Original Research Paper

Automatic Recognition System of Vehicle Plate for Recording Incoming Vehicles to the University Campus and the Outgoing

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Abstract: Automatic recognition of vehicle plate characters became a very important in our daily life because of the unlimited increase of vehicles that enter or leave a supervised area. This paper describes an automatic intelligent system that captures the images of vehicles and has the ability to recognize the plates of vehicles entering the university campus or leaving. A camera is built on the university gate for taking images of incoming or outgoing vehicles. A rear image of a vehicle is captured and processed. The system applies an intelligent filtering of the input image based on a set of filters removing unnecessary image elements preserving the position and shape of characters of the vehicle plate, histogram manipulation and edge detection techniques for plate localization and characters segmentation. Adaptive Neuro Fuzzy Inference System (ANFIS) is chosen as a classifier for recognizing the characters in the vehicle plates. This system can extracts the letters and numbers from vehicles plates. So, the extracted vehicle characters can be used to record the incoming vehicles to the university campus and the outgoing. The recognized vehicle characters are saved in the university database.

Keywords: Vehicle Plate Recognition, ANFIS System, Feature Extraction

Introduction

License Plate Recognition (LPR) was detected using some applications. These applications were used for identifying vehicles in a restricted area and for detecting stolen vehicles (Kranthi *et al*., 2011; Chenhong and Zhaoyang, 2008; Hongliang and Changping, 2004; Sunghoon *et al*., 2002; Sang *et al*., 1996). Recognition of license plates using traffic video databases was carried out on global edge features with various parameters based on blob detection algorithm. The LPR results due to a faster and more precise identification (Lihong *et al*., 2013; Jianbin *et al*., 2009). Well-organized system has the ability to translate Arabic text found in images into English. This system can detect images, character recognition and machine translation. The experimental results show improvements in accuracy for word recognition (Chang *et al*., 2009). Efficient algorithms can detect license plate location from car images. Their results show that the proposed methods are more effective (Ioannis *et al*., 2010; Danian *et al*., 2005; Nicolás *et al*., 2012).

This method was applied on database, containing car images taken from different distances and viewing angels. The method was given a precise evaluation with other related work (Vahid and Alireza, 2009). The license plate based strategy can identify means of integrated horizontal and vertical projections that are scanned using a search window. This system was carried out on license plate images in effective way. Experiments show that a recognition rate was 95.7% (Yo-Ping *et al*., 2009). Two algorithms were used to map a car plate image into an invariant vector magnitude based on Gaussian low pass filter. They are robust to the disturbances for instances non-uniform brightness distribution on the different positions of a license plate images using various colors. The algorithms can precisely detect car plate images (Ching-Liang, 2011; Sedighi and Vafadust, 2011). A license plate image is identified without the depending on the location of the license plate. Then, this system can determine the accurate location of a license plate. The mean shift was used to make filtering and segmentation of a color vehicle image providing candidate regions. These

regions were then classified to choose a candidate region contains a license plate (Wenjing *et al.*, 2007).

An automatic method for vehicle identification was applied using a plate clip, character segmentation and recognition. The recognition process was used an adaptive iterative threshold algorithm. This method was proposed based on an invariant to use a suitable character size and thickness for identifying vehicle license plate (Vladimir *et al.*, 2006). The proposed system was tested on big database containing 1334 vehicle images having different backgrounds. The license plates were correctly segmented with performance equal to 96.5%. The architecture of this system was designed with two layers. This system was trained to classify alphanumeric characters from car plates. The system can identify characters from license plates images without the need to specify the size and inclination of the license plate or the color of the vehicle (Christos *et al.*, 2006).

For identifying the vehicles of a garage entrance, a camera was fixed on the door; so, cars that entered can be detected and matched to the database of authenticated cars. Then, LPR was applied based on the character detection and recognition. After that the license plate number was matched with the database of authenticated plates. If the car was allowed access, the door will be opened in automatic way (Rob and Peter, 2011). This system was proposed to detect car number plate for Malaysian. It was used matching technique to approximate the location of the number plate region. It was found that the number plate region can be determined more accurately (Mohd and Suandi, 2010).

The problem of our concern is: Given a vehicle license plate image and apply preprocessing techniques to enhance this image. The image is converted to black and white. Then, isolate the license plate and apply histogram followed by edge detection techniques. After that, separate the areas of Arabic and English for letters and numbers. Finally apply the AI system to recognize the license plate information. The proposed algorithm is able to find a better solution. Extensive simulations have been conducted and the results have evaluated of the proposed algorithm.

The paper is organized as follows. In section 2, we describe the feature extraction process in general. The section 3 is used to present the proposed system in more details. Section 4 shows the image segmentation and feature extraction model and the designed functions for the proposed system. Section 5% the structure, the training and the test processes of ANFIS algorithm. Section 6 includes the results, discussion and comparing with others. Section 7 concludes the system and provides future work.

Feature Extraction

A complete image cannot be used or processed every time as the required memory may be large. Feature extraction process can reduce the processing speed.

Hence only prominent features are extracted from each image and an image feature database is formed. Also pixel by pixel comparison with the query image may consume most of the time of the processor and a shift by one pixel value may lead to complete mismatch and pseudo results (Patrick, 2011).

Feature extraction involves detecting and isolating various desired features of patterns. It is the operation of extracting features for identifying or interpreting meaningful information from the data. This is especially relevant in the case of image data where feature extraction involves automatic recognition of various features (Murty and Devi, 1988). Eigen feature extraction is proposed (Latha and Devarajan, 2014). Coarse grid, Directional element, Invariant moment and Permeability Number features are presented (Kranthi *et al.*, 2011; Miguel *et al.*, 2010). Conventional, Gradient Directional Gradient, Directional Gradient Features Extraction are presented (Singh *et al.*, 2014). The Cross-Corner Feature Extraction is presented by (Manju and Yogesh, 2011). Shadow and 64 dimensional features are purposed by (Deepali and Manasi, 2015). Finally the author will apply some of features extraction to collect the training and test data.

Features are characteristic properties of the objects whose values should be similar for objects in a particular class and different from the values for objects in another class. Features may be continuous or categorical. Examples of continuous variables would be length, area and texture. Categorical features are either ordinal or nominal. The choice of appropriate features depends on the particular image and the application at hand. However, they should be robust, discriminating, reliable and independent (Anke and Volker, 2014).

A good feature should remain unchanged if variations take place within a class and it should reveal important differences when discriminating between patterns of different classes. In other words, patterns are described with as little loss as possible of pertinent information. There are four known categories in the literature for extracting features:

1. Non-transformed structural characteristics: moments, power, amplitude information, energy, etc. Let $I(x, y)$ is a continuous image function. The geometric moment equation of order $p + q$ is:

$$m_{pq} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x^p y^q \mathrm{I}(x, y)\, dx\, dy \qquad (1)$$

Similarly, let $I(x, y)$ is a digital image with $i = 0, 1, ..., N_x - 1$, $j = 0, 1, ..., N_y - 1$ the corresponding moment equation of order $p + q$ as in Equation 2:

$$m_{pq} = \sum_i \sum_j I(x, y)\, i^p j^q \qquad (2)$$

2. Transformed structural characteristics: Frequency and amplitude spectra, subspace transformation methods, etc
3. Structural descriptions: Formal languages and their grammars, parsing techniques and string matching techniques
4. Graph descriptors: Attributed graphs, relational graphs and semantic networks (Anke and Volker, 2014)

The Proposed System

The process of identifying data plate for cars in Saudi Arabia mechanically by cameras installed in specific places at traffic lights or other places so necessary to help maintain discipline street traffic in all cities and villages of the Kingdom. It is also very necessary in a particular University because it provides a database of license plate numbers and time of entry to the campus, as well as license plate numbers and the time they leave campus.

Automatic License Plate Recognition (ALPR) is one of the most important aspects of applying computer techniques towards building intelligent system. A camera is built on the university gate for taking images of incoming or outgoing vehicles. ALPR is the extraction of vehicle license plate information from an image or a sequence of images used to identify a vehicle by its license plate. The extracted information can be used with or without a database. The system processes are firstly captured a rear image of a vehicle. Then, an intelligent filtering is applied for removing unnecessary image elements preserving the position and shape of characters of the vehicle plate. The image is also changed from color into black and white. License plate location is an important stage in vehicle license plate recognition for automated system (https://goo.gl/vLRPn6).

The main stage is the isolation of the license plate, from the digital image of the car obtained by a digital camera under different circumstances such as illumination, slop, distance and angle. Then, histogram manipulation and edge detection techniques are used to identify the location of vehicle plate; Fig. 1a. After that, the segmentation process is applied to separate the areas of Arabic letters, English letters, Arabic numbers and English numbers; Fig. 1b. ANFIS system is applied as a classifier for recognizing each character in the vehicle plate. Finally, the recognized vehicle characters are saved in the database.

The detailed steps of the proposed algorithm are given as follow:

1. *Capture the image using Matlab preview function.*
   img = preview (obj, target-Image).
2. *Store the captured image into an image file for further processing.*
3. *Resize the capture image into 140×260×3.*
4. *Transfer the image to gray level image.*

5. *Filter the noise level present in the image.*
6. *Transfer the gray image to black and white image*
7. *Enhance the BW image.*
8. *Segmentation process as follows (Fig. 1):*
   a- Divide the image into two parts of characters and label.
   b- Clip the plate area in such a way that separates numbers (Indian and Arabic) of plate area extracted.
   c- Clip the plate area in such a way that separates alphabetic (English and Arabic) of plate area extracted.
   d- Separate each character from the plate.
9. *Resize all characters into 64x64.*
10. *Extract the features*
11. *Build the training and test data.*
12. *Design the ANFIS system (Fig. 6).*
13. *Train the system on the training data.*
14. *Test the system on test data.*
15. *Apply the system on the separated characters from the plate.*
16. *Get the results.*
17. *End.*

Preparing Data

The pattern data is used for training and testing the system. This data contains 296 images representing the Arabic letters, Arabic numbers, English letters and Indian numbers. These images are constructed using different font sizes. The images are divided into two parts; they are 75 and 25%. The two data parts are used for training and test respectively. Features extraction processes are applied as preprocessing on each image; see the next subsection for more details. The image size must be modified to $2^p \times 2^q \times 3$, where p and q are integer numbers.

Image Segmentation and Feature Extraction Model

Each image is firstly divided into 48 partitions. A feature is extracted from each partition. This division is constructed through four stages. The first stage contains five partitions; the whole image, two halves vertically and two halves horizontally; Equation 3 and Fig. 2:

$$
\left.
\begin{aligned}
S2 &= A\left(0:n, \quad 0:\frac{m}{2}\right) \\
S3 &= A\left(0:n, \quad \frac{m}{2}+1:m\right) \\
S4 &= A\left(0:\frac{n}{2}, \quad 0:m\right) \\
S5 &= A\left(\frac{n}{2}+1:n, \quad 0:m\right)
\end{aligned}
\right\}
\tag{3}
$$

where, $S2$, $S3$, $S4$ and $S5$ represent the four partitions, n and m are the number of rows and columns respectively. $S1\_5$ represents the partitions 1 up to 5.
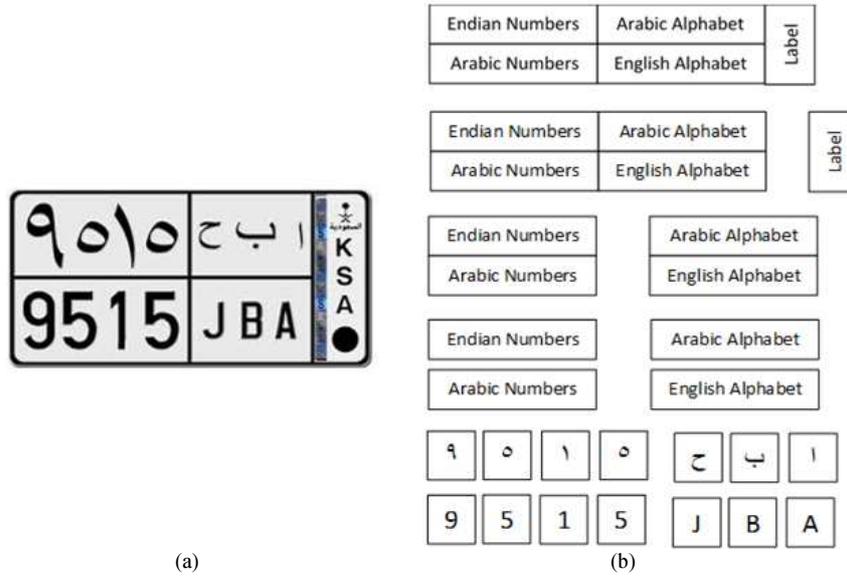
Fig. 1. (a) Original Image plate (b) Segmented areas
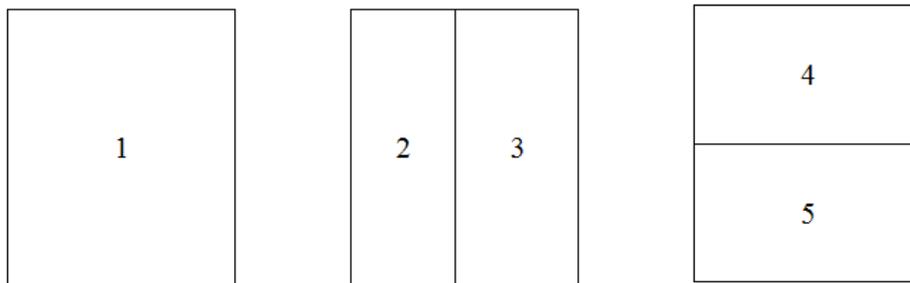
Fig. 2. Partitions 1-5 of the image
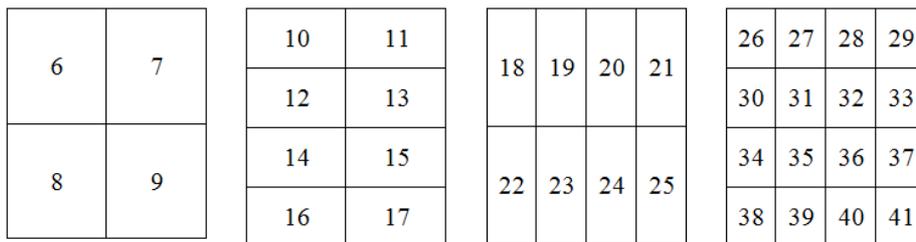
Fig. 3. Partitions 6-41 of the image
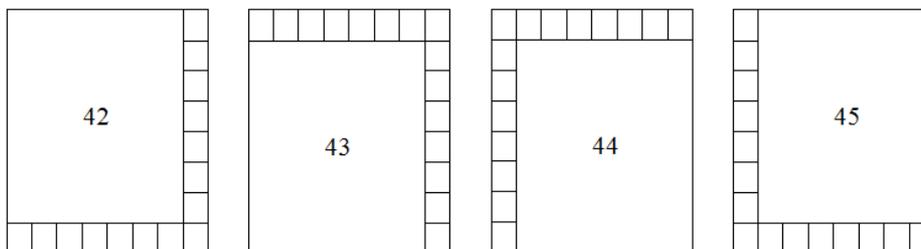
Fig. 4. Partitions 42-45 of the image
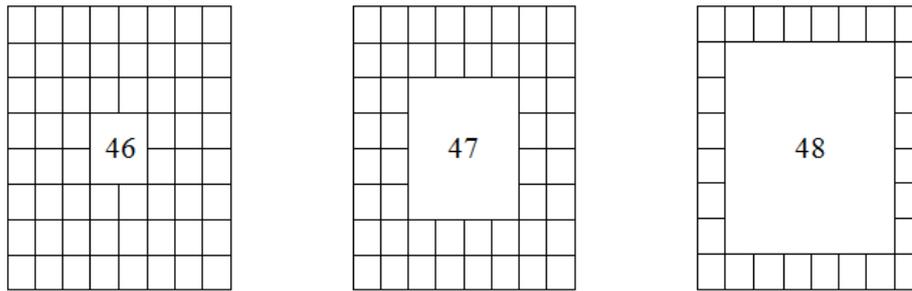
Fig. 5. Partitions 46-48 of the image

The second stage contains 36 partitions started from 6 up to 41. Firstly, the whole image is divided into 4 partitions. Then, the whole image is divided into 8 partitions vertically and horizontally. Finally the image is divided into 16 partitions with the corresponding marks as shown by Equation 4 and Fig. 3:

$$S6\_41 = A \left(\begin{array}{c} i + \dfrac{i*n}{C} : i + \dfrac{i*n}{C} + \dfrac{n}{C}, \\[2mm] j + \dfrac{j*m}{R} : j + \dfrac{j*m}{R} + \dfrac{m}{R} \end{array} \right) \tag{4}$$

where, $S6\_41$ represents the partitions 6 up to 41 considering the row number i and the column number j. The horizontal and vertical numbers of blocks are C and R respectively.

The third stage includes four cases divided diagonally, the first two starting from left to right and the last two from right to left; Equation 5 and Fig. 4:

$$\left. \begin{array}{l} S42 = A \left(0 : n - \dfrac{n}{8}, \quad 0 : m - \dfrac{m}{8} \right) \\[3mm] S43 = A \left(\dfrac{n}{8} + 1 : n, \quad 0 : m - \dfrac{m}{8} \right) \\[3mm] S44 = A \left(\dfrac{n}{8} + 1 : n, \quad \dfrac{m}{8} + 1 : m \right) \\[3mm] S45 = A \left(0 : n - \dfrac{n}{8}, \quad \dfrac{m}{8} + 1 : m \right) \end{array} \right\} \tag{5}$$

where, $S42$-$S45$ represent the partitions 42 up to 45.

The last stage contains three partitions. Partition 46 is made by taking the innermost 4 cells. Partition 47 is done by taking 16 innermost cells. Partition 48 is made by taking 32 innermost cells; see Equation 6 and Fig. 5. These partitions are used to extract the features that are built the required database:

$$S46\_48 = A \left(\begin{array}{c} \dfrac{n*B}{8} + 1 : n - \dfrac{n*B}{8}, \\[3mm] \dfrac{m*B}{8} + 1 : m - \dfrac{m*B}{8} \end{array} \right) \tag{6}$$

where, $B = 3$, 2 and 1 for the partitions 46-48.

That is means, the input data to the system are 48 features was their pulling out from the base of the verified data consisting of 10 preparing Arabic and Hindi numbers 10 and 26 English letters and 28 Arabic letters in four different sizes, 18, 22, 26, 30 and one fixed fonts because printed plates all fonts one. This means that the database consists of 296 image size 64×64.

ANFIS Algorithm

Neuro-fuzzy refers to the combination of fuzzy set theory and neural networks (Zounemat-Kermani *et al.*, 2009). Jyh-Shing Roger Jang proposed a novel architecture called ANFIS (Jang, 1993), which conserve as a basis for constructing a set of fuzzy if-then rules with appropriate membership functions to generate the stipulated input-output pairs. These techniques provide the fuzzy modeling procedure to learn information about a data set, in order to compute the membership function parameters that give best allow of the associated fuzzy inference system to track the given input-output data. This learning method works similarly to that of neural networks (Dlala and Arkkio, 2006). ANFIS implements a Tokagi Sugeno FIS having a six layered architectures as shown in Fig. 6. This figure is drown based on (https://goo.gl/rc5jyH).

Layer 1: The first layer of this architecture consists of a membership degree of input variables (features extraction) to corresponding terms: $\mu_{ij} = \mu_i (x_j, P_i)$, where $j = 1,2,\dots,N$- N is number of features, x_j is the calculated j^{th} feature, $i = 1,2,\dots,L$, L is the number of given terms, P_i is the vector of membership function parameters of ith term. For example: For membership functions, generalized bell membership function (Equation 7), a Gaussian membership function (Equation 8), or any membership functions:

$$\mu_{ij}(x) = \frac{1}{1 + \left| x - \dfrac{c_i}{a_j} \right|^{2b_j}}, j = 1, 2, \cdots N \tag{7}$$
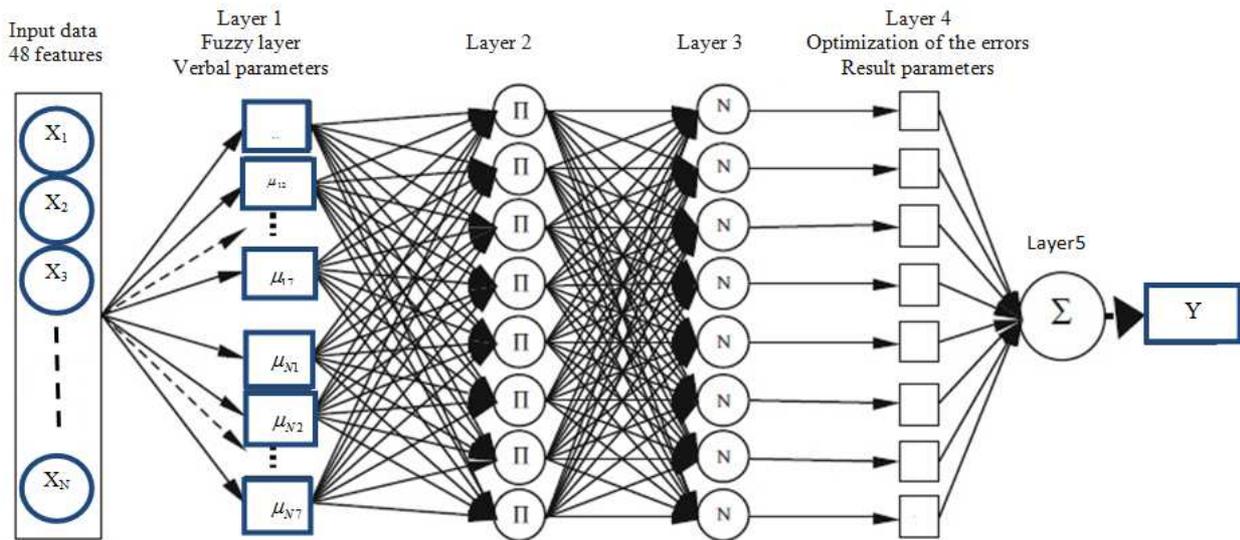
Fig. 6. ANFIS architecture based on Takagi–Sugeno model

$$\mu_{ij}(x) = \exp\left[-\left(\frac{x - c_j}{a_j}\right)^2\right], \quad j = 1, 2, \cdots N \tag{8}$$

where, $\{a_i, b_i, c_i\}$ is a set of the premise parameters.

Layer 2: Every node in this layer is a fixed node, marked by a circle, labeled Π and is calculated by the fuzzy "AND" connective of "PRODUCT" of the incoming signals, i.e., Π-norm operation (Equation 9):

$$w_i = \mu_{Aj}(x_k) \times \mu_{Bm}(x_z) \tag{9}$$

Layer 3: The nodes of third layer calculates the ratio of given rule to the sum of all rules' values as in Equation 10:

$$\overline{w}_i = \frac{w_i}{\sum\limits_{t=1}^{N} w_i} \tag{10}$$

Layer 4: Each node in the fourth layer is connected with a node of the third layer and inputs of the network. The node of the fourth layer counts a contribution of one fuzzy rule to a network exit as in the following Equation 11:

$$y_i = \overline{w}_i \left(b_{0i} + b_{1i}x_1 + b_{2i}x_2 + \cdots + b_{Ni}x_N\right) \tag{11}$$

where, $\{b_{ki}, \quad k = 1, \cdots, N, \quad i = 1, \cdots L\}$ are the set of parameters.

Layer 5: The single node of the last layer computes the overall output using center average defuzzification method.

In order to evaluate the proposed ANFIS algorithm, a comparison is made in the last subsection. The obtained

results of the ANFIS system are presented in the following subsections, respectively. All programs are written using the MATLAB software.

The proposed system is designed to find the best ANFIS that has the ability to have the best recognition of vehicle license plates by changing the type and number of membership functions and the number of epochs. Thus, many attempts are made to find the best ANFIS that uses a low number of epochs and membership functions. The experiments are trained using the proposed numbers of membership functions for 100 epochs and continue up to 2000 epochs. The ANFIS system reached the optimal solution using 1500 epochs and seven membership function with the 'gbellmf' membership. The proposed system is trained. After the training, it is found that the results using two up to six membership functions are not enough. The results at seven membership functions are good, having the best result at 1500 epochs. The system was trained and tested using the two main database sets respectively and the overall average performance was 98.6%.

Results and Discussion

The proposed system using image processing and the best trained ANFIS is applied on 150 plates, part of them are taken from (https://goo.gl/vLRPn6) and the other by camera from different distances and angles. The ANFIS algorithm reached the optimal performance using the 7 membership functions at 1500 epochs. Figure 7 shows the results for recognizing one plate, the plate and ANFIS result are given in the Fig. a and b respectively. The results showed that, the average of performance for Arabic digits, Indian digits, Arabic letters and English letters are 97.4, 94.6, 96.2 and 96.7% respectively.

(a)

(b)

Fig. 7. (a) Vehicle plates (b) ANFIS results

Table 1. The obtained performances

Average	Arabic digit	Indian digit	Arabic letter	English letter	Overall average
Success rate	%97.4	%94.6	%96.2	%96.7	%96.23

Table 2. Comparison with other researches

	Syed *et al.* (2013)	Sandeep *et al.* (2013)	Tahir *et al.* (2010)	Deriche and Zidouri (2008)	Al-Audah *et al.* (2012)	Yusuf *et al.* (2014)	Proposed System
Arabic digits	N/A	N/A	N/A	N/A	N/A	N/A	%97.4
Indian digits	N/A	N/A	N/A	N/A	N/A	%91.6	%94.6
Arabic letters	N/A	N/A	N/A	N/A	N/A	%96.55	%96.2
English letters	%98	N/A	N/A	N/A	N/A	N/A	%96.7
Overall average	N/A	%83.84	%92.1	%93	%94	%94.08	%96.23

It is found that the results obtained indicate that ANFIS is more effective and feasible specially for extracting Arabic letters, English letters and Arabic digits. It is also noticed that the performance with extracting Indian digits is slightly low comparing with the obtained performances of Arabic letters, English letters and Arabic digits; see Table 1. The overall average performance is 96.23% for recognizing the above mentioned four characters' types.

In order to evaluate the proposed system, it is compared with other researches.The performances of them are calculated as overall average. Moreover, this comparison shows that the overall average performance of the proposed system is more efficient from the others especially for extracting Arabic letters, English letters and Arabic digits as shown in Table 2.

Conclusion

This paper highlighted the importance of identifying information on the metal plate in Saudi Arabia automatically using the computer, depending on image processing and artificial intelligence. The proposed system developed KSA license plate recognition system using the image processing and ANFIS system. The pattern data contains images of the Arabic letters, Arabic numbers, English letters and Indian numbers. Hence, each image is divided into 48 partitions to extract a feature from each partition. These features are detailed

mathematically in section 3.1. The ANFIS algorithm is trained and tested to choose the best one as a classifier.

The proposed system is applied on many KSA license plates, it is found that the obtained results are more efficient for extracting the Arabic letters, Indian numbers, English letters and Arabic numbers. The obtained performances for the above four characters types are shown in Table 1 and theoverall average performance is 96.23%.The results are compared with other researches. The performances of them are calculated as overall average. Moreover, this comparison shows that theoverall average performance of the proposed system is the best.

It is also found that the proposed system is not treated well with the Arabic letter "ا" because its width is very thin and we will try to develop this system in the future to solve this problem.

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Author's Contributions

All authors completed the paper together as well as read and approved the final manuscript.

Ethics

It is declared that there are no ethical issues that may arise in the present study.

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