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Conference Paper · March 2011

DOI: 10.1109/NCETACS.2011.5751407

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# Number Plate Recognition for Use in Different Countries Using an Improved Segmentation

Ankush Roy

Dept. of Electrical Engg.

Jadavpur University

Kolkata, India

ankush1123roy@gmail.com

Debarshi Patanjali Ghoshal

Dept. of Electrical Engg.

Jadavpur University

Kolkata, India

ghoshaldp@gmail.com

**Abstract**— Automatic Number Plate Recognition (ANPR) is a real time embedded system which identifies the characters directly from the image of the license plate. It is an active area of research. ANPR systems are very useful to the law enforcement agencies as the need for Radio Frequency Identification tags and similar equipments are minimized. Since number plate guidelines are not strictly practiced everywhere, it often becomes difficult to correctly identify the non-standard number plate characters. In this paper we try to address this problem of ANPR by using a pixel based segmentation algorithm of the alphanumeric characters in the license plate. The non-adherence of the system to any particular country-specific standard & fonts effectively means that this system can be used in many different countries – a feature which can be especially useful for trans-border traffic e.g. use in country borders etc. Additionally, there is an option available to the end-user for retraining the Artificial Neural Network (ANN) by building a new sample font database. This can improve the system performance and make the system more efficient by taking relevant samples. The system was tested on 150 different number plates from various countries and an accuracy of 91.59% has been reached.

**Keywords**- ANPR, Artificial Neural Network, license plate, region growing, Component tag

## I. INTRODUCTION

The automatic number plate recognition systems (ANPR) exist for a long time, but only in the late 90s it became an important application because of the large increase in the number of vehicles. The information extracted from the license plates is mainly used for traffic monitoring, access control, parking, motorway road tolling, and border control, making car logs for parking systems, journey time measurement etc. by the law enforcement agencies.

The recognition problem is generally sub-divided into 5 parts: (1) image acquisition i.e. capturing the image of the license plate (2) pre-processing the image i.e. normalization, adjusting the brightness, skewness and contrast of the image (3) localising the license plate (4) character segmentation i.e. locating and identifying the individual symbol images on the plate, (5) optical character recognition. There may be further refinements over these (like matching the vehicle license number with a particular database to track suspected vehicles etc.) but the basic structure remains the same. A guiding parameter in this regard is country-specific traffic norms and standards. This helps to fine tune the system i.e. number of

characters in the license plate, text luminance level (relative index i.e. dark text on light background or light text on dark background) etc. So the problem can then be narrowed down for application in a particular country. For example, in India the norm is printing the license plate numbers in black colour on a white background for private vehicles and on a yellow background for commercial vehicles. The general format for the license plate is two letters (for state code) followed by district code, then a four digit code specific to a particular vehicle [1]. In U.S.A no strict guidelines [2] have been set regarding the fonts that can be used for this purpose.

### A. Related Works

Such has been the impact of the ANPR systems that the scientific community started to take immense interest in this field since its introduction and today many commercial systems like the Smartreg [3], Car Plate Recognition by J.A.G. Nijhuis [4], Automatic Number Plate Recognition (ANPR) by Shyang-Lih Chang, Li Shein Chen, Yun-Chung Chung, and Sei-Wan Chen [5] are now available.

One of the approaches was by S.Ozbay and E.Ercelebi [6]. They used a black pixel projection based image segmentation scheme to recognize Turkish number plates in the binary domain. They tried to localise the number plate in the image by using a smearing technique. Vertical and horizontal runs of the binarized image were taken. This was followed by segmentation of the plate from the rest of the image based on a particular threshold number of pixels. A similar algorithm was used to segment the component characters from the plate after the image was filtered and dilated. Cross correlation coefficient technique have been used to classify the text.

Classical Hough transform is another approach by which the boundary lines and eventually shapes are detected. The lines are first changed into parameter space of slope and intersect. Two parallel lines are then searched and the region in between the lines is passed as a potential plate region. Tran Duc Duan, Tran Le Hong Du, Tran Vinh Phuoc, and Nguyen Viet Hoang [10] tried to use a contour based algorithm in association with the Hough transform to bring down the computational overhead. This contour algorithm narrows down the sample points on which the Hough transformation is to be applied. This is followed by a projection based segmentation scheme for the component letters. Finally a

HMM based recognition algorithm is suggested for the character recognition part.

A problem of the projection based method is that sometimes it leads to under segmentation. A threshold value of pixels needs to be assigned for segmentation. For mutilated fonts thinning around some parts may lead to under segmentation. As shown in (Fig.1) under segmentation would be in the case of T and C due to the optimum threshold shown by red line

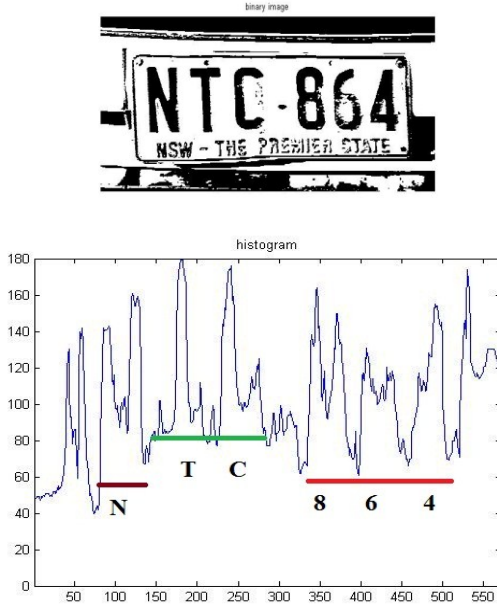


Figure 1: Projection Based approach

The Hough transform method on the other hand requires huge amount of memory for processing because of the large amount of computational processes involved. It requires computing every possible case in the parameter space and then using a gradient direction to vote the most probable case. If the license plate is big or contains too much noise then this Hough transform approach would become very cumbersome to implement.

#### B. Contribution of our work

After going through the existing literature it was seen that the Hough transform and the projection based scheme have been extensively used as the segmentation algorithm but there has been some shortcomings in both of these methods. The projection based method may be susceptible to error due to predefined threshold as shown. Considerable computational speed maybe compromised due to large memory requirement of the Hough transform process. Another noteworthy point is that a country-independent general framework was not developed in many of those studies. Most of the work is country specific [10, 11, 12,13] i.e. it will work for a particular countries traffic rules but will fail in case of other countries.

All these shortcomings motivated us to take up the present research. Considerable focus was given on the segmentation algorithm that was based on tagging the pixel cluster and a

region growing approach. This approach is a new one and not previously adopted.

We have attempted to formulate a general framework that will work in different countries. This has been addressed by providing the user with the option of re-training the artificial neural network (ANN) according to their needs (e.g. if different fonts are to be recognised). The first part describes the segmentation algorithm. Second part describes the interactive building of the database for training. This is optional i.e. the users can use it if they wish to do so to improve upon the recognition results. This is followed by the recognition module using a neural network based on a well defined back propagation algorithm. Finally the results of recognition and the conclusion follow. A flowchart of the entire process is provided in Fig. 2.

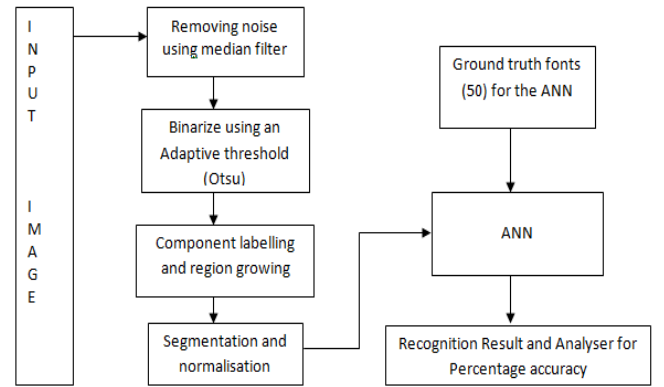


Figure 2: Flowchart

## II. SEGMENTATION

The number plate is localised on the basis of algorithm developed by M.Nasipuri et al [11,12] shown in Fig.3. Further processing is done as stated below.

#### A. Median Filtering

A statistical Median filter is used to remove salt and pepper noise from the image inn gray scale before binarizing. We have used a  $3 \times 3$  masking sub window for this purpose.

#### B. Adaptive thresholding

The images are converted into the binary domain. An adaptive thresholding scheme has been used for this purpose. We have initially tried both Otsu method and Ni back's method [8]. But the Otsu method was finally used as it was globally adaptive which would increase processing speed as compared to Niback's threshold scheme.

#### C. Component Labelling and region growing

The adaptive threshold technique was followed by a component labelling algorithm where clusters of 8-connected white pixels were tagged with a particular label. (Fig:4(b)). A graph was drawn of the number of pixels vs. the component tagged number. It was observed that the character strokes are the ones that take up majority of the pixel count. So only a few

more than the expected number of characters (specification of traffic regulatory body) are passed as candidate glyph. A few more were passed to minimize any error (oversegmentation) that might have occurred while binarizing. An effort was made to incorporate the stylish fonts that are used now a days by using the following steps.

1. Checks the neighbour label distance between the nearest pixel
2. If  $d_{(neighbour\ clusters)} < d_{critical}$ , use region growing to bridge the gap. ( $d_{critical}$ =critical distance set after experimentation)
3. Seed point on the basis of spatial position of the component label
4. Re-label based on eight connected white pixel labelling

The algorithm runs both in the horizontal direction and in the vertical direction, accordingly the seed point changes (rightmost & leftmost pixel for horizontal, and lower most and uppermost for vertical). Mostly the intercharacter distance is generally more than the distance between over segmented glyphs (intracharacter glyphs) which are the part of one particular glyph.

#### D. Segmentation and Normalization

The individual character images were finally segmented using the bounding box method. The segmented glyphs varied considerably in size. So they were normalized on the basis of size of the extracted images. All of them were scaled to the same size ([15x15] pixels).



Figure 3: Number plate of India

TABLE I. PIXEL COUNT VS. COMPONENT TAGGED NUMBER

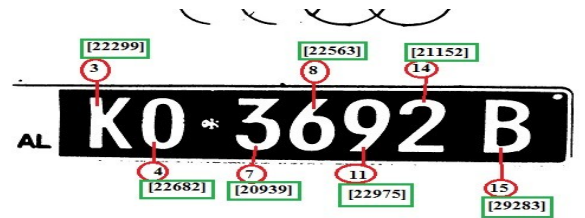
Character Extraction majority pixel based		
Character	Component Number Tag	No of Pixels
0	35	933
5	34	811
5	31	797
D	3	790
A	19	771
3	28	746
Y	12	551
L	4	482
1	10	406
[]	37	390
[]	16	252
[]	29	121
[]	30	118

a. [] denotes Junk class

An example of the entire segmentation algorithm is provided with the help of a Korean License Plate (Fig: 4(a)) having only one row of characters. The adaptive binarizing of the plate was followed by tagging the component glyphs as shown in Fig: 4(b). The pixel count is sorted and the tagged numbers that are associated with the majority of the pixels (Fig: 4(c)) are used to bring out the characters. Some junk clusters do creep in so a tolerance is set for the segmenter by cutting a few more glyphs than the number of characters specified in the plate. The junk classes may be due to various reasons like improper image acquisition, filtering process etc. which may be improved upon. The region growing algorithm is used and the image is relabeled. Region growing in turn helps us to reduce the junk class as an effort is given to associate the necessary glyphs and neglect the non necessary ones. The segmented letters are then normalized and arranged according to their spatial occurrence (Fig. 4(d)) in the plate. This information further helps us to regenerate the number plate letters after recognition.



Figure 4(a): Localized Korean number plate



- a. Circles have component tag inside  
b. Rectangles have the number of pixels

Figure 4(b): Tagged components with Pixel Counts

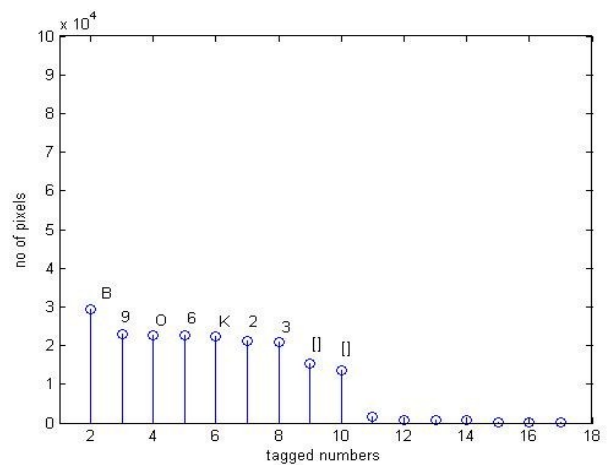


Figure 4(c): Pixel count vs.rank in majority matrix



Figure 4(d): Segmented Letters

### III. RECOGNITION MODULE

A multiple layer perception (MLP) neural network was used in the supervised learning mode. It consisted of 225 input nodes i.e. the 225 pixel values of the training image, and the output nodes consisted of 36 nodes i.e. the 36 classes (26 uppercase letters and the 10 digits). It was observed that number plates use mostly uppercase letters so only uppercase letters were considered. The neural network had only 1 hidden layer with 300 neurons in it. A sigmoid function (explained in the next section) was used as the activation function of the network. This neural network was based on the general gradient-descent algorithm.

A threshold value of confidence was set to pass a glyph as a recognized character or else it is considered as a junk class. This threshold value is decided after a few trials keeping in mind the allowable tolerance of the Artificial Neural Network (ANN).

A database of 50 font samples was used. The system is designed in such a way that the end-user would have the option of rebuilding the database. This feature means the end-user can fine-tune the system to meet their specific needs. (E.g. for identifying different fonts used in different geographical regions or countries). The pixel values of the images are passed to the neural network as input. In case of rebuilding the sample font database, the end-user needs to provide image of the sample font (letters and numbers) written in a horizontal or vertical line. (The performance of the system will improve with increase in number of sample fonts. We recommend 50 font samples.) The system will then automatically segment the individual character images, normalize them to a particular size, arrange the pixels values in a column format and store them in a Microsoft Excel file. The sample data of multiple fonts is thus automatically generated from the provided sample images. This sample data will then be used to retrain the neural network.

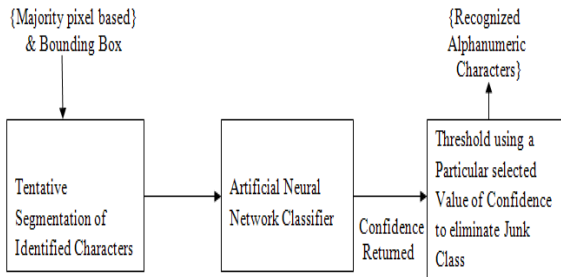


Figure 5: Recognition module

### IV. DATABASE

We have tested our algorithm on 150 different images of license plates used in 58 different countries. These images were obtained from a database (of about 4083 images) made by Jerome Coninx [7]. All of these images were of standard jpeg format. These images were taken under varying lighting conditions.

### V. EXPERIMENTS

The well defined back propagation algorithm was used to train the neural network. The network uses the following activation function or the logistic function.

$$f(x) = \frac{e^x}{1 + e^x}$$

Here the slope parameter in the sigmoid function has been set to 1. A gradient descent algorithm was followed to find the optimised set of connection weights that were updated (according to the following equation) as the training progressed and more epochs were taken into consideration.

$$W_{(t+1)} = W_{(t)} + \alpha * \left(\frac{\partial y}{\partial x}\right) W_{(t)} + \beta * (W_{(t)} - W_{(t-1)})$$

Where  $W_{(t+1)}$  is the new weight  $\alpha$  is the learning parameter,  $\beta$  is known as the momentum term.

The experiments were conducted on 150 license plates of different countries under varying lightening condition and the results are illustrated in (Fig.6). The percentage accuracy here is based on the character wise reconstruction of the license plate after passing through the recogniser. The skewness of the number-plate and improper lighting condition in many cases are the main limiting factors that affect the recognition percentage adversely.

Table II provides the recognition results of the license plates for some of the countries taken up in research. The plates are deemed to have failed in the recognition test if more than two component characters in the license plate are not recognised correctly.

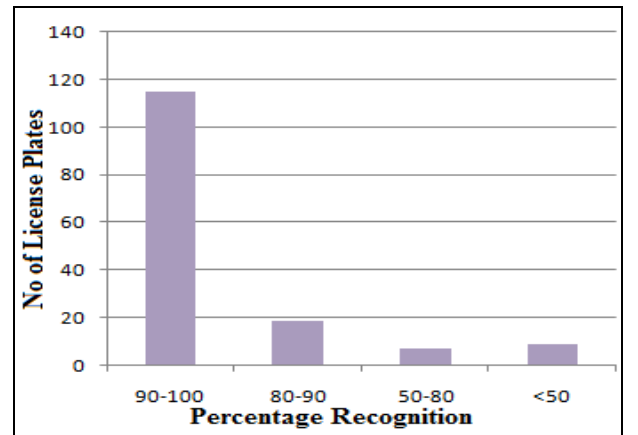


Figure 6: Percentage Recognition vs. No of License Plate

TABLE II. RECOGNITION RESULT FOR NUMBER PLATES OF DIFFERENT COUNTRIES

Recognition Results			
Country	No. of Plates	Pass	Fail
Algeria	3	3	0
Cyprus	4	3	1
Denmark	3	2	1
Germany	5	5	0
Estonia	3	3	0
Finland	4	4	0
France	3	3	0
India	8	7	1
Norway	3	3	0
Slovakia	4	3	1
Portugal	4	4	0
U.S.A	5	3	2
Bulgaria	2	2	0
Czech Republic	3	3	0

## VI. CONCLUSION AND FUTURE RESEARCH

In this paper we have presented a new method of segmenting the characters of the license plate based on a majority pixel value data. We have also addressed the issue of building the databases as per user convenience so that the user has the option to train the neural network with the fonts those are more relevant and mostly used in any particular geographical location. This is totally optional i.e. The user can change the network if they want to for better results. This algorithm has been tested on 150 images and it is found that the accuracy of the system is about 91.59%. The major sources of error were the skewness of the number plate and extreme variation in illumination conditions, which can be aptly removed by enhancing the approach further.

The recognition scheme here is tested on number plates of those countries which use English alphabets and numbers in their plates, but this recognition can be extended to other languages apart from the English script too. In that case the automation of the system would be intact. The entire system was designed on Matlab (Version R2008a) platform but for real time implementation this needs to be developed in C or any similar IDE specific to the hardware used. This would also lower the cost of the system as the C compiler is cheaper than Matlab.

## ACKNOWLEDGEMENT

We would like to thank Prof. Anjan Rakshit of the Department of Electrical Engineering, Jadavpur University, Kolkata, and West-Bengal, India for his valuable suggestions and discussions regarding various aspects of this research work, particularly in the building of the recognition module.

We would also like to thank Jerome Coninx [7] whose collection of number plate's images was immensely helpful in this endeavor.

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