	99.2%
8	character contour	exact boundaries of the characters	Long time complex	[20]	90%
9	Pixels	LPs, skew, and procedure	broken character extraction	[21]	94.1%
10	mathematical morphology	more robust morphology	time long and complexity	[22]	95.10%
11	Classifiers Image	real-time application, advanced and	broken characters, complexity Low brightness	[23]	96.7%

		robust computational intelligence architecture			
12	Prior characters	straightforward procedure	limited depending on the alteration	[24]	96.4%
13	image filtering	real-time architecture	Low brightness	[25]	95.3%

RESULTS AND DISCUSSION

Table 1 discussed the methods, simplicity, and complexity of each algorithm class. In the VLPR framework, at any stage, the recall sign is confirmed by displaying the license plate number of the image of input vehicle LP, called the output, which is the level of segmentation in the image. This step has an important part in determining the LPs number. Generally, license plate symbols differ in thickness [2] and size, as well as camera zoom. Thus algorithm No. 2 (rotation of characters LPR) based on character method has a best time execute and accuracy around (99%), but the problem in this algorithm the binary objects has error in image segmentation because different letters style, followed algorithm No 7 also has accuracy around (99%), but the problem in this algorithm big noise letter in segmentation if the letters not clear enough. Followed algorithms 4 and 6 respectively with accuracy (97%) but they have complex and taking long time in the segmentation phase. Through what has been presented in table 1 (Accuracy Ratio), find that algorithms No 2, and 7 has best accuracy comparing with the rest of the algorithms, if the appropriate conditions are available, such as clear letters and numbers, and other factors that help in the image segmentation process for Vehicle License Plate Recognition.

CONCLUSION

Analytical comparison presented according to each algorithm based on method, process, and recognition results. Additionally, the state-of-the-art VLPR model is focused on license detection, segmentation and recognition. As a result, it is necessary to consider in system design the letters style with clear letters and numbers to achieve the accuracy and speed time of the VLPR system to build a strong VLPR system in the future.

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