A New Approach for Recognizing Saudi Arabian License Plates using Neural Networks

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Abstract— **In this paper, a neural networks (NN) based automatic license plate recognition system (ALPR) is proposed for Saudi Arabian license plates with Arabic characters. The license plate region is first localized by first tracing the exterior and the interior close boundaries of objects in the car image and then separating the license plate by determining the rectangularity characteristic of these close objects. Character segmentation is performed via vertical and horizontal projection profiles. Finally, a Multilayer Feedforward Neural Network (MFNN) with a back-propagation (BP) algorithm is used for character recognition. We discuss new features from the characters for training the NN. The results obtained from a medium size data base are very promising, i.e., 98%. The alogoritms discussed here were tested at the entrance of a praking lot to mimic a real life situation.**

I. Introduction

Research in developing robust Automatic License Plate Recognition (ALPR) systems has attracted a lot of attention in recent years. For local authorities, ALPR systems can be used in law enforcement, border protection, vehicle thefts, automatic toll collection, and perhaps traffic control. For others, automatic license plate recognition systems can be applied to access control in housing areas, automatic parking control and marketing tools in large shopping complexes, and perhaps for surveillance [1].

There are numerous commercial license plate recognition systems available in the market and discussed in the literature [2]. Among the commercial license plate recognition systems available worldwide are Car Plate Recognition by Nijhuis et.al. [3], Car Plate Reader (CPR) by Barosso et.al. [4], and Automatic Number Plate Recognition (ANPR) by Chang et. al.[5], to mention a few.

Image acquisition is the first step in an ALPR system. Different image acquisition methods have been used in previous work. Naito et. al. [6] developed a sensing system, which uses two Charge Coupled Devices (CCDs) and a prism to split an incident ray into two lights with different intensities. Salagado et. al. [7] used a sensor subsystem having a high resolution CCD camera supplemented with a number of new digital operation capabilities. In our work, a single high resolution CCD Sony camera was used.

After acquiring the car image, one of the important tasks is the localization of the license plate region. License plate regions have been localized by looking for rectangular regions in the image edge map. The prerequisite for this method is that license plate should exhibit sharp rectangular edges. However, if the color of the car and the license plate are almost the same, the rectangular edges of the license plate will not be visible. Therefore, license plate localization using only the edge map was shown to be not very robust [8]. Color histograms were also proposed to locate the license plate by Lee [9]. The technique fails under different lighting conditions when the actual color of the license plate differs from its reflected color. Different approaches for the extraction of the license plate depending upon the background color of the image have also been presented in [10], [11], [12].

Before any classification can be carried, there is a need to segment the license plate region from the taken picture. A number of techniques have been developed for this purpose. Nieuwoudt et. al [13] proposed a technique using region growing while Hansen [14], developed a connected-component method for segmentation. Morel used neural networks and partial differential equations based techniques to segment the license plate while vertical projection profiles were proposed in [11] and [12].

For the recognition stage of ALPR systems, a number of statistical, syntactic, and neural approaches have been developed. Hansen et. Al [14] proposed an approach that uses a probabilistic model while Cowell and Hussain [15] identified the characters based on the number of black pixel rows and columns of the character and comparison of the values to a set of templates or signatures in a database. Furthermore, the thinning of Arabic characters was also discussed in [15] to extract essential structural information of each character, which is then used for the classification stage. Template matching was proposed by Zidouri [11]. Numerous systems have used neural networks (training the network using the ideal and noisy input data) for recognition [12].

Saudi Arabian plates are different from others in many aspects. First they have Arabic characters which unlike the English characters are very similar to each other. For example the only difference between two different letters may only be a dot. Second, Saudi Arabian plates have word "Saudia" written in Arabic. Third, their LP dimensions are different from others and themsleves take different shapes.

This work presents an NN based ALPR system for Saudi Arabian LPs. In particular, we propose a new method for localizing the Saudi Arabian LPs. Images are taken from the front end of cars by a high resolution digital camera. The license plate is localized by first tracing the exterior and the interior close boundaries of objects in the car image and then separating the license plate by determining rectangularity of these close objects. Character segmentation is performed via vertical and horizontal projection profiles. Characters are recognized using MFNN with BP algorithm.

This paper is organized as follows: In section 2, the proposed algorithm is presented. In section 3, we discuss the recognition stage and the ANN implemented for this purpose. In section 4, our experimental results are presented followed by a conclusion.

II. Proposed ALPR System

The proposed ALPR System involves 5 major steps; Image acquisition, License plate localization, LP segmentation, Feature extraction and Character recognition as shown in Figure 1. Next, each of these steps is discussed in details.

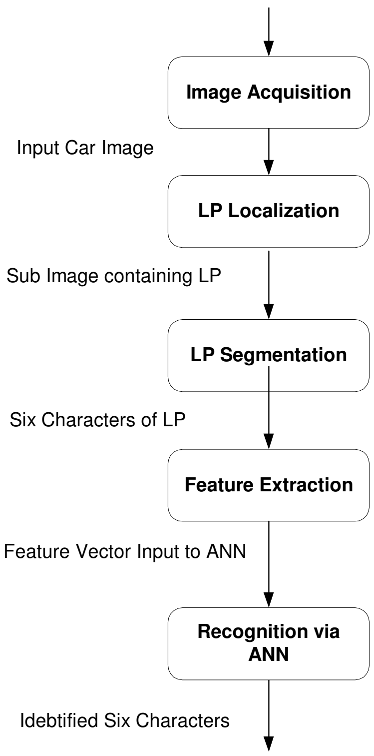

Fig. 1. Flow chart of the proposed ALPR system

A. Image Acquisition

The very first stage is the image acquisition phase where in the image of the vehicle is captured. In our work, the image is captured using a high resolution Sony digital camera with a resolution of 640x480 pixels.

B. License Plate Localization

This step plays a vital role in any ALPR system. In the proposed system, the license plate is extracted by applying a series of operations which are explained below.

1) Image Pre-processing: The RGB car image obtained from high resolution digital camera is first converted into grayscale format shown in Fig 2, and then converted to a binary image using adaptive thresholding. Before detecting closed boundaries, the binary car image is first dilated using matlab function "imdilate". The dilation process enhance the boundary detection performance by thickening mask. An example of binary dilated image is shown in Fig. 3.

Fig. 2. Original Gray scale Car Image

Fig. 3. Binary dilated image

2) Detecting Closed Boundaries: In this step, the different closed boundaries are first detected in the dilated binary car image. The outermost objects (parents) are first detected followed by their children (objects completely enclosed by the parents). This tracing is carried using 8-neighborhood scheme. Results of detected closed boundaries is shown in Fig. 4 After tracing the connected pixels, a set of predefined conditions, discussed next, is then applied to these boundaries to detect the closed contours that are valid LP candidates.

3) Extracting The LP Region: The LP region is extracted based on certain predefined conditions which are as follows:

- Normal Saudi license plates are white with black characters. It is found that the black to white ratio is around $20 - 25\%$. Only regions satisfying this condition are considered as potential LP candidates.
- Usually LP has area in the range $[23000,\ 25000]$ (in our experimental setup). Hence, all areas of closed objects satisfying this condition are kept as valid LP candidates.

Fig. 4. Detected closed boundaries

- Rectangularity of the closed boundaries is determined (Rectangularity is the ratio of object's area to rectangle's area formed by the extreme points of the object). Its value is in the range $[0,\ 1]$. For a pure rectangle, its value is 1. In the proposed system, the regions with a rectangularity greater than or equal to 0.9 is considered as valid LP candidates.

LP localization results based on above mentioned conditions (all) is shown in Fig. 5 while the resulting extracted LP is shown in Fig. 6.

Fig. 5. Final localized LP within car image

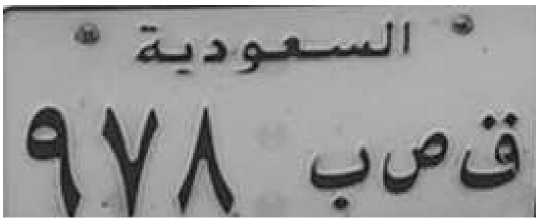

Fig. 6. Extracted LP

C. LP Segmentation

After localizing the LP, its segmentation is required in order to extract the 6 characters. Before extracting the characters, we need first to identify and remove the word "Saudia", then carry vertical and horizontal projections.

1) Removing the Word "Saudia": Filtering out the word "Saudia" will depend on the type of license plate under analysis.

Case 1: Long LP: For this case, we take 40% from the middle region on the x-axis and 50% from the middle region on the y-axis as shown in Fig 7. This region is then filled and replaced with the average gray level of the plate.

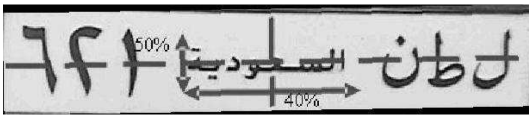

Fig. 7. Long LP

Case 2: Normal LP: For normal license plates, we take the top 33% from the area as the region containing the word "Saudia" and remove it as shown in Fig 8. In the example above, we have a normal LP. The resulting LP after removing the word "Saudia" is shown in Fig 9.

Fig. 8. Normal LP

Fig. 9. Extracted LP after removing word Saudia

2) Horizontal and Vertical Projections: To obtain the character's region from the segmented image, horizontal and vertical projections are determined. The horizontal projection is used to remove unwanted noise in upper and lower regions that do not carry information about the characters as shown in Fig. 10. While the vertical projection aims at separating the different characters as shown in Fig. 11. For the example considered above the resulting segmentation of the different characters is displayed in Fig. 12.

D. Feature Extraction

Before the character recognition stage, suitable features need to be extracted:

- Roundness: This property determines roundness in a character.
- Number of Points Above Baseline: The baseline is first obtained by looking maximum in the horizontal

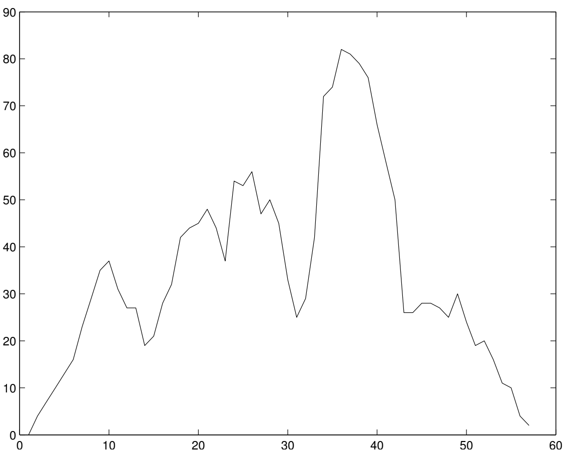

Fig. 10. Horizontal Projection

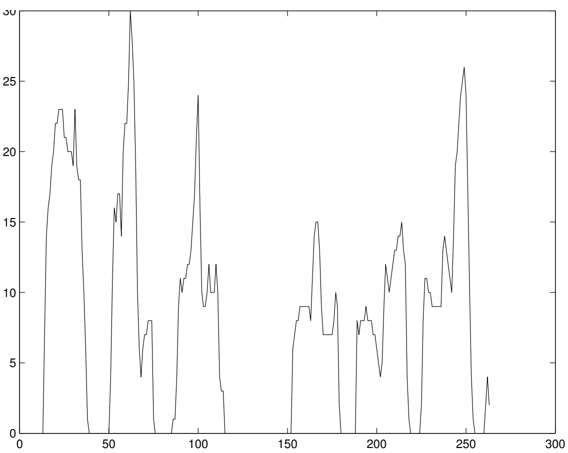

Fig. 11. Vertical Projection

projection of a character. Second, isolated closed objects above the baseline are determined.

- Number of Points Below Baseline: Here isolated closed objects below the baseline are found.

The feature vector is obtained for each character by stacking rows of isolated character matrix having binary values (0 or 1). This vector is concatenated by the above mentioned features of the corresponding character.

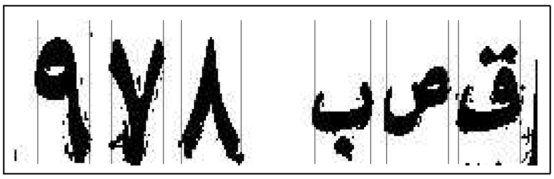

Fig. 12. Segmented Characters

III. Character Recognition using Artificial Neural Networks (ANN)

Finally, characters of LP are recognized using ANN. An ANN is a computation model inspired by the way biological neural systems work. It uses neurons as its processing elements; working in parallel as a well unified network to work out particular problems. The interesting aspect of a neural network is that it, like people, learns by example and improves by training. There are different structures of ANN. The most popular is the MFNN shown in Fig 13. It consists of input, output, and hidden layers each of which has a number of neurons. Each neuron is connected to the input via a link having some weight. The output of the neuron is applied to a non linear function. If $y_i(n)$ is the output of i^{th} neuron at the n^{th} iteration, $w_{ji}(n)$ is the synaptic weight connecting the output of the i^{th} neuron to the j^{th}neuron, then the local field $v_j(n)$ induced at the input of the activation function associated with neuron j is:

$$v_j(n) = \sum_{i=o}^{m} w_{ji}(n) y_i(n), \tag{1}$$

where m is the total number of the inputs applied to the neuron j. If the $\Phi()$ shows the nonlinear function applied to the output of any neuron, then the output at the j^{th} neuron is:

$$y_j(n) = \Phi_j(v_j(n)). \tag{2}$$

According to the conventional BP algorithm, the synaptic weights $w_{ji}(n)$ are updated by the following principle:

$$w_{ji}(n+1) = w_{ji}(n) + \eta \delta_j(n) y_i(n), \tag{3}$$

where, η is the learning rate, and $\delta_j(n)$ is called local gradient associated with the j^{th} neuron. If the neuron j is an output neuron, then the local gradient is defined as follows:

$$\delta_j(n) = e_j(n) \Phi_j^{'}(v_j(n)), \tag{4}$$

where $e_j(n)$ is the error between the output of neuron $y_j(n)$ and its desired response $d_j(n)$. If the neuron j is a neuron from the hidden layer, then the local gradient is calculated as follows:

$$\delta_j(n) = \Phi_j^{'}(v_j(n)) \sum_k \delta_k(n) w_{kj}(n). \tag{5}$$

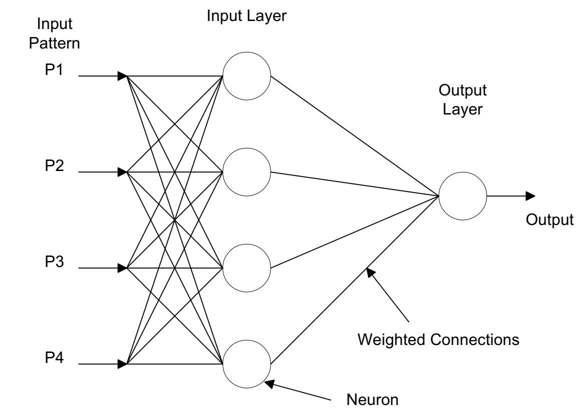

Fig. 13. Structure of Feed Forward NN

(a) (b)

Fig. 14. A letter before (a) and after (b) normalization

1) Application of the ANN to Character Recognition: The input characters are normalized as 45x30 matrices. Figures a and b of 14 show the binary images of an Arabic letter before and after normalization, respectively. Therefore, the network receives the 1350 Boolean values (the matrix rearranged as a vector) plus 3 real values (features mentioned in II-D) as a 1353-element input vector. It is then required to identify the character by responding with a 27-element output vector. The 27 elements of the output vector represent either a letter or a number. The Saudi Arabian LPs possible characters include 17 Arabic letters and 10 Indian numbers. In the proposed ANN, two hidden layers are used with 100 and 70 neurons, respectively. Nonlinear activation function in the two hidden layers is "Tangent sigmoid" while in the output layer is "Logarithmic sigmoid". Training is performed via Back-propagation algorithm.

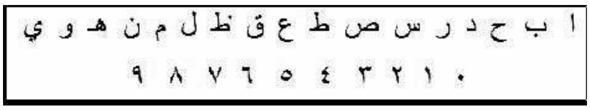

Fig. 15. Alphanumerics included in Saudi LPs (17 letters and 10 numbers)

IV. Experimental Results

A number of experiments were performed to test the efficiency the proposed ALPR system. The test images were taken under various illumination conditions and 200 car images were used for testing the proposed system. The LP localization technique used in the proposed ALPR system is found to be 98%. The LP segmentation is successfully performed with 97% success rate. The neural network recognition is about 99%. Finally, the overall system performance has 98% efficiency. Table I summarizes our experimental results. We have also included results when additive while Gaussian noise is considered in the extracted LP region.

Successful LP extraction	98 %
Successful LP Segmentation	97 %
Successful Character Recognition via ANN	99 %
Success of the overall proposed ALPR system	98 %
Performance at 10 db SNR	94 %
Performance at 5 db SNR	90 %

TABLE I

Overall Sytem Performance

V. Conclusion

Most of the past work for Saudi Arabian license plates are based on template matching which requires a lot of computations and is prone to noise. In this work, an ANN based ALPR is proposed for Saudi Arabian license plates which is more efficient and needs less computation. Saudi Arabian license plates have several unique features that are taken care in the segmentation and recognition phases. Moreover, some new features of characters are used for the training of the ANN. The results obtained from a medium size data base are very promising, i.e., 98%. The new features introduced together with the NN considered have also proven to be robust under noisy environments.

Acknowledgments

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