RESEARCH-ARTICLE

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Automatic Number Plate Recognition on Electronic Toll Collection Systems for Vietnamese Conditions

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ABSTRACT

Due to unlimited increase of cars and transportation systems, a real time embedded system called Automatic Number Plate Recognition (ANPR) is very important for humans to detect and manage. This paper presents results of developing and deploying an ANPR applied to electronic tolling collection (ETC) systems in Vietnam with some special issues. Our model is designed and investigated by using a VIVOTEK IP8361 camera to capture an image. After that, the image is transmitted to an industrial computer to process. In detail, the image is processed first to reduce noise and artifacts by a low-pass filter before our software detects plate candidates. The characters in the candidates are then extracted by an optical character recognition utilizing neural network. We also employ Microsoft visual C sharp integrated development environment to build graphical user interface. Experimental results manifest the high accuracy of our method achieving approximately 85.00% and the processing time of only about 20-30ms.

Categories and Subject Descriptors

C.0 [**General**]: Hardware/software interfaces.

D.2.8 **[Metrics]**: Performance measures.

I.4.3 [**Enhancement**]: Filtering; Smoothing.

I.4.6 **[Segmentation]**: Edge and feature detection.

General Terms

Algorithms, Measurement, Performance, Design, Reliability, Experimentation, Theory, Verification

Keywords

Automatic Number Plate Recognition, Neural Network Model, Optical Character Recognition, License Plate

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1. INTRODUCTION

A technique to read license plates on vehicles like cars or motorbikes, which is named Automatic Number Plate Recognition (ANPR), was first invented in 1976 by the UK's Police Scientific Development Branch [1]. Recently, thanks to significant improvements of digital camera, this method attains lots of interest [2-5]. In fact, ANPR detects the license plates through optical character recognition on images. In detail, it makes a camera to capture images, and subsequently finds the location of the plate before extracting the characters via employing some segmentation tools. Nowadays, ANPR becomes much attractive thanks to not only innovation of digital camera technology and the computational complexity process but also its advantages in many real-life applications [1]. To name a few, it can be used in many areas from traffic management as a speed prosecution or administration of car logs in parking systems. Moreover, it is also used to detect criminal activities and violations of speed limit in the prohibited areas.

The system of processing and recognizing number plates automatically has been developed by many companies and research organizations over the world [6]. The authors in [2] investigated a method of segmenting characters in license plate based on a majority pixel value data. The suggested method is already tested with 150 different images of license plates coming from 58 countries. Apart from this, M. T. Quadri and M. Asif [4] developed an ANPR system for security control of a highly restricted area. Acquiring the digital signal processor TMS320DM6437, P. Kulkarni et al. [5] deployed an embedded system for the ANPR according to Indian conditions. All experimental results in [4, 5] are attained by using Matlab which is easy to implement. However, nowadays, not only analyzed simulation results are proposed but also increasing requirements are made available for testing system performance in real-life application. Hence, the programming language should be Android, C/C++ or C#. The authors [3] designed and implemented an ANPR system to detect car plate number in Malaysia based on Android mobile platform.

Especially, in Vietnam, several ANPR systems have been developed [7, 8]. The economic version 3.0 of Bien Bac Company [7] identifies all kinds of number plates composing of both 4 and 5 numbers in a license plate. The processing time ranges from 30 to 50ms for images of size 640x480. This technology is already

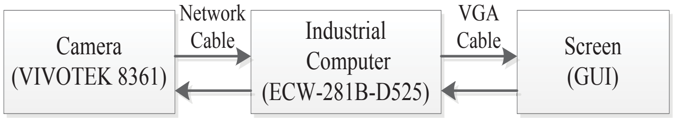

Figure 1. Hardware architecture of ANPR

applied in managing and operating facilities (e.g. parking, toll stations) and in transport control (e.g. red light violation, lane management, and speed violation). However, this version has not mentioned the specific issues of plates in Vietnam, for example many cars having their plates with some blurred characters. In addition, there are a number of ANPR technologies of other companies in Vietnam which can just identify digit parts of 4 or 5 characters in the 2-line number plates [8]. They can only fully recognize 1-line number plates. The processing time is more than 300 milliseconds for images smaller than 352×288.

In this paper, our objective is to investigate and deploy the ANPR system on ETC in Vietnam which can overcome the above existing problems. We utilize a VIVOTEK IP8361 camera [9] to capture image and an industrial computer (i.e. ECW-281B-D525 computer [10]) to recognize license plate. Moreover, our software is developed by acquiring Microsoft visual C sharp. It is worth emphasizing that, due to special standards in Vietnam as fonts, plate size, the number of characters contained a plate [11], processing modules of ANPR should be adapted to become more suitable with these requirements. Especially, the software is able to detect characters in plates in the following steps. The image containing plate candidate is processed first to reduce noise and artifacts by a low-pass filter, and then, a binarization approach with Sobel operator and adaptive thresholding level using Otsu method [12] is employed to create the binary image. This work helps to highlight objects in regions with unequal brightness. Furthermore, with contour finding method [13], we can eliminate border of the plate and extract its characters as well. Experimental results demonstrate significant accuracy of our model for Vietnamese conditions along with a short time-consuming.

The rest of this paper is organized as follows. Section 2 presents our hardware implementation model. The developed software of ANPR for ETC systems in Vietnam is depicted in details in section 3. Experiment results are analyzed in section 4. Finally, some conclusions and future work are shown in section 5.

2. HARDWARE IMPLEMENTATION MODEL

The illustration of the implementation model of our system is illustrated in Figure 1 including a camera, an industrial computer, and a screen.

Camera: In this paper, the VIVOTEK IP8361 camera [9] is selected. It is suitable for outdoor surveillance. This camera can support image of high resolution as well as high performance codec as H.264/MPEG-4/MJPEG. Moreover, thanks to integration of many outdoor-specific features, the VIVOTEK IP8361 camera is a good choice for ETC systems.

Industrial Computer: Although computer becomes more and more popular in all aspects of real life, many areas (e.g. too high temperatures, airflow restrictions) have difficulty with conventional computer systems. Especially, at ETC systems, computers usually suffer from harsh conditions, so these issues greatly affects the recognition performance of traditional computers (e.g. personal computers or laptops) [14]. As a result, requirements of a better one, which can overcome these problems, are necessary. In this implementation, we use an industrial computer ECW-281B-D525 since it can deal with bad outdoor conditions via removing all moving components and being equipped with fans.

Screen: It lets us use a proper programming language to design a graphic interface of our model. Microsoft visual C sharp express edition 2010 integrated development environment (IDE) is employed to construct the Graphical User Interface (GUI) to display some functions supporting for ANPR.

3. SOFTWARE DEVELOPMENT

As aforementioned, we use Microsoft C sharp to design our software. Functionally, ANPR is roughly divided into three major stages: plate detection, character segmentation, and optical character recognition [1] (in this paper, for simplicity of expression, we combine the second and the third stages to be one stage named license recognition). The first stage eliminates plate candidates from captured images (i.e. in our model, a VIVOTEK IP8361 camera is used to capture images). Hence, in the second stage, character segmentation stage will separate all characters in the license plate image (i.e. contain a plate candidate). Finally, these characters along with sample trained using artificial neural network (ANN) are considered as input of optical character recognition (OCR) module to detect the correct license plate.

3.1 Plate Detection

The region containing a plate has the gray density that changes significantly (color character always contrasts with the background plate) and has high value intensity in the intensity histogram. Moreover, car plates in Vietnam usually contain 7 to 11 characters. We can utilize this property to identify number plate region. Our method to detect a plate is depicted in implemented steps in Figure 2.

3.1.1 Image Filtering

When images are captured, they usually suffer from noise and artifacts. Therefore, it is necessary to enhance quality of images using a low-pass filter. Among many low-pass filters (e.g. Wiener filter, Median filter, Average filter, Gaussian filter), the Gaussian filter is a good candidate because of its good performance and easiness in controlling the degree of smoothness via the standard deviation [15].

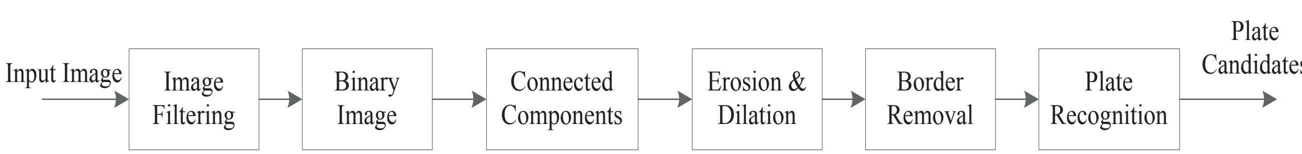

Figure 2. Plate Recognition Method

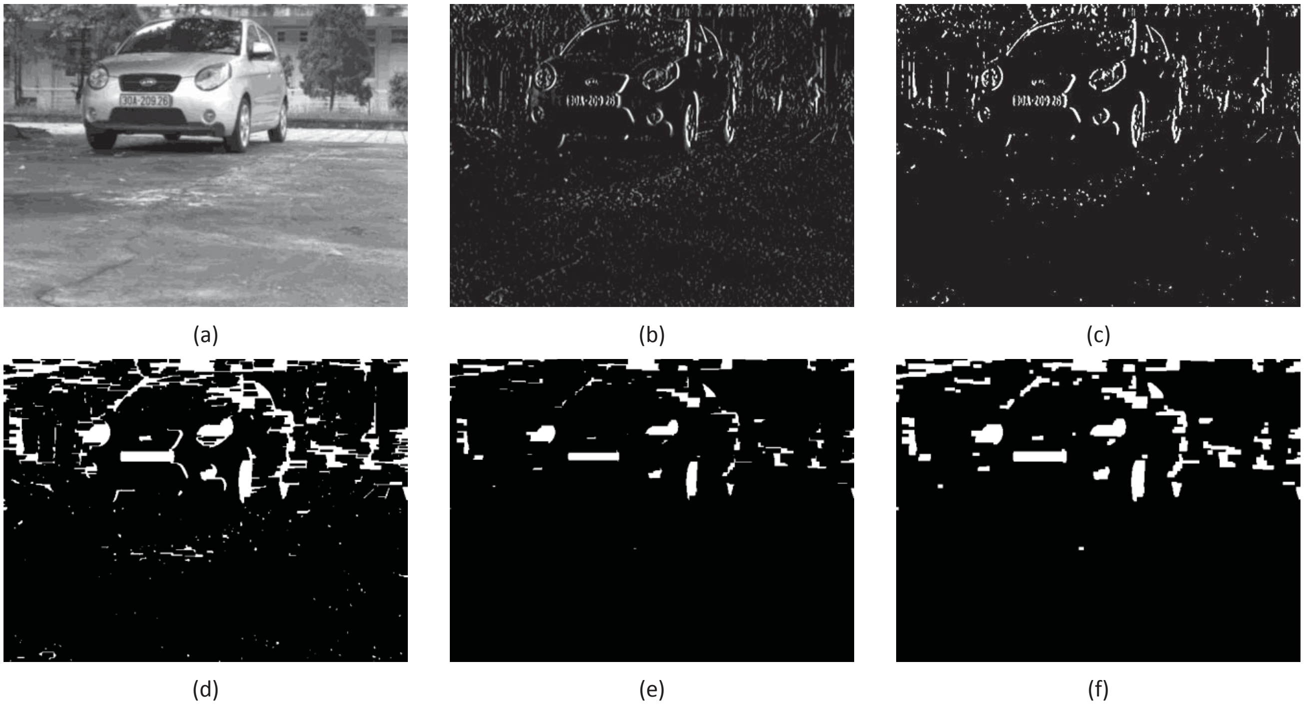

Figure 3. (a) Filtered image; (b) Image after using Sobel operator; (c) Image after using Otsu method to define local threshold values ; (d) Image after using connecting components ; (e) Image after using erosion ; (f) Image after using dilation

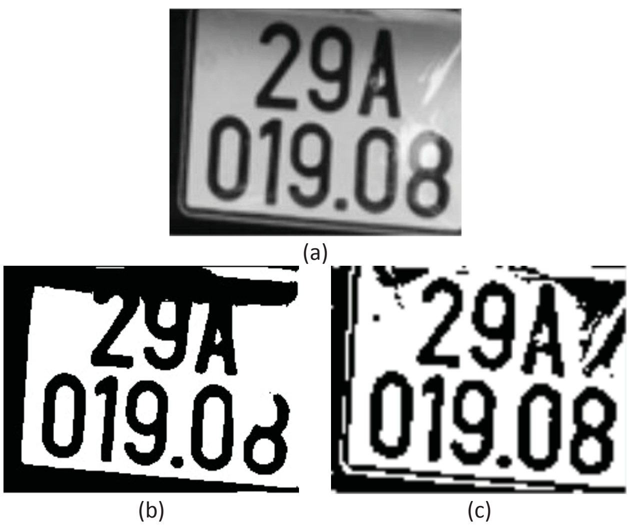

Figure 4. (a) Portion of original image; (b) Result of using the Otsu method to define the global threshold value; (c) Result of using the Otsu method to define local threshold values with a sliding window of size 17x17

3.1.2 Binary Image

The filtered image is then converted into binary domain. For better preserving edge objects and boundaries of image, we first use the Sobel operator to enhance these kinds of information [11]. The output is shown in Figure 3(b). Most edge objects can be well seen. This image (i.e. image in Figure 3(b)) is further converted to a binary image by using a proper threshold. The proper threshold may be global or local. A global threshold is defined as a fixed value used for all pixels in an image and therefore only if the intensity histogram of the input image contains neatly separated peaks corresponding to the desired subject(s) and background(s). Hence, it cannot deal with images containing, for example, a strong illumination gradient. By contrast, the local threshold selects an individual values for each pixel based on the range of intensity values in its local neighborhood. It allows for thresholding of an image whose global intensity histogram doesn't contain distinctive peaks. In this paper, we use the Otsu method [12] to define the threshold value. To evaluate effect of local versus global thresholds, we perform a mini-test as shown in Figure 4. A portion of original image contains a contaminated object (i.e. see the character “8”). The results of two kinds of thresholding methods are shown in Figure 4(b) and Figure 4(c), respectively. The superior improvements of local threshold defined by the Otsu method with a sliding window over a global threshold are easily observed. Characters in plate are sometimes blurred (for example, by mud or dust), so a global threshold cannot preserve this part as in Figure 4(b) with losing a part of character “8”. Otherwise, local thresholding can work well with this problem (i.e. see Figure 4(c)).

3.1.3 Connected Components

After attaining a binary image, there are plenty of single edge pixels in the image (i.e. see Figure 3(c)). Some of them belong to true edge, but others might be noise and artifacts. Therefore, we first connect the true single edge pixels to the nearest edge object. In detail, if a single edge pixel is not far from edge objects (i.e. consider this condition via a predetermined threshold), then it is thought as belonging to true edge. Otherwise, it is treated as noise and is eliminated out by the erosion method as follows.

3.1.4 Erosion and Dilation

Binary image obtained as in Figure 3(d) has plenty of tiny white areas which are then considered as noise. The removal of these objects whilst retaining larger objects will help reduce the computational complexity for next operations. This work is called erosion process. This process which eliminates small objects while retaining bigger objects has decreased brightness and

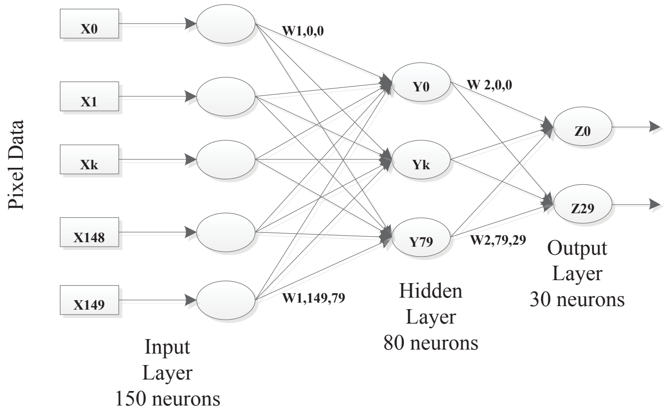

Figure 6. Neural Network Model

thickness as shown in Figure 3(e). Unfortunately, objects seem to be smaller than what are desired. Therefore, the image needs a dilation operation to enlarge edges and boundaries for better plate recognition. The result of dilation is depicted in Figure 3(f).

3.1.5 Plate Detection

Image after dilation process will have bright areas consisting of connected pixels. These areas are delineated to identify the number of their characters. Plate candidates are further defined as regions that are brighter than the others and have ratio of width/height from 1 to 5 (i.e. according to Vietnam standards, there are often two kinds of plates of size 470×110mm and 280×200mm for the 1-line plate and the 2-line plate, respectively). Hence, a true plate can be identified by checking number of characters in it.

3.1.6 Border Removal

After erosion and dilation, size of an object is different from the original one. From experimental viewpoint, the objects are often defined in larger areas. Plates usually contain border which can cause error in character segmentation operation. Therefore, it is necessary to remove border of the plate candidates before segmenting its characters. We use contour finding method [13] whose height of new plate candidate is larger than ½ of the height of original one. It is applied to the width of candidates in the similar way.

3.2 License Recognition

In this subsection, characters of a plate are detected by the artificial neural network (ANN) as illustrated in Figure 5. The left-hand side part describes the character segmentation algorithm whilst the right-hand side part is to describe the iterative constructing of the training database.

3.2.1 Character Segmentation

For character detection, we still acquire contour finding method [13] to search bound of each character in a plate. In detail, this bound is considered as a rectangle whose height is larger than ½ of the height of the original plate candidate. Moreover, if the ratio of the number of black pixels in an area is in range of [0.23, 0.7], this is further defined as a character. Finally, if a plate candidate having number of character is higher than 6, then it is a correct plate.

3.2.2 OCR identification using neural networks

Pursuant to the Vietnam Government's decree No. 36/2010/TT-BCA [10], the regulations of plate standards are clearly defined. According to these regulations, each plate includes the digits and alphabets as follows, 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, A, B, C, D, E, F, H, G, K, L,M, N, P, S, T, U, V, X, Y, Z. We have surveyed over 400 static images in order to obtain 3063 specific samples.

These samples are trained a neural network with the configuration including three layers as in Figure 6. Input layer has 150 neurons (i.e. they are numbered $[X_0, X_1, \ldots, X_{149}]$ as in Figure 6 corresponding to the number of pixels lying on the identified area, while the output layer has 30 neurons (i.e. they are expressed $[Z_0, Z_1, \ldots, Z_{29}]$). The number of hidden neurons (i.e. defined as $[Y_0, Y_1, \ldots, Y_{79}]$) greatly depends on sample sets. Moreover, $\mathrm{w}(i, j, k)$ is a weight denoting the relationship of neurons. Nonetheless, the network tends to learn by rote, or in other words, the identified capacity is not in space of samples. We have extracted whole characters used to train the neural networks via heuristic analysis. In the existing configuration, the network has been trained from 3063 samples and 80 neurons in hidden layer (i.e. see Figure 6).

4. EXPERIMENTAL RESULTS

The effectiveness of our model is evaluated by 200 different images of license plate taken from popular cars in Vietnam under varying lighting conditions. Experiment results are obtained via two kinds of plates composing of one line and two line plates. In summary, the tested conditions for our implementation are summarized in Table I.

Performance of our model is tested several times when cars are moving through the ETC system in Thai Nguyen province, Vietnam under normal conditions. The cars went through the ETC system in different speeds. Results are shown in Table II and Table III.

Table II depicts performance of our model under various conditions including one line, two line, and skew-captured plates. The high accuracy rate for both one line and two line plates obviously confirms correctness of our method. Moreover, for skew-captured plates, performance of the proposed model still achieves quite good accuracy rate of 87.56%.

The overall accuracy of character and plate recognition rates is reported in Table III. The character segmentation rate is approximately 92.57% and the character recognition rate (i.e. the correct character is detected based on the ANN training) is about 92.00%. Finally, the corrected license plate recognition rate under our investigation is about 85.00%. For computational complexity, the system spends 20-30 milliseconds to detect a license plate.

Additionally, the graphic interface for a result of one plate

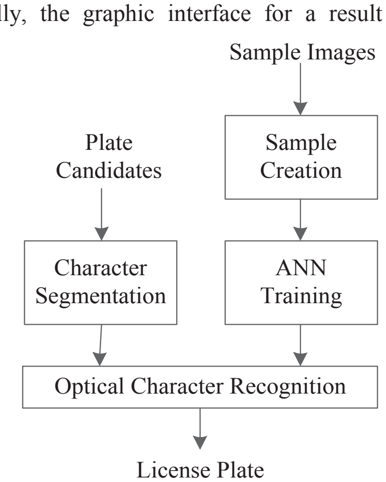

Figure 5. License Recognition Method

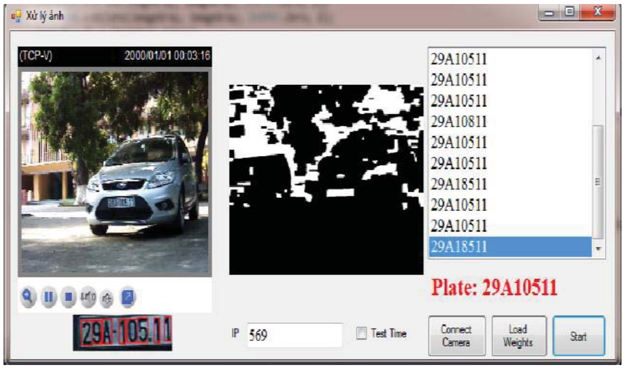

Figure 7. Graphical interface of our model

recognition is shown in Figure 7. It lets us observe not only plate recognition result but also the captured image. The button "connected camera" connects our software with the VIVOTEK IP8361 camera, while the button "load weights" is used to show the results of ANN training.

5. CONCLUSION

This paper investigated application of automatic number plate recognition (ANPR) applied to electronic toll collection systems according to real conditions of Vietnam. From the hardware viewpoint, the system composed of a VIVOTEK IP8361 camera to capture images, and the camera is connected with an industrial computer to detect characters of plates automatically. We also used Microsoft visual C sharp to develop the modules of ANPR. Experimental results demonstrated that our model not only attained high accuracy of plate recognition in a very short time but also overcome several existing problems in Vietnam.

6. ACKNOWLEDGMENTS

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Table 1. Test Conditions

Configuration	Value
Typical Plate	One line, two line
Electronic Shutter	1/100.000
Image Size	640×480
Experimental condition	Outdoor
Number of real-scene sample	200
Snapshot corner	10-30^0

Table 2. Plate Recognition Results

Typical Plate	Accuracy rate
One Line Plate	90.43%
Two Line Plate	89.33%
Skew Captured Plate	87.56%

Table 3. Accuracy Rate & Processing Time

Character Segmentation	92.57%
Character Recognition	92.00%
License Plate Recognition	85.00%
Time-consuming	20-30ms

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