Improved OCR based Automatic Vehicle Number Plate Recognition using Features Trained Neural Network

Bhavin V Kakani
E&C Engineering Department
Institute of Technology
Nirma University
bhavin.kakani@nirmauni.ac.in

Divyang Gandhi
E&C Engineering Department
Institute of Technology
Nirma University
13bec028@nirmauni.ac.in

Sagar Jani
E&C Engineering Department
Institute of Technology
Nirma University
13mecc26@nirmauni.ac.in

***Abstract*—Significant research and development of algorithms in intelligent transportation has grabbed more attention in recent years. An automated, fast, accurate and robust vehicle plate recognition system has become need for traffic control and law enforcement of traffic regulations; and the solution is ANPR. This paper is dedicated on an improved technique of OCR based license plate recognition using neural network trained dataset of object features. A blended algorithm for recognition of license plate is proposed and is compared with existing methods for improve accuracy. The whole system can be categorized under three major modules, namely License Plate Localization, Plate Character Segmentation, and Plate Character Recognition. The system is simulated on 300 national and international motor vehicle LP images and results obtained justifies the main requirement.**

Keywords—*Automatic Number Plate Recognition (ANPR), Optical Character Recognition (OCR), Licence Plate (LP), Binary Image, Number Plate Localization (NPL), Segmentation, Neural Network(NN)*

I. Introduction

Automatic number Plate recognition systems compromises integration of Artificial Intelligence along with computer vision and pattern recognition. Optical character recognition (OCR) which plays chief role in automatic number plate recognition is among the main aspect of research in artificial intelligence and computer vision and have evolved greatly since its inception.

ANPR consists of three main stages: Number Plate Localization (NPL), character segmentation, OCR matching. In the first stage Number Plate (NPs) are identified and localized in the scene and improve plate visual using preprocessing techniques. In the second stage characters are segmented from the detected NP so only useful information is retained for recognition. In the final stage OCR transforms character into encoded text information [1, 2].

This paper presents a feed-forward Artificial Neural Network (ANN) based OCR algorithm that is specially designed to meet the requirement of an ANPR system. The system is then implemented and tested on MATLAB.

The paper is organized as follows: After Introduction, Related work is produced in section II. Preprocessing and localization technique is discussed in section III. Novel OCR implementation is explained in IV. Results and Analysis is presented in section V and section VI concludes the paper.

II. Related Works

A. Licence plate localization techniques

Efficient licence plate localization is a difficult task as vehicle used under various conditions makes plate dirty, moreover different weather conditions and light condition challenges the efficiency of LP localization. The algorithm proposed in [3] fight against this challenges where localization using sobel edge detection technique is proposed. The drawback of previous algorithm is that unwanted areas are also displayed in intensity images thus making detection difficult. This ideally occurs in images having complex background where intensity variations of background dominate the number plate region [3, 4]. To avoid this drawback window function is used. Maximum summation value obtained in the window coordinate is supposed to be region containing LP [5]. This technique detects out number plate more efficiently and accurately from complex background than the former method. There are many other methodologies for number plate localization technique such as using Adaptive Threshold [6], using direction sensitive window filtering [5], etc. but as the accuracy increases so as the computational period and thus to make real time difficult. Localization of number plate using morphological operations provides very accurate and efficient solution.[7]. The localization technique extracts useful region shapes such as skeletons, boundaries and convex hull. Operators which are all a combination of dilation and erosion are mainly used to identify features of various shapes in the image.

B. OCR methodologies

[8] Provides novel OCR technique which authors claims 100 accuracy for digital fonts. It involves partial segmentation of character using features and correlating segment set with the ASCII characters. OCR based on matrix matching is proposed in [9]. OCR using non determined solution using fuzzy set and fuzzy equations is presented in [10]. OCR is proposed for low resolution character image or low quality images using structural analysis in [11].

III. Preprocessing and Localization

For efficient output the image is altered intensely in this stage. Color image is converted to HSV color space which is two dimensional in nature. The advantage of HSV color model is we can neglect the effect of shadow in an image as shown in fig, 1. The Saturation value is extracted that gives us the image by neglecting the shadows. It is then transformed to binary image using edge detection technique for better processing.

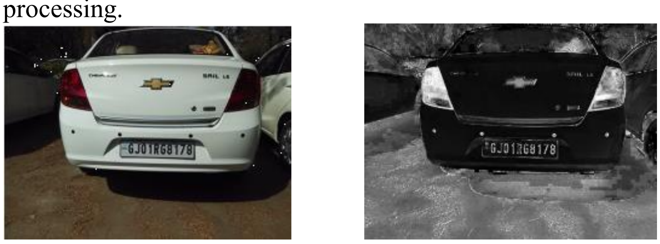


Fig 1. The RGB and HSV color image

A. Edge Detection

Edges in an image are calculated by periodic convolution of function *f* with specific types of matrix **m [7]:**

$$f'(x,y) = f(x,y) \tilde{*} \mathbf{m}[x,y] = \sum_{i=0}^{w-1}\sum_{j=0}^{h-1} f(x,y)\cdot \mathbf{m}\left[\mathrm{mod}_w(x-i), \mathrm{mod}_h(y-j)\right]$$

Here *w* and *h* are dimensions of the image represented by function *f*.

Each filter for edge detection is defined by a convolution matrix and it varies for different edge detection methodologies. Individual cells in the matrix represent the neighbors related to the pixel situated in the center of the matrix. The pixel represented by the cell y in the destination image (fig. 2) is affected by the pixels $x_0 \ldots x_8$ according to the formula

$y = x_0 \text{ X } m_0 + x_1 \text{ X } m_1 + x_2 \text{ X } m_2 + x_3 \text{ X } m_3 + x_4 \text{ X } m_4 + x_5 \text{ X } m_5 + x_6 \text{ X } m_6 + x_7 \text{ X } m_7 + x_8 \text{ X } m_8$

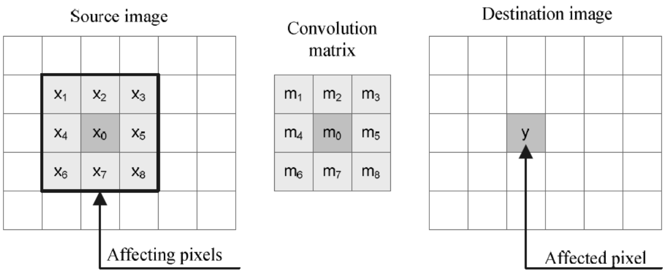


Figure 1 pixel affected by neighbours according to convolution matrix [7]

a) Horizontal and Vertical Edge Detection

The shown matrix m_{he} and m_{ve} are horizontal and vertical convolution matrix for edge detection in horizontal and vertical detection respectively. Note that the size of the image is much smaller than the actual image resolution. Bigger matrix can be used to detect rough edges in case of undesirable image conditions.

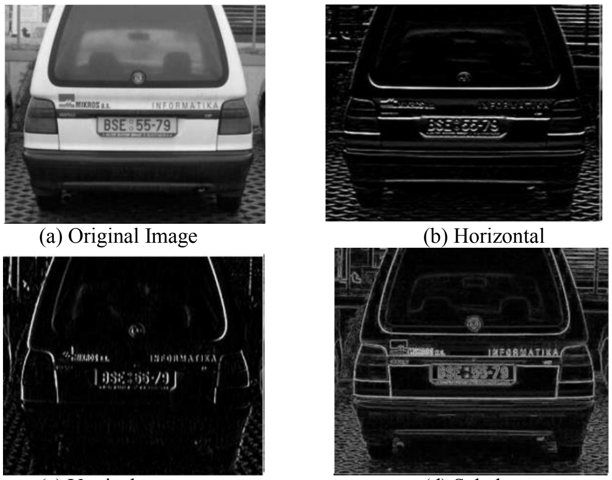
$$m_{he} = \begin{pmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{pmatrix}, \quad m_{ve} = \begin{pmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{pmatrix}$$

b) Sobel edge detection

Below shown are two 3x3 convolution matrix dedicated in evaluation of vertical and horizontal edge detection.

$$G_x = \begin{pmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{pmatrix}, \quad G_y = \begin{pmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{pmatrix}$$

Approximate magnitude is then calculated as $|G| = |G_x| + |G_y|$.



(a) Original Image (b) Horizontal (c) Vertical (d) Sobel

Fig 2. Edge Detection

B. Localization

It is necessary for the Localization algorithm to yield high accuracy as the Character Recognition Technique would be ineffective if the Number Plate is not localized correctly. Two techniques are utilized and compared for localization of number plate.

a) Localization using projection technique

This is one of the simplest method to analyze an image. It projects the image in horizontal x axis and vertical y axis and plots the intensity values on it. Fig. 3 shows the vertical projection of the image with respect to y axis. The region containing the number plate gives a higher peak value given the fact that the intensity variation in that region is higher as a number plate normally have black characters with white background. The horizontal projection of the image is then carried out with respect to the x axis. The horizontal projection are carried out only at the vertical region where the magnitude of projection gives the curve.

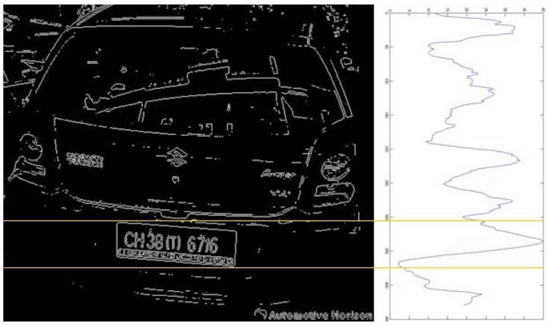


Fig. 3 Vertical projection of edge image

These projection are calculated using the set of mathematical formula as shown below:

$$p_x(x) = \sum_{j=0}^{h-1} f(x,j) \qquad p_y(y) = \sum_{i=0}^{w-1} f(i,y)$$

Where w and h are dimension of the image.

b) Vertical band clipping

Vertical and horizontal band clipping apply on the same method only the region of clipping changes with respect to the image. The vertical band clipping is done by selecting the band from the vertical projection of the image. It is observed that most of the images containing complex background have three variation curve in the vertical projection. We cannot ignore these curve as any of the three can contain the NP region. Thus it is need to perform band clipping in iterative process to clip the image in three bands shown in fig 4.

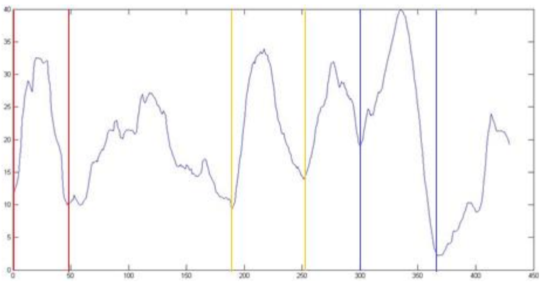


Fig. 4 Vertical band clipping showing three possible LP region

The mathematical logic for band clipping is if h is the height of the analyzed image, corresponding vertical projection $P^r_y(y)$ contains h values, such as $y \in (0; h\text{-}1)$.

The peaks correspond to the bands with possible candidates for number plates. The maximum value of $P_y(y)$ corresponding to the axis of the band can be computed as [7] :

$$y_{bm} = \arg \max_{y_0 \le y \le y_1} \{p_y(y)\}$$

The y_{b0} and y_{b1} are coordinates of band which can be extracted as:

$$y_{b0} = \max_{y_0 \le y \le y_{bm}} \{y | p_y(y) \le c_y . p_y(y_{bm})\}$$
$$y_{b1} = \max_{y_{bm} \le y \le y_1} \{y | p_y(y) \le c_y . p_y(y_{bm})\}$$

C_y is a constant which is computed as 0.55 after calibration over multiple values. The final 3 bands obtained by vertical band clipping are shown in Fig 5.

Fig. 5 Bands after vertical band clipping

c) Selection of appropriate band

This is accomplished by applying correlation of all the band's projection with projection an ideal band of number plate. The projection of Ideal band of the number plate is shown in fig 6. By this matrix containing set of correlation coefficient is generated that contains different value of correlation of number plate band with the ideal band. Under ideal condition maximum correlation is shown when the coefficient is '1' and minimum if the coefficient is '0' that is there is no correlation between the two bands. The band that gives maximum correlation coefficient is selected as the band containing the number plate. The equation applied for cross-correlation between two bands is given as:

$$(f * g)(\tau) = \int_{-\infty}^{\infty} f^*(\tau) g(t+\tau) dt$$

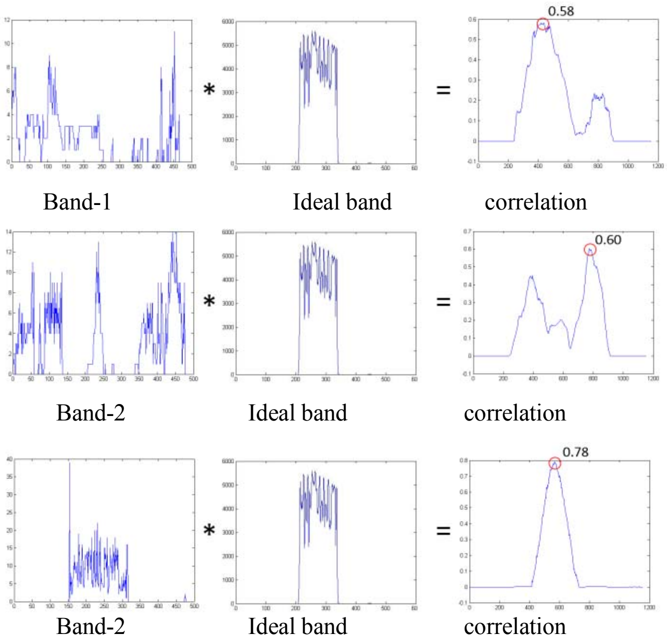


Fig 6. Selection of band

d) Horizontal band clipping

It is same as vertical clipping given the fact that the band selected for horizontal band clipping contains the number plate. As we can observe in horizontal projection the area where the number plate is located is having high variation in intensity magnitude, this is due to the contradictory intensity values of numbers and the background (black-white). By clipping horizontally we obtain the final extracted output of the number plate as shown in fig 7.

Fig 7. Localized number plate

The mathematical procedure of horizontal plate clipping is obtained as follows: If *w* is width of the band (or width of the analyzed image), the corresponding horizontal projection $P^{r}_{x}(x)$ contains w values:

$$p_x(x) = \sum_{j=y_{bo}}^{y_{b1}} f(x, j)$$

Note here that $p_x(x)$ is the projection of the band and not of the whole image. This can be achieved by a summation in interval (y_{b0}, y_{b1}), which represents the vertical boundaries of the band. Then, the maximum value corresponding to the plate can be computed as [7]:

$$x_{bm} = \arg \max_{x \le y \le x_1} \{p_x(x)\}$$

The x_{b0} and x_{b1} are coordinates of band which can be extracted as:

$$x_{b0} = \max_{x_0 \le x \le x_{bm}} \{x | p_x(x) \le c_x . p_x(x_{bm})\}$$

$$x_{b1} = \max_{x_{bm} \le x \le x_1} \{x | p_x(x) \le c_x . p_x(x_{bm})\}$$

C_x is a constant which is computed as 0.55 after calibration over multiple values.

e) Skew correction and segmentation

The main challenge in image deskewing is to calculate the angle at which the number plate is rotated or skewed. Hough transform is used to extract shapes and features of that specific shape out of the image as a special operation as shown in fig. 8

(a) Skewed image (b) Deskewed image

Fig. 8 Skew corrected image

Character segmentation of the detected LP can be obtained by a novel developed technique. The binary image of the localized number plate contains the character with noise and special characters. The binary image is passed through a special dilate function that converts the binary image into dilated image as shown in fig 9

(a) localized LP (b) Dilated image

Fig 9 Image dilation on number plate

Using vertical and horizontal projection of the dilated image, we can obtain peaks at the character regions thus simplifying the cropping process by setting a threshold. The threshold is set at 70% of the peak. The unwanted areas are removed with repetition projection techniques. The localized number plate and its segmented characters are shown in fig. 10.

Fig 10. Segmented Characters

IV Optical Character Recognition

A. *Character recognition using feature extraction*

This algorithm uses the fact that every character have unique set of features such as corners, ending and bifurcations. Inheriting this features makes the algorithm fast and less complicated. The input character is converted to edge image and the features are extracted from it in iterative process. These features are then stored in the feature vector with the number, direction and state of the features. It is explained detail in [12].

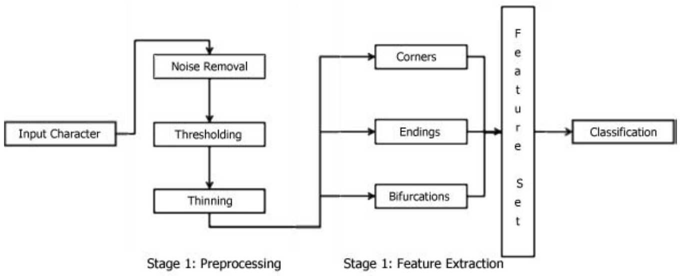


Fig. 11. Block diagram of feature extraction based OCR

Another feature of character is obtained using i-novel technique proposed by Sushruth [8] which works on a special feature set called segments. Tracing segments from different directions and saving the projection values makes a particular character unique in terms of their one dimensional vector.

Next the character feature is obtained by a unique width analysis technique. Every character have unique lines or slopes when observed from the boundary of the segmented character image. This methodology uses this feature to recognize the characters.

After the character is segmented out, it is resized in such a way that the character touches from all sides to the boundary. Now the distance of first black pixel for each and every character is calculated from the left boundary. Similarly, the distance of first dark pixel is calculated from the right boundary. This process is shown in below fig 12. The size of the obtained feature set is of the size (2xh), where 'h' is the height of the resized character. The height of the character image should be fix for all characters.

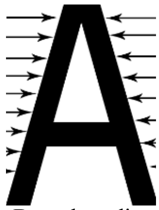


Fig 12. Boundary distance of character

Now the character width for each and every row can be calculated from the boundary feature set. The width of the character is basically the distance between leftmost dark pixels to the rightmost dark pixel which is extracted in boundary feature set. This way a feature set of (1xh) is obtained.
This stage is very important as it normalizes the character width feature set. Normalization is required as we have resized the segment keeping the aspect ratio constant. Thus the height of each and every character is same but width varies depending on the type of the character. E.g., the characters M and H have maximum width, where as the characters I and 1 have minimum width, thus normalizing the feature set gives character width feature between 0 and 1. The feature set can be realized as shown in Fig. 13.

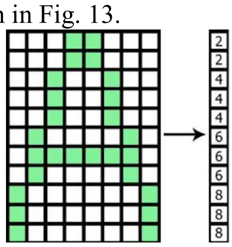


Fig 13. Feature vector extraction of character

Character Recognition using Template matching is one of the best algorithm as it provides robust recognition with higher accuracy even for low resolution images. The methodology utilized simple two dimensional correlation with other predetermined templates of the characters [13].

C. *Training the Feature set using ANN*

A Neural Network is trained to perform particular operation by adjusting the values of the connections (weights) between elements in the function. The basic procedure of adjusting or training the neural network is by giving particular input to get definite target. Main decision making part in recognition system is the classification stage. For Training, Classification and Recognition a feed forward back propagation neural network is used in this work to detect number plate characters. The image is resized to 15_10 pixels that yields total of 150 pixels for the input to the classifier. Total 36 neurons are there in the output layer as proposed system is designed to recognize English alphabets as well as Digits.

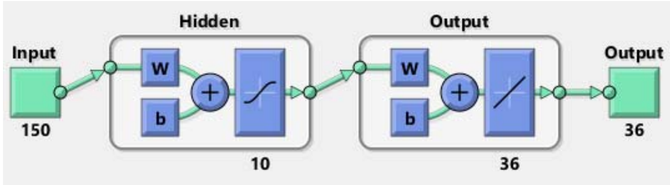


Fig 14. Neural Network architecture

The final stage of the algorithm is post-processing stage where the character is recognized on the basis of classification. To identify the output, the target matrix applied for training consists of all flag as '0' except the character flag. Thus at output the high flag indicates the recognized character. The algorithm prints the corresponding recognized characters in the structured text form by calculating equivalent ASCII value using recognition index of the test samples.
Fig 15a and fig 15b shows the Error histogram and performance plot of the neural network respectively.

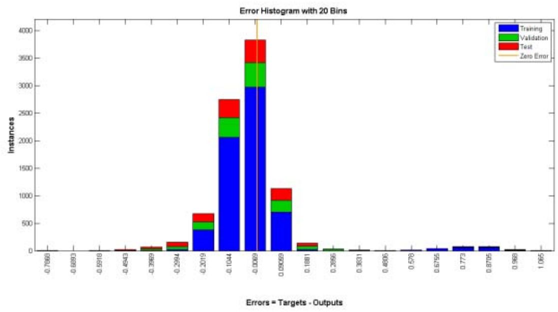


Fig 15 a. Error histogram of NN

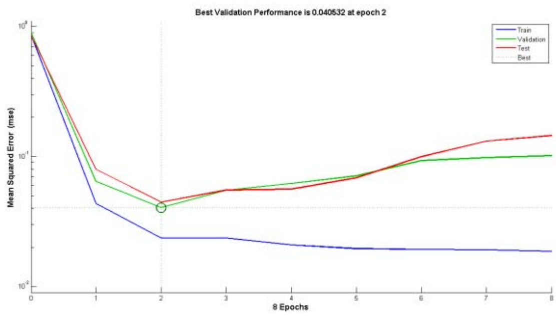


Fig 15 b. Performance plot of NN

D. *ANN and Feature extraction*

Artificial neural network needs to be trained with multiple images. To obtain greater accuracy the network needs to be less complicated and should be trained with more training data. In ANN without feature extraction, the input data is very large as whole character segment is included for training. Thus the network complication increases so as the training period. To reduce this drawback training is done on the features of the characters extracted. For simple feature extraction, the accuracy is not very high as due to the resolution and variation in character fonts. But when this feature data is trained using neural network the obtained network is robust, more accurate and gets trained in less period with large input database. We have used 300 images of different characters for training of the network. Thus, a matrix of 30_300 values is fed to the ANN for training purpose to obtain 36 different values at the output, one for each character in the database. Here the neural network uses Feed Forward Back Propagation technique for learning and logsigmoid function at the hidden layer. the number of neurons are 10 for single hidden layer. Input comprises of 30 neurons and output comprises 36 neurons. The ANN was trained for 300 iterations, which took around 15 seconds to complete. An error goal of 0.0001 or 0.01% was achieved by the ANN.

V. RESULTS AND ANALYSIS

The result of proposed localization gave accuracy of 96.7% whereas the character recognition technique yielded 92.2% accuracy. The complete Automatic Number Plate Recognition System Gave 94.45%.

Table 1: Comparison of localization Algorithm with different methods

Algorithm	**Accuracy**	**Computation Period**	**Comments**
Projection Technique	89%	0.91s	Effective for different styles of NP
Morphological Operation	96.7%	0.54s	Effective on noisy images
Feedback self-learning and Hybrid binarization	97.1%	0.51s	High complexity, low resolution images required
Feature salience	97.3%	0.23s	High resolution, low noise images required.

Table 2: Computation of different OCR algorithms

Algorithm	**Computational time (ms)**	**Detection rate (%)**
i-novel	470	73%
Template matching	1000	94%
Width analysis	430	86%
ANN using template matching	176 (post training)	89.4%
ANN using feature extraction	**75 (post training)**	**92.2%**

The Localization and OCR algorithm are selected due to its optimized output over other algorithms for the application of ANPR. For other applications depending upon the requirements and image source, algorithms can be modified or changed to prove better and are suggested to apply for optimized results.

VI. CONCLUSION

The proposed algorithm designed after all the work and survey gives an accuracy of 94.45% in less than 1 second when tested upon 300 odd images of vehicles at different viewing angles and environmental conditions. Using Artificial Neural network the system showed better results on single set of templates.
The training period taken by ANN was 12 seconds and once trained, it recognizes the test samples fed to the network efficiently.

The chief advantages of the system is less time complexity, High Adaptability to untrained test inputs with much less features to calculate. On the other hand, it has some limitations; The image deskew algorithm applied for skewed image up to 30 degrees, Accuracy of the algorithm is largely dependent on the change in the environmental conditions and also depends upon the quality of the image captured by the device (CCTV or Camera) and Matlab software, which we used for processing of the image, which is not good for real time because of its large processing time. The system still has a large scope for further developments.

REFERENCES

[1] C. Anagnostopoulos, T. Alexandropoulos, V. Loumos and E. Kayafas, “ Intelligent traffic management through MPEG-7 vehicle flow surveillance,” in Proceedings of IEEE International Symposium on Modern Computing, 2006, pp. 202-207.

[2] N. Mani, and B. Srinivasan, “Application of artificial neural network model for optical character recognition,” presented at the IEEE International Conference on Systems, Man, and Cybernetics, 1997.

[3] R. P. van Heerden, E. C. Botha, Optimization of Vehicle License Plate Segmentation and Symbol Recognition, Department of Electrical, Electronic and Computer engineering, University of Pretoria, South Africa, 2010.

[4] F. M. Rodrguez, X. F. Hermida, New Advances in Automatic Reading of V.L.P.s (Vehicle License Plates), Proceedings in SPC-2000 (Signal Processing and Communications), Marbella, September 2000.

[5] F.M. Rodrguez, M. G. Saburido, J. L. A. Castro, New Methods for Automatic Reading of V.L.P.s (Vehicle License Plates), SPPRA-2002 (Signal Processing Pattern Recognition and Applications), June 2002.

[6] A. E. Savakis, Adaptive Document Image Thresholding Using foreground and Background Clustering, International Conference on Image Processing, October 1998.

[7] Ondrej Martinsky, Algorithmic and mathematical Principles of automatic number plate Recognition systems, Brno University of technology, 2007.

[8] Sushruth Shastry, Gunasheela G, Thejus Dutt, Vinay D S and Sudhir Rao Rupanagudi, i - A novel algorithm for Optical Character Recognition (OCR), IEEE 2013.

[9] W. Badawy, ”Automatic License Plate Recognition (ALPR): A State of the Art Review”, 2012

[10] Sukhpreet Singh Optical Character Recognition Techniques: A Survey, Journal of Emerging Trends in Computing and Information Sciences, Vol. 4, No. 6 June 2013.

[11] T. Naito, T. Tsukada, K. Yamada, K. Kozuka, and S. Yamamoto, Robust licenseplate recognition method for passing vehicles under outside environment, Trans. Veh. Technol., vol. 49, no. 6, pp. 23092319, Nov. 2000.

[12] M. Usman Akram, Zabeel Bashir, Anam Tariq and Shoab A Khan, Geometric Feature Points Based Optical Character Recognition, IEEE Symp. Industrial Elec. & App., Sept. 2013.

[13] Dr Savita Gael and Savita Dabas, Vehicle Registration Plate Recognition System Using Template Matching, IEEE 97B-1 -4799-1 607-B/13, 2013.