An Intelligent Approach for Robust Detection and Recognition of Multiple Color and Font Styles Automobiles License Plates: A Feature-Based Algorithm

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***Abstract*—This paper presents a robust real time feature based algorithm for localization and recognition of multiple color and font style license plates. The algorithm uses digitized license plate images for robust detection and recognition. The resolution of the captured image is adjusted and the brightness and contrast are set to appropriate levels. An optimal threshold is applied to detect white regions of the enhanced image. The algorithm uses segmentation and component labeling to create candidate regions intelligently. For localization of the license plate, features of each region are extracted and analyzed by rectangularity percentage of the automobile's license plate. The use of color filter renders the algorithm more robust on license plate localization. Moreover, we use HSV color space to find the specific color regions. After localization of license plate in small sized image, the proposed algorithm uses rapid intelligent method for localization of license plate form the original image. The localized license plate image is cropped and processed by the recognition algorithm. Each character's region is identified by using segmentation algorithm based on the profile which includes character dilation and resizing for subsequent operations. In this paper, correlation optical character recognition and multi-layer perception neural networks techniques are used for recognizing the characters. The performance of the proposed algorithm is acceptable even in low-quality or bad light images.**

I. Introduction

Automatic license plate recognition (ALPR) belongs to mass surveillance techniques, which is used to recognize vehicle license plate numbers. Recently, ALPR has become popular due to its practical importance in image processing applications. Several improvements are proposed in literature, which present efficient and accurate algorithms to detect license plate and identify the numbers [1]–[7].

ALPR uses digitized images of vehicles on the road to recognize the vehicle license plates.These captured images are processed by the computer and features are extracted by applying different image processing techniques and algorithms. Such extracted information is then used for the recognition of vehicle's license plate by applying optical pattern recognition techniques.

Recently, ALPR is being widely used in various parts of the world for monitoring and controlling the transportation. Many algorithms for implementing ALPR algorithms are found in literature. In [3], the authors propose a region-based license plate detection approach, which uses mean shift algorithm for detecting the location of license plate and filters/segments the vehicle's image. After segmentation, the regions of interest are analyzed to determine accurate license plate location. Using intensity variance and edge density features in numbers plate, an algorithm is proposed in [8]. As intensity variance and edge density are approximately constant over the license plate region, a matched filter based on edge density is used for candidate regions extraction. Then the object authenticity is checked using morphological operation.

In [9]–[11], the presented methods exploit the abundant vertical edges in license plate regions, which indicates the presence of characters and these features are used for classification by generating the regions of interest. By using geometrical properties of number plates, significant performance gains are achieved in noisy license plate images [11]. The Hough transform is one of the commonly used techniques for detection of lines and curves, as proposed in [12]. It uses angle-radius parameters to simplify the computation. For detecting the frames, Hough transform is used in [13].

The methods based on the color information have notable significance for detection and recognition of a license plates. In these approaches, the unique color of license plate and the color contrast between the license plate and the vehicle is used as key feature for localization of license plates. Neural network classifier [14], [15] and generic algorithm [16] are commonly applied for detection of exact color of certain pixel. In [17], the license plates are localized as an image area, having rectangular shape and maxima of response to line filters computed by a cumulative function.

In previous works [1]–[7], [18], ALPR is implemented on a unique colored license plate having a unique font in a

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Fig. 1: License plates samples of Punjab's vehicles

single line. We propose a new region based approach, which has efficient localization for complex license plates having multiple colors and font styles that are not found in a single line.

II. Pakistani Automatic License Plate Recognition (PALPR): Proposed Algorithm

The proposed algorithm **Pakistani Automatic License Plates Recognition (PALPR)** is designed for the recognition of Pakistani vehicles license plates with combination of colored regions. For the performance evaluation of PALR, we use samples of license plates that are used for vehicles registered in the Punjab province of Pakistan. The proposed algorithm can be easily extended to license plates of vehicles from other regions. In general, the license plates have some acronyms and numbers, which give classification information about the respective vehicle. Some license plates examples of Punjab's vehicles are shown in Figure 1.

A. *Features of License Plate*

License plates of Punjab vehicles and of other regions are of rectangular shape. Twenty percent of plate's background portion is green and eighty percent of plate's background is of white color. Figure 2 shows the features of the license plate. Region 'Punjab LP' shows the rectangularity of plate and regions A1, A2 are the white and green portions respectively. Moreover, the segment A1 represents the white area of license plate, which is divided into three regions B1, B2 and B3. These regions represents information about the registration of the vehicle. This region is used for recognition of the license plate. The B1 and B2 regions have same font style named as FE. The region B3 has font style named 'SAA-A class'. Three different data sets are used for recognition process. Moreover, the segment A2 in Figure 2 is the green portion of license plate.

III. PALPR Framework

The framework of the proposed PALPR algorithm has two parts and are shown in Figure 3, i.e., localization and recognition of license plate. subsectionVehicle RGB Image Preprocessing In the localization process, entire vehicle's image is captured using a digital camera. Initially, the captured image has a higher (for example: 1024x684 pixels) resolution. Since it is high resolution image, we resize the vehicle's image to 240 pixels sized image as shown in Figure 4(a), for making the localization processing fast and robust. This resized image is then converted into gray scale image as shown in Figure 4(b).

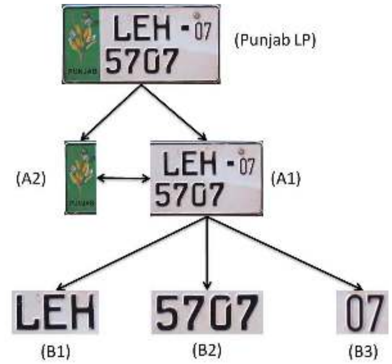

Fig. 2: Features of license plate

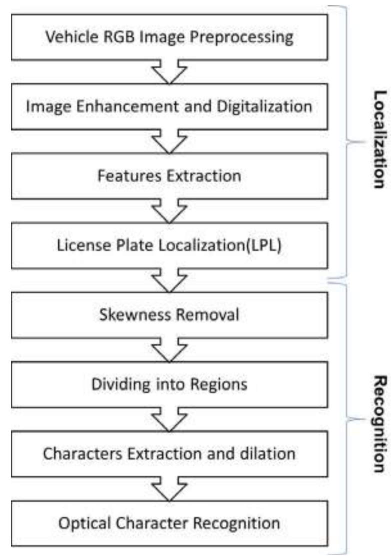

Fig. 3: Block diagram of framework of PALPR

A. *Image Enhancement and Digitalization*

The vehicle's image may be noisy and have disturbance of light and shadow as well, therefore, the image is enhanced for locating the target license plate. Image intensity values are enhanced in order to make white regions brighter, as shown in Figure 5(a). Using $Image(x)_{Intensity}$ filter, the intensity values are filtered to make image brighter.

$$Image(x)_{Intensity} = \begin{cases} Image(x) & 0.3 > \text{x} > 0.7 \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

After the enhancement, the threshold is applied to obtain a binary image, as shown in Figure 5(b)

(a) (b)

Fig. 4: (a) Vehicle image (b) Gray image

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(a) (b)

Fig. 5: (a) Enhanced image (b) After applying the threshold

(a) (b)

Fig. 6: White regions on (a) Binary image (b) RGB image

B. Features Extraction

Four way component labeling connectivity is used for segmentation on the binary image that plays a pivotal role in detecting various regions. The segmentation partitions the image into targeted regions so that the features are extracted for license plate detection.

1) White Regions: After the component labeling, objects corner points are calculated using their unique labels. Therefore boundary information of all white regions regions is processed and prepared. Detected white colored regions in the binary image are shown in Figure 6. The corresponding detected region in RGB image are also shown in Figure 6(b).

2) Green Areas: The license plate has about 20% green color region on the left. The algorithm to detect the white color portion is presented in the previous section. Green color detection from an image is relatively not easy. In the image, the green color in not pure, therefore we cannot apply simple RGB approach by using (0,255,0) combination. In the first step, the image is converted into HSV format and then the filter $f(H,S)_{green}$ is used to determine the green colored regions for all weights of HSV values.

$$f(H,S)_{green} = \begin{cases} f(H,S) & \text{H \& S} > 0.5 \text{ and H} < 0.25 \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

where H and S represents hue and saturation of pixel respectively. After applying the above filter, the detected green colored regions are shown in Figure 7, which is used for the original LPL detection.

(a) (b)

Fig. 7: (a) Original vehicle image (b) Detected green colored regions

TABLE I: CANDIDATE REGIONS

Number	Candidate Regions	Ranges for Rectangularity Plate
1	Aspect Ratio	1-2.5
2	Perimeter of Object	30-300(pixels)

Fig. 8: Real LPL detection

3) Primary Filtering and Candidate Selection: It is observed by Figure 6 that there are unwanted white color objects of smaller or larger perimeter values. So we apply primary filtering to remove all such types of regions by keeping in view the aspect ratios (width to height) and perimeter of the objects. Candidate regions selection is accomplished by applying primary filtering, as depicted in Table I.

C. License Plate Localization (LPL)

After the candidate selection and green colored region detection, the algorithm determines the exact location of license plate. As shown in Figure 2, the green colored region is on the left side adjacent to white colored region. License plate location (LPL) is detected in the low resolution image. The real license plate is then intelligently cropped from high resolution image and is shown in Figure 8.

D. Skewness Removal

Skewness in images is one of the problems confronted in license plate images, which create difficulties in the recognition process. We use Hough transform for estimating the skew angle and retaining the license plate image to zero degree. The cropped image is then rotated after determining the angle, as shown in Figure 9.

(a) License plate having rotation (b) Straight license plate

Fig. 9: Removing skewness from license plate image

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Fig. 10: License Plate Partitioning

Fig. 11: After segmentation

E. Dividing into Regions

In Figure 10, the characteristics of license plate are shown. *A, B, C* and *D* represents the corners of license plate. *E, F* and *G, H* are the mid points of vertical and horizontal edges respectively. If points *E, F, G* and *H* are connected then the license plate is divided into four parts, as shown in Figure 10. In the next step, the midpoint *I* is calculated. The points *J* and *L* are mid points of lines $\overline{GB}$ and $\overline{IF}$, respectively. The points *M* and *N* are determined by calculating mid points of lines $\overline{GJ}$ and $\overline{IL}$. License plate is divided into three major parts whose partitioning is mentioned using bold dotted lines in Figure 10. The portion '*AMNE*' (B1) always have alphabets of 'FE' font, '*ELKD*' (B2) have digits of 'FE' font and '*MBFN*' (B3) will have digits of 'SAA A-class' font.

F. Characters Extraction and Dilation

Segmentation is processed using the automatic threshold technique. After converting license plates' RGB image to gray image, a binary image of license plate is created. The automatic threshold technique is feasible for noisy and low light images. The resultant image after segmentation is shown in Figure 11. For the candidate regions selection, secondary filtering is applied in a similar manner as primary filtering, which yields objects characters. Component labeling is applied for detecting candidate regions such as characters in the license plate, which are further used for recognition process. After applying the threshold, the character has some noise or weakness. The characters are dilated and resized to objects of size 42x24 pixels, as shown in Figure 12. Using the location information of object and characteristics of license plate, as shown in Figure 10, unique tag of characters are created to their corresponding regions, such as B1, B2 or B3.

IV. Optical Character Recognition(OCR)

Three different data sets of are used for configuring templates in the process, which correspond to recognition of

(a) (b) (c) (d) (e) (f) (g)

Fig. 12: Segmented characters of license plate

character for regions B1, B2 and B3.

A. Correlation OCR

Templates are prepared using FE and SAA-A class fonts for the correlation OCR. After the resizing each character image, we use correlation coefficient for classification. The correlation OCR is processed between templates of original character images and license plate extracted characters. Equation 3 refers the correlation between A and B.

$$r = \frac{\sum_m \sum_n (A_{mn} - \overline{A})(B_{mn} - \overline{B})}{\sqrt{\left(\sum_m \sum_n (A_{mn} - \overline{A})^2\right)\left(\sum_m \sum_n (B_{mn} - \overline{B})^2\right)}} \tag{3}$$

Where $\overline{A}$ and $\overline{B}$ are the mean values of A and B respectively.

The target characters are those that exhibit maximum correlation with the license plate's characters.

B. Neural Networks

Thirty different images of each character are digitized and the learning data sets are prepared with the help of MATLAB using neural network toolbox. We trained data sets for multi-layer perceptron (MLP) with three hidden layers with sigmoid functions as shown in Figure 13. Gradient descent back propagation (GDBP) model with adaptive leaning rate is used for training MLP neural network.
Gradient decent is used to minimizing the mean square error E.

$$w_{ij}(t+1) = w_{ij}(t) + \triangle w_{ij}(t) \tag{4}$$

Where $\triangle w_{ij}(t) = -\eta \frac{\partial E}{\partial w_{ij}}$ and η is the learning rate.

Equation 4 shows that the weights are updated in proportion to the negative of an error derivative with respect to each weight. Significantly, weights are changed in the direction of steepest descent on the error surface named as total error E.

$$E = \frac{1}{2} \sum_l \sum_m (t_{lm} - o_{lm})^2 \tag{5}$$

where o_{lm} be the activation of output unit in response to pattern l and t_{lm} is the target output value for unit.

As shown in Figure 2, Pakistani automobile license a plate has three regions B1, B2 and B3. Three different neural networks are prepared for simulations on these three areas. After training the networks, the extracted character is simulated using their corresponding region's neural network to recognize the characters of license plate. We trained the neural network and weights are adjusted by iterating the Equation 4 until we have $1 \times e^{-9}$ mean square error.

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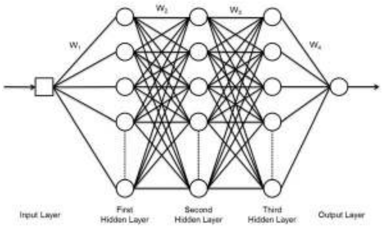
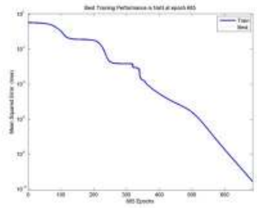
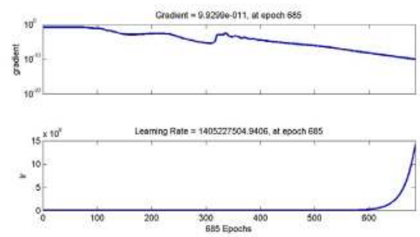


Fig. 13: Architecture of MLP with three hidden layers

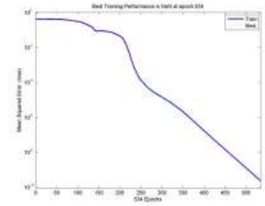


(a)

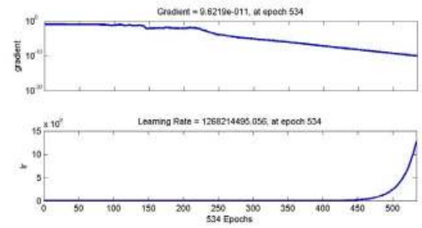


(b)

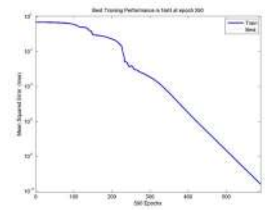
Fig. 14: Training for B1 (a) Performance plot (b) Gradient and learning rate



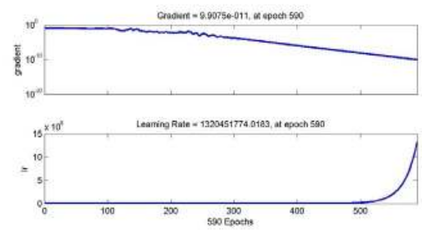
(a)



(b)



(c)



(d)

Fig. 15: Training for B2 and B3, (a) and (c) are performance plots, (b) and (d) show gradient and learning rate plots

V. Simulation and Experimental Results

The training region for B1 is performed using alphabets of FE fonts as input data along with MATLAB's Neural Network toolbox. The performance for least mean square error is met after 685 iterations, as shown in Figure Fig 14(a). The corresponding plots of learning rate and gradient are shown in Figure 14(b). Similarly, the training for regions B2 and B3 are processed using FE and SAA-A Class fonts' decimals characters, respectively. The performance for least square error is attained after 534 iterations for region B2 and 590 iterations for region B3. The corresponding performance plots for B1 and B2 are shown in Figure 15(a) and Figure 15(c), respectively. The learning rate and gradient plot for regions are shown in Figure 15(b) and Figure 15(d), respectively.

Different images of Punjab vehicles' are processed by PALPR for testing and evaluation. Testing images consists of two batches of 50 images each. The first batch is captured from the front side of vehicles at different camera positions and orientations in normal light settings while the second batch consist of images of vehicles taken in high sun light and shadowy settings. Moreover, PALPR is tested on those captured images which have same color of license plate with a vehicle in background.

The localization accuracy of PALPR is approximately 98 percent while the remaining 2 percent of vehicles' images have strong sunlight or dirty license plates. Forty six characters are used to make templates for correlation OCR of license plate. Training data sets for B1, B2 and B3 regions in MLP neural network consist of 780, 300 and 300 characters respectively. The MLP neural network is trained by 1000 characters and tested using 380 characters. Table II shows the results of correlation OCR and MLP on these data sets. It is evident from Table II, that MLP neural network model has higher performance in character recognition. Therefore the MLP neural network model is used in PALPR for character recognition.

VI. System Performance

The system performance is measured by the time required for localization and recognition using PALPR. The performance results, shown in Table III, are simulated on personal computer equipped with Core i3 microprocessor and three

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TABLE II: PERFORMANCE FOR CORRELATION OCR AND MLP NEURAL NETWORK

Numbers	Techniques	Percent Correct (%)	Training Times
1	Correlation OCR	85	-
2	MLP	98	15

TABLE III: PERFORMANCE FOR OVERALL SYSTEM IN SECONDS

Techniques	Reading RGB	Localization Time	Recognition Time	Overall Time
OCR	0.07	2.16	0.21	2.44
MLP	0.07	2.16	0.51	2.74

GB of random access memory. Both the correlation OCR and MLP neural network models are simulated for the performance comparison.

Although the correlation OCR consumes less time to analyze, the results of MLP neural network model are more accurate then the correlation OCR. Hence, the performance difference is not too much, therefore we propose PALPR systems based on MLP neural networks.

VII. CONCLUSION

In this paper, we develop an intelligent vehicle license plate recognition system based on efficient localization process for designs with multi color and multi fonts data. The MLP neural network model is chosen because of its high performance of character recognition. The developed system is successfully implemented in experimental setup, which can be used in many practical applications. The results show that the developed method is capable of locating and recognizing a car license plate efficiently. Performance of the system can be significantly improved by implementing on FPGA devices. It is shown that the system is capable of working with low resolution, low light and noisy images. Moreover, a study of different parameters of the training and recognition segments show that the developed system gives good results in most cases and achieves a high success rate. Also, the license plate localization time is significantly minimized by using the proposed algorithm, as verified by experimental results.

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