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Research Article

Arabic License Plate Recognition System

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Abstract

In this paper, a new low cost Arabic vehicle license plate recognition (LPR) method is proposed which is easily extendable to other plates. A novel LP segmentation technique with three sets of feature vectors was used with template matching to form the two main modules: license plate localization module and LPR module. This method was tested on more than 238 vehicle images taken from various scenes with different fonts and backgrounds from two Arab countries. The segmentation accuracy of the implemented system was 97.5% with a recognition accuracy of 99% for fairly distorted images. The presented model shows that despite the negative impact of shadows, cracks, dirt, and character separations, the system demonstrated an overall success rate of 92% for plate localization, 95% for plates segmentation, 92% for country and city recognition, and 99% for number segmentation and recognition. Combining all rates led to an overall system accuracy of 93%. Compared to many state-of-the-art LPR systems, this newly developed system uses 3 small training sets which cut the run times of the proposed solution to less than 5 seconds using the MATLAB R2008A running on a Compaq 8510W with 4G RAM. The results are comparable, and in some cases better with restricted conditions such as skew place, plate size, illumination and background.

Keywords: Arabic letters; text recognition; license plate recognition; automatic license plate recognition; automatic vehicle identification; character segmentation; plate localization

1. Introduction

For decades the need for a reliable approach for license plate recognition has been growing, and in response to new security demands, there has been an abundance of work done in this area. Vehicle identification tracking applications such as area access control, parking restriction, and law enforcement use automatic LPR systems, which are being used all over the world, not just for commercial use, but also in private and military applications as well. While each country may have a unique set of issues driven by the types of plates, language and designs used, there are common approaches taken and there are generally three well documented modules considered in order to achieve this. These common denominators are plate localization, character segmentation, and

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optical recognition, as mentioned by M. Yu and Y. D. Kim, (2000); S. Soh, et al, (1994) and S. Zhang, et al, (2004).

Localization of the license plate is based on the assumption that the contrast between the background (license plate) and foreground (letters) is significant. Locating license plates inside a larger image has previously been accomplished in many different ways and is considered to be the most crucial step of Automatic license plate recognition as stated by Jing-Ming Guo, (2008). Luning Pan and Shuguang Li Proc, (2010) presented a practical system that outlines in detail the LPR steps. Rong Li, et al, (2008) presented a system that explored a method called "sliding concentric windows" for plate localization and a "probabilistic neural network" for character recognition. In another example presented by Anagnostopoulos, et al, (2006), neural networks were used. Using spatial arrangement to identify objects as indicated by Seetharaman, et al, (2004) and C. Grigorescu, et al, (2003) or "distance sets" is another way. K. M. Kim, at al, (1997) has used morphological operations like smoothing, closing, opening and threshold to isolate the desired features while J. Hsieh, et al, (2002) researched the process of image positioning based on connected regions combined with mathematical morphology while S.W. Lee and S.Y. Kim, (1999) dealt with similar issues for handwriting recognition. Sos S. Agaian, et al, and L. Xu, et al, (2006) discussed similar issues dealing with characters of degraded quality images.

Arabic license plates have several unique features that need to be taken into account during the segmentation and recognition process. Arabic writing is connected even if it is printed or typewritten as discussed by He, et al, (2010) that previous approaches fall short in accuracy, speed and cost. What is needed is a fast, reliable, and repeatable method for capturing and reporting the Arabic license plate (ALP) data. The challenges we face in achieving this for ALP include the variable orientation of the plates as indicated by Abdelmalek Zidouri and Mohammed Deriche, 2008 and P. Cornelli, et al, (1995), which affects the contrast, the actual plate size and aspect ratio of the characters, the alignment as mentioned by T. Naito, et al, (2000) and the separation of the features. Additional challenges as presented in research done by Cristian, M., Rosa, (2004) include the changing in visibility of the plates due to background lighting, dirty surfaces, and overly illuminated plates. These complex issues have been addressed by systems evaluating Chinese, Korean, US and EU license plates, but little work has been done on plates bearing Arabic scripts as indicated by He, et al, (2010).

This paper proposes a highly effective approach to plate segmentation using plate characteristic and uniqueness of Arabic license plates to overcome the issues raised in the literature. We also propose a new approach to improve the classification step by using a combined feature vector approach of templates and characters. Because the accuracy and reliability of the system results depends on the amount of training data, the proposed approach uses three small and unique sets of training to likely quicken the recognition process.

The remaining sections of the paper are organized as follows: Section 2 provides the background, Section 3 discusses the proposed system, Section 4 provides the results and a look at the actual graphical user interface (GUI) and its implementation. In Section 5, a summary is provided which not only highlights the major points of this research, but also provides some ideas for potential further study in this area.

2. Background

Human operators reading the images and taking the appropriate actions could handle these applications. However, many organizations don't have enough personnel to handle these tasks manually. It is also more efficient and less costly to handle it all automatically. These factors make the automatic detection of license plates a topic that has generated a lot of interest.

It should also be noted that changes in computer processing power and available memory combined with lower camera prices have allowed for real-time processing of license plate recognition systems. Wavelet transforms are also introduced to improve the recognition accuracy.
To establish a system capable of capturing fine images under greatly varied illumination conditions, and resulting in non-blurred images, the recognition algorithms need to be flexible enough to localize and recognize characters that are adequate for inclined plates. Guangming Li, et al, (2010) developed a system in which cameras are mounted on the hoods of police cars, for public safety, monitoring gate entrances, security parking checks and alert systems are all targeted applications for such a system.

In addition to the three main models shown in Figure 3, a complete LPR system includes: pre-processing, plate region extraction which is used by Adel Sewisy, (2007), plate region threshold used by Xifan Shi1, et al, (2005), character segmentation, and post-processing used by Syed, Y.A. and Sarfraz, M. , (2005).

The first processing stage deals with locating the position of the LP within the image. This is referred to as license plate localization.

The second step is to detect, locate position, and isolate individual LP parts (country, city, and number) before segmentation of the numbers and sometimes normalizing their size to prepare them for the next stage. Then, the last step primarily deals with recognizing the individual parts of the LP based on the features extracted for the different elements.

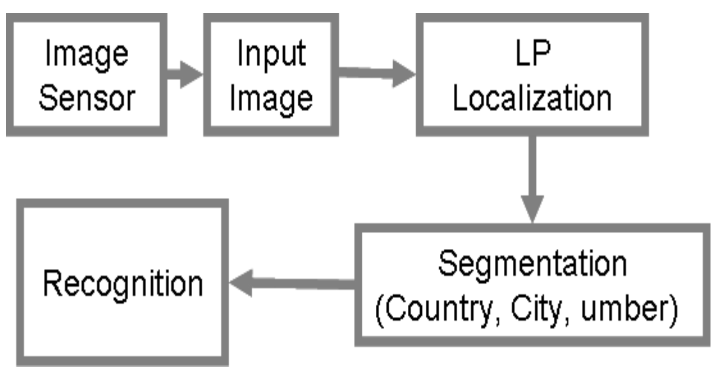

Fig 1. LPR steps

Fig 2. Results from camera with/without improved shutter speed, (B) LP (Guangming Li, et al, 2010)

J. Hsieh, et al, (2002) presented an algorithm for the extraction of license plates and recognition of Arabic characters and numbers. Their segmentation phase was based on the pixel counting of 300 private car images which were captured under various illumination conditions and the system build using MATLAB 7.0 had a run time of 5 seconds. It produced an overall recognition accuracy of 96%. For Arabic characters, some of the techniques mentioned by Syed, Y.A. and Sarfraz, M., (2005) such as statistical, syntactic, and neural networks have also been in use. The source of the errors in these systems comes from the segmentation stage where it is, in this case, time-consuming and requires accurate pixel counts, and the plates need to have separated characters. This limits the system to only one set.

In the research of S.H., Kim, et al, (1999), a recognition rate of 95% for Arabic License plate recognition system was reported using 65 images captured under varied conditions. They assume Lines of image must not be optically distorted and license plate alignment with the axes (vertical and horizontal). Another Arabic LPR system has been presented by Mohamed El-Adawi, et al, (2005). A template matching method was used; their system accuracy was 96%. Ahmed, M. J., et al , (2003) presented a plate recognition method using multi-valued (gray image) template matching, which they claim operates even under adverse illumination conditions in which the image contrast is degraded with accuracy of 95%.

An established practical system for English LPR has been developed by Guangming Li, Zhenqi He, (2010) where they emphasized the demand for a camera with a faster shutter speed to reduce motion blur. This was driven by a need to compensate for the vehicle's velocity. Camera shutter speeds of 1/1000 sec may actually be necessary to overcome this issue.

Takahashi, Y., et al, (2007) developed a system with a video camera located at a fixed point and a frame grabber was used to collect the grayscale images containing the license plates. It uses neural network based recognition and reported results of 98% accuracy. Greek license plates under different illumination conditions as input were represented by Anagnostopoulos, C., (2006). That particular method uses grayscale images. The results reported had an 86% accuracy. In "The Automatic Recognition of the Plate of Vehicle Using the Correlation Coefficient and Hough Transform" presented by K. M. Kim, et al, (1997), and Draghici, S., (1997) a high contrast between the background and the characters was used to search for the greatest gray-level contrasts within an area.

T. Kula and J. Cicero, (1990) presents an approach to extract license plates where it was revealed that the combination of gray-scale morphology with a log gray-scale transform provided accurate extraction. The LP localization step proposed by M. Shridhar, (2001) utilizes the Support Vector Machine (SVM) approach for character classification with direct segmented pixel values as input and reported a result of 96%. A complete recognition of license plates mentioned in M. Shridhar, (2001) used color images containing Taiwanese license plates and used Kohonen's Self Organizing neural network to compare the segments of the license plate against templates of characters for classification.

Finding highest contrast rows within an image and then examining the columns in each row for the greatest pixel contrast has also been used by Viola, P. and Jones, M. J., (2004), and generic algorithms have been applied in the decision-making process of identifying plates.

Some systems, like the one developed by the University of Newcastle-upon-Tyne, (2002) use a threshold to locate the number plate text. Another approach uses neural networks to locate the text in license plate characters in the image developed by C. Murdoch at Safe-T-Cam, (1995). According to this research, the neural network appears to be the best method for number-plate recognition.
The edge detection method is also used in the research conducted by Bruce Parker, (1999), which uses the moment invariant method, where difficulties encountered in isolating the boundaries of the license plates.

Many researchers using new automatic recognition methods try not to have the vehicle pass the gate to stop, either by reading license plates and recognizing it or by reading a sticker coded with specific vehicle info. This research simulated the method used as mentioned by R. Gonzalez, (2004) and reproduced some of their data as shown in Figure 3. The results were promising, however the good results are achieved because the evaluated images have solid characters that are evenly spaced and usually the text is limited to a set of numbers.

One approach has used a threshold technique which requires having a clear, good contrast between background and text. One of the limitations of this approach is the negative effect that shadows, character separation and adjacent characters have on the results. These parameters impact the individual characters and they can become joined during the threshold process.

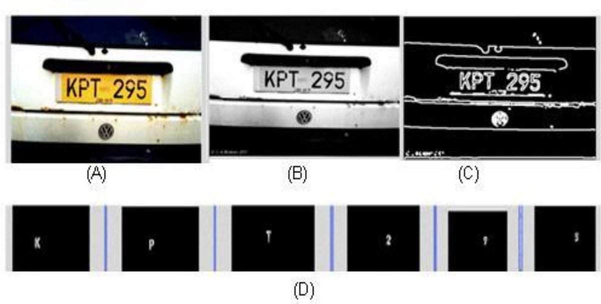

Fig 3. LP Test Case (A) Original image, (B) Gray image, (C) Connected component, (D) Segmented text result

One of the strong points of using neural networks for LPR is that the template matching techniques for recognition offer a higher degree of accuracy, and template matching does not require any training as shown by N. Ketelaars, (2002). The drawback is that one needs to store all the templates so that matching to those stored templates can be accomplished.

Different classification methods are used in previous system for LPR. In this research, the SVM was chosen as a classifier because of processing speed and flexibility in using different minimum distance methods, and for better accuracy. The SVM classifier is derived from a statistical learning theory by Kerry Widder, (2004). It has been used in different applications like Bioinformatics, Machine Vision, Text Categorization, and Handwritten Character Recognition. The basic principle of SVMs is to find an optimal separating hyperplane used to separate two classes of patterns with maximal margin as mentioned by K. Duan, et al, (2009). It has also been mentioned that a vehicle classifier based on acoustic signals and a license plate identification system using a camera is implemented for energy efficiency and scalability purposes.

To summarize, recognition algorithms reported in previous research are generally composed of several processing steps using different methods for specific systems as shown in Figure 4, some were pixel-based, others were template matching-based and some were conventional-based. The previous technique can yield a better result when applied on the recognition of individual characters from examples other than Arabic license plates. It may not be appropriate for Arabic characters with low resolution but may work for numerals.

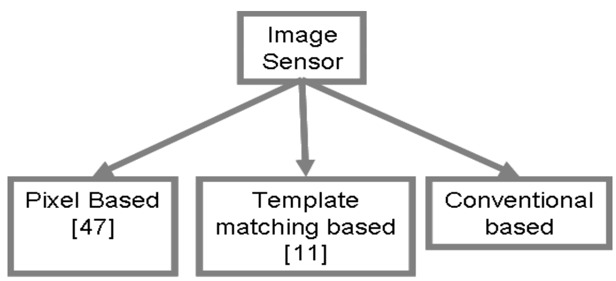

Fig 4. Previous art summary

3. Proposed License Plate Recognition System Design and Implementation

3.1 System Overview

Since most commercial LPR products were expensive, we had to start our system primarily from scratch. We used available software (MATLAB) to build the LPR system with images posted from two Arab countries. The system was designed so that it costs less, fixes problems like distorted images, and becomes portable for different country recognition systems. Since accuracy depends on the size of the training set, it is easier and more effective than other systems, using 3 small decision sets for classification so that it runs in competitive time and achieves a high accuracy rate.

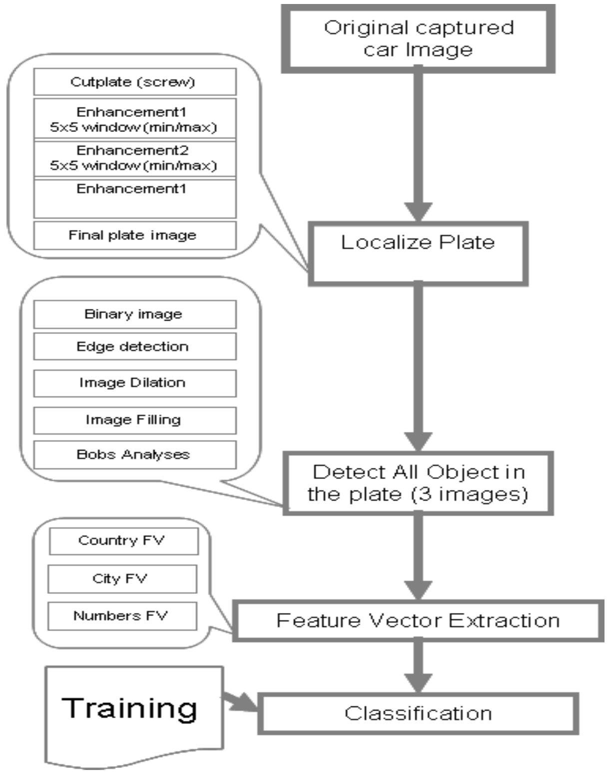

Fig 5. Arabic License Plate Algorithm

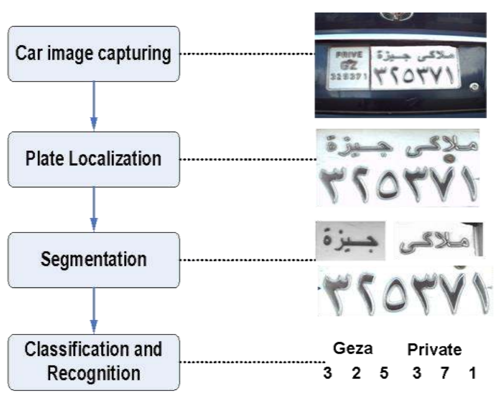

Fig 6. LP flow

For Arabic plate recognition to occur, a new algorithm has been implemented as shown in Figure 5. Firstly, the localization of the license plate in the image occurs, followed by the separation of country name, city and plate number before starting the recognition process. The system uses different training sets for countries, cities, and plates which are used to compare feature vectors separately in the recognition phase.

The flow of the system is shown in Figure 6, where the main steps are applied. The following assumptions have been made for the proposed system: first, letters are black and solid on a rectangular plate (dimensions are known), second; each plate has 3 parts as shown in Figure 7 (country, type (city) and numbers). Third; country and city are in one line, numbers are in another line. Finally, we assume country and type will not be segmented, but will compare as an image since these are fixed for a specific system (template matching). The algorithm followed in this research is shown in Figure 5. We will explain the algorithm in the coming sections.

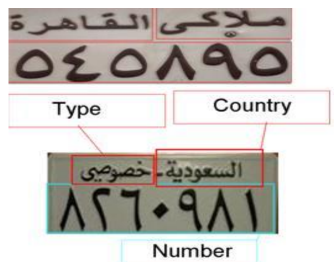

Fig 7. Example of plate format for Saudi Arabia and Egypt

3.2 Plate Localization

One of the most difficult tasks for an LPR system is to locate the license plate. In this step we are only interested in finding the LP and removing other areas. Our plate localization step is based on intensity and uses the color of the screws that hold the plates in place. Gray threshold specifically accounts for the screws and knowing the dimension of the plate. Initial localization is done using these features. Figure 9 shows the screw locations with the required dimension (xl : left screw starting x, xr : right x dimension, yb: bottom y dimensions, yt:top y value). Once screw location is identified; gray threshold specifically accounts for the screws and calculates the dimensions of the plate. This initial localization is followed by an enhancement. This process is shown in Figure 8.

The process of localization as shown in Figure 8 (A):

1. The first level of enhancements (after binarization) is followed by filtering.
2. Another averaging step is then added using a 5x5 window and replacing above averages with max intensity and below averages with minimum intensity.
3. An additional level of enhancement follows, replacing each pixel above min with the max.
4. The enhancement is then repeated using a 5x5 window.
5. Using the original coordinate and the new enhanced location a final crop is achieved on the license plate and the image is formed.

The ratio of width to height for the plates is taken into account along with intensity levels. Different plate localizations have been tested for different images and sample results and are shown in Figure 8 (B).

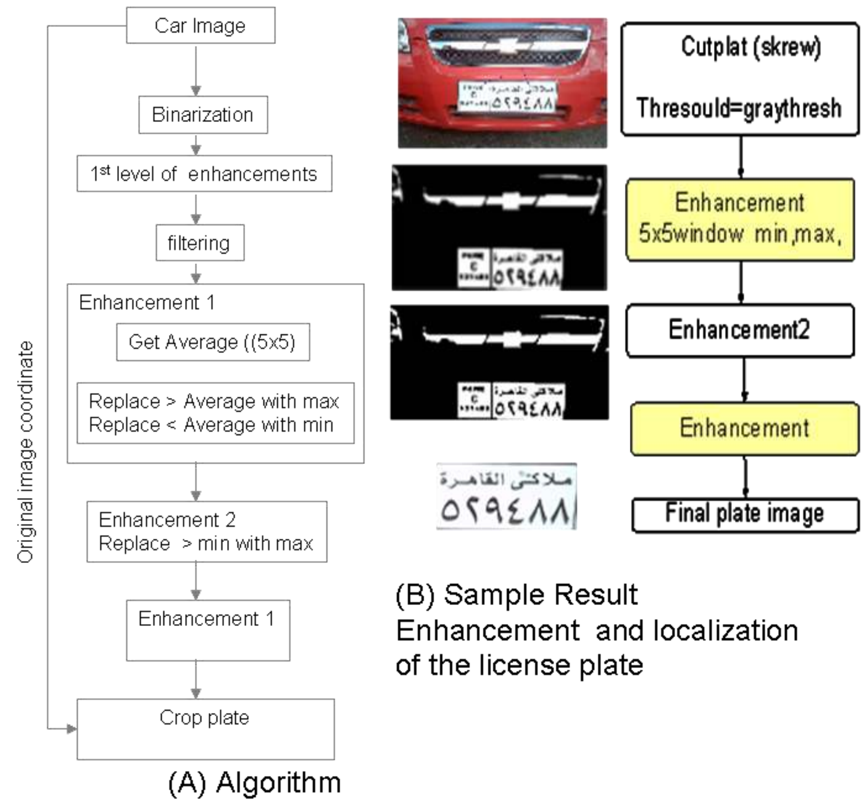

Fig 8. Plate localization flow

Fig 9. Plate localization

3.3 Segmentation

All objects get detected in this step. The localized license plate image will be split into 3 pieces as shown in Figure 11: one for country, one for city, and one for numbers. The number image will be segmented again based on how many numbers there are.

The process of segmentation is shown in Figure 10. First, the binary image is generated followed by edge detection which is applied before the image is dilated. Filling is applied on the dilated image and finally the Blob analysis - which implies another filling and generates groups based on labels. Vertical and horizontal projection along with a histogram leads into a splitting process where the image is split into 3 images: one for country, one for type and one for numbers .These groups will be segmented again depending on which extracting feature vectors (based on Haar transform) for numbers, country and type images are applied before final classification and recognition.

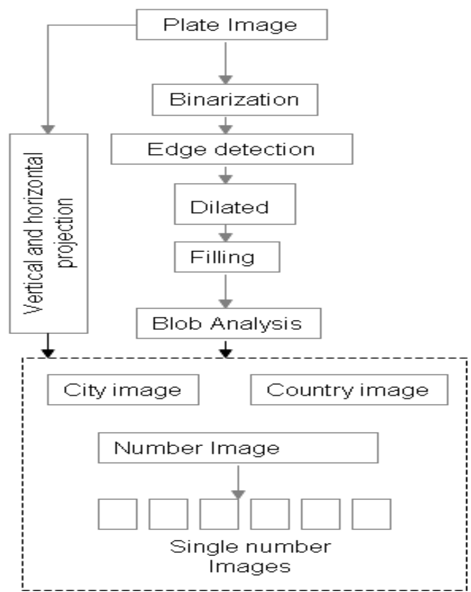

Fig 10. Segmentation algorithm

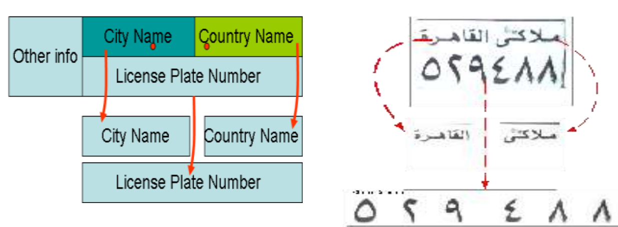

Fig 11. (A) Segmentation flow (B) Detects and splits objects

3.4 Recognition (Feature vector extraction and classification)

The classifier will process each number and match it to the English equivalent for country and type (city) matches we did apply a template matching algorithm in order to have a faster processing time.

The SVM is chosen as a classifier in this paper because of processing speed and flexibility in using different minimum distance methods, and for better accuracy. Figure 12 shows our classification implementation module for each segmented image.

Our classifier is based on a Matlab's built-in functions with the following 6 inputs:

out = mysv classify (Data, Training, Ggoup, K, Distance, Rule)

The data input represents extracted features in each image. Training feature vector data represents an array of all vectors in our training directory. Group represents the name of each vector/text. Each group name corresponds to one vector in the training set. The classifier first compares vectors once it finds the closest match; based on the index, it will find the group/character that matches. K represents the number of nearest neighbors used in the classification. Distance allows us to select the distance. A Euclidean distance is used because it gives the best results. Rules allow us to specify the rule used to decide how to classify the sample. Choices are: Majority rule with nearest point tie-breaker ('nearest').

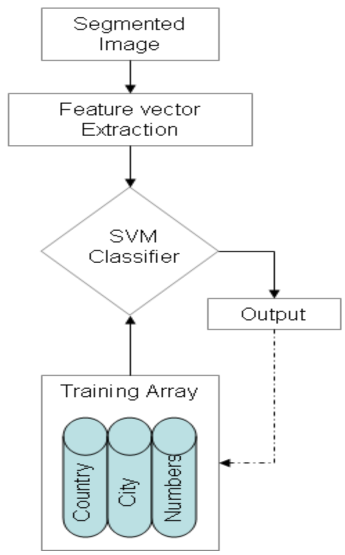

Fig 12. Classification algorithm

The feature vectors are based mainly on 4 levels of the Haar transform. Feature vector images for numbers, country, and type are extracted (one set of features for each part). These features are used in the classification of each part in parallel, which speeds up processing time.
The Haar transform is derived from the Haar matrix.

We get 4 levels of features. First, the right size image is divided into 4 parts (original, horizontal, vertical and diagonal). This is followed by a computation of the matrix coefficients for a matrix (all) and detailed ones for the subsequent parts horizontal, vertical and diagonal. The coefficients are obtained by a wavelet decomposition of the input matrix from the right size image using the Haar wavelet. Figure 13 shows selected Haar feature vectors and the sum of all applicable vectors. The graph shows a steep slope so it is easy to distinguish characters.

4. Arabic License System Experimental Results and GUI

4.1 Tool and Experimental results
MATLAB R2008A was used to implement the system. Three groups of images have been collected for our experiment.

The first group (200 images) was taken from Misr University (Egypt license plate) and Saudi Arabia, so we can be sure the system is portable. These images have some dirt, colors, and some have degradation. An example of such a group is shown in Figure 14. A MatlaB GUI is built for the system. Examples of Group 1 results are shown in Figure 15. The class of images used is shown in Table 1.

Table 1 Class of Vehicle

Vehicle category	Group	Plate color	Type	Example
Private cars	Group1 200 images	White, red, yellow	black	
Trucks and heavy cars	Group2 28 images	red	white	
Government and special cars	Group3 10 images	black	white	

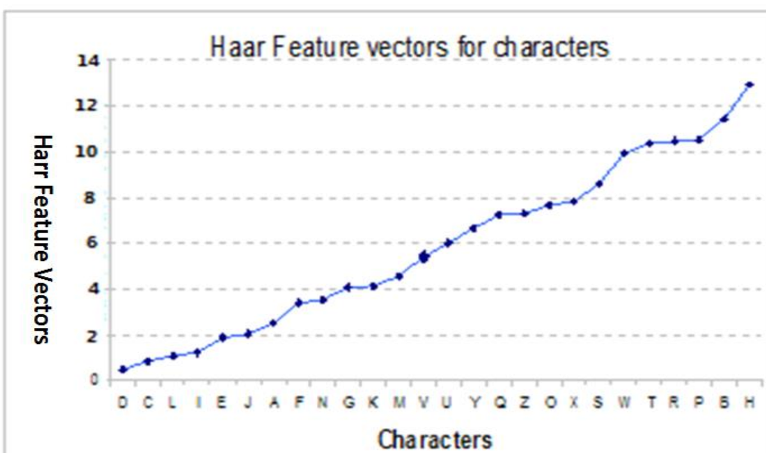

Fig 13. Haar feature vectors - results of tests

An example of such a group is shown in Figure 14. A MatlaB GUI is built for the system. Examples of Group 1 results in the GUI are shown in Figure 15.

In the GUI we show the three main steps along with buttons for training and system initialization. The first step was to load the image followed by plate localization and finally the results of the recognized country, city and numbers in English (in the blue boxes).

Fig 14. Test case group 1 sample

Table 2 Result of Group 1 segmentation and recognition

Plate localization and segmentation				
	Locating plate	Plate segmentation	Character segmentation	Overall recognition
Group 1	.99	100	.99	0.99

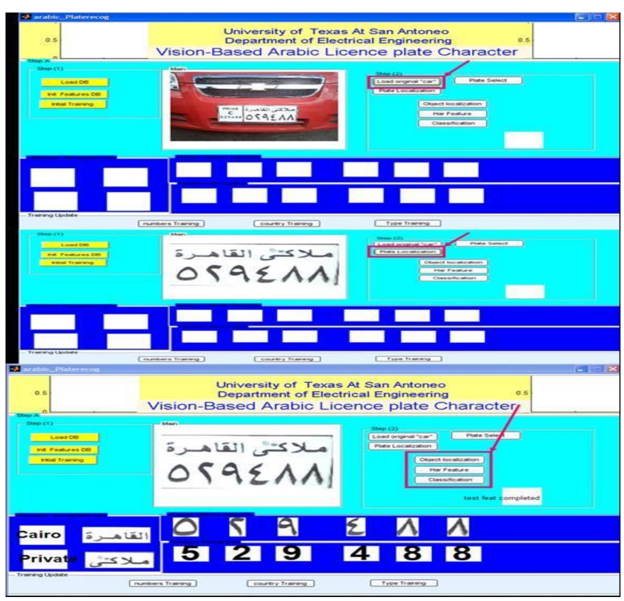

Fig 15. GUI test cases for good images (step 1 load image, step 2 train, step 3 recognition)

Experimental results of the first group are shown in Table 2. The percentage of correctly located license plates is the key in getting a high success rate.
The second group of pictures (total of 28), some of which are shown in Figure 16, were less clear and in some cases as in (A) where the writing is in different fonts, in (B, D), the screws were not clear, (C) the city and country names are connected and the plate numbers are different, and (E,F) were dark and blurry pictures, which affects the plate localization and the recognition process. Experimental results of the second groups are shown in Table 2.

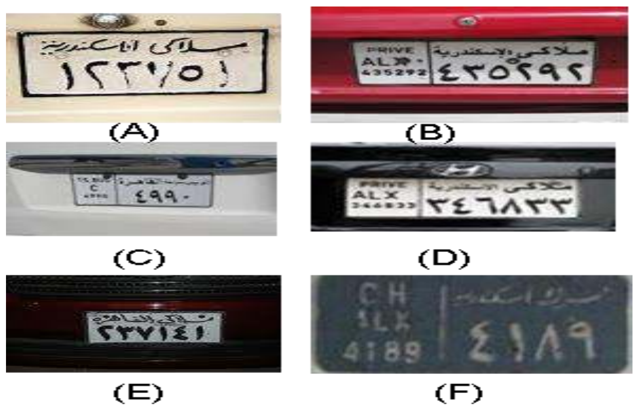

Fig 16. Test case group 2 sample

Table 3 Result of Group 2 segmentation and recognition

Plate localization and segmentation				
	Locating plate	Plate segmentation	Character segmentation	Overall recognition
Group 2	.85	.90	.96	0.87

The third group contains images (10) taken under different conditions as shown in Figure 17. Examples of these images were captured with different angles (A,B,C), in some the writing used a different format (D). some were taken with poor camera setup (I.F, E), others where the country and city are not clear as in (H) and others from a far distance and plates with other background.
Our system did not have good results for localizing plates in government and heavy trucks (Group 3) cases, so future work will be done in this area.

Fig 17. Test case group 3 samples

4.2 Interpretation of results

We tested the algorithm for plate localization, segmentation and recognition in a total of 238 images. The results are summarized in Table 4 where:

1. 92% in localizing plate across various images including Groups 1 and 2. the systems fails to localize plates in group 3 and this is due to not having right colors for background and text, and to camera setup when the angle an image is captured.
2. 95% of plate segmentation to the three images (country, city and number). The failure in this step is sometimes when the country and city were connected and color of the car is not different from the plate or the aspect ratio which we fixed in the system for the plate size is different, and finally images with very poor quality.
3. 97.5% success rate for character segmentation, the algorithm failed in areas where plates have a major problem and the screws do not have enough intensity or contrast difference from the background.
4. Almost 93% recognition rate for country, city and plate numbers.

The results presented above are a fully trained system. When the system is not trained, the accuracy results of the recognition process is about 50%. Figure 18 shows the test case for localizing license plate recognition without training.

Table 4 System result summary

Plate localization and segmentation				
	Locating plate	Plate segmentation	Character segmentation	Over all recognition
Group1	.99	1	.99	0.99
Group2	.85	.90	.96	0.87
Average	0.92	0.95	0.975	0.93

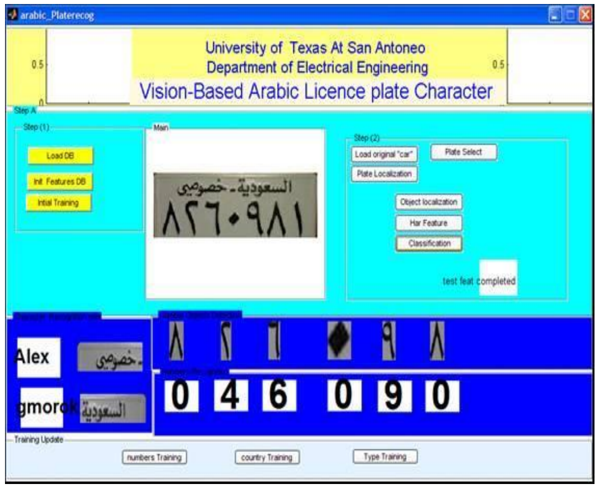

Fig 18. Test case without any training

The system run (MATLAB on Compaq 8510, Windows XP with 3G RAM and 2.4 GHz speed) times using the GUI in less than 5 seconds per license plate from loading the image up to recognition.

The new methods we used for localizing plate and segmentation work much better than the algorithm presented in the literature, assuming the intensity contrast between license plate characters and the license plate itself remains constant across all images, whereas intensity contrast between the license plate and the surrounding region changes from vehicle to vehicle. Test case results for Groups 1 and 2 had good results, but there were still some test cases that failed. This was due to a lack of the right capturing devices or not having the right setup. Other difficulties faced in the segmentation stage were due to the methods used in providing the Algorithm. Problems also arose when dealing with blurry images, low contrast images, and/or images with illumination problems as shown in Figure 19 and Figure 20. For example, in Figure 20 the blurry image and the low contrast between the background and foreground, caused characters to be divided as a single segment. Illumination conditions can affect the separation of each part of LP. For example, if the illumination varies in a region or if the screw which holds the plate has touched the text, the part will not be separated correctly. An image with illumination problems can suffer the same difficulty.

Fig 19. Sample of distorted pictures

Another place where our implementation struggles is where the country type script is not straightforward. This is something that can be worked out through new training for those country types. Even with those difficulties, an 80% success rate is achieved for Group 2 for number recognition. So comparing number recognition vs. country and city recognition summarizes the results.

Fig 20. Pictures with shadow

Table 5 City and country accuracy vs. number matching

Recognition with template and character training			
	Country and city recognition	Number recognition	Overall recognition
Group 1	98	99	0.99
Group 2	85	80	0.87
Average	91.5	89.5	0.93

4.3 Comparison with other research results

A high accuracy system for the proposed system reached a 99% for good images. Comparing the images used by the proposed system to other systems shows in figure 21 how clear the images used by other systems which reported high accuracy rates. Figure 22 summarizes the accuracy of selected systems as shown in Table 6, a comparison of accuracy rates compared to other language recognition systems and Figure 23 for Arabic systems.

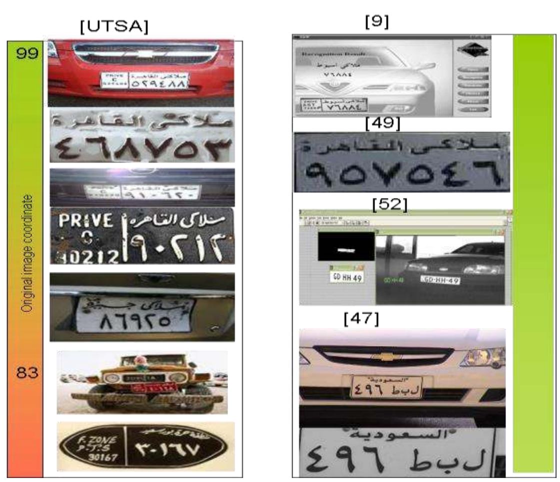

Fig 21. Proposed image compared to high accuracy systems

Table 6 compares the proposed algorithm with other methods. It highlights important issues in comparing various LPR systems. The proposed (UTSA) system results are compared with the past couple of years' systems including the one for Arabic license plates (has * next to ref. number). It also shows that the proposed system produces excellent results compared to other systems, even when we have some failures for fairly distorted images.

On the system developed He, and Huilin Zhang, (2010), where edge detection and NN (neural network) methods used and presented by Syed, Y.A. and Sarfraz, M., (2005) where filtration is added they based their recognition system mainly on recognition of plate number only and they did not include the city and country (they assume it is known to the system) while our system does this which gives it the advantage of being portable to other countries and other languages.

Our system shows superior results. Although the new methods deal with Arabic numbers only, we can say that our work has recognition ratio of 93% and 97% for overall and character recognition against 89%/96% success rate mentioned in similar systems developed by S.H., Kim, et al, 1999, (92.3%/95.7%) in the research conducted by J. Frigo, et al, (2009) and (100%/92.5%) by H.-J. Lee, et al, (2004). In addition, the system shows a 5 second run time using MATLAB while other systems use C++, which has advantages.

The correlation method with template matching was moderately successful in matching the country and city type. The difficulty with this template matching is creating a generic template. Creation of a better and more generic template may produce better results and would be an area for further study. This template matching method would probably be less successful if the images had greater variation in size or orientation of the plates.

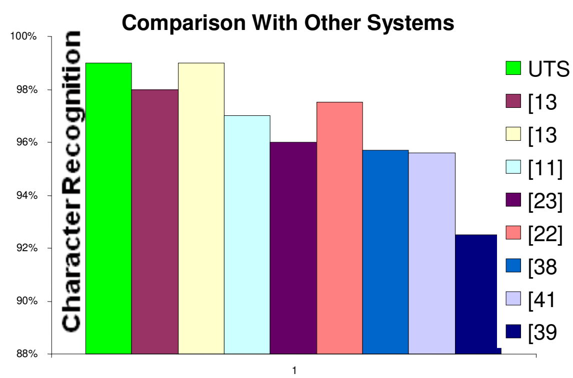

Fig 22. Comparing LP system

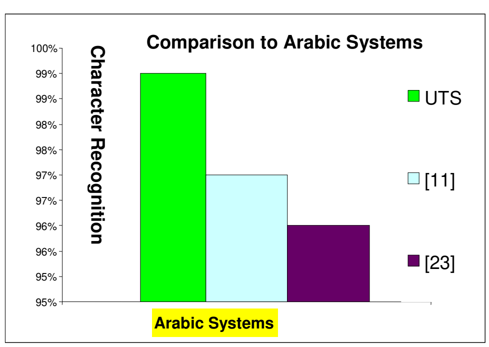

Fig 23. Arabic Systems

Table 6 Detailed Comparison of Selected Systems

Ref.	Plate recognition (P)/overall recognetion (O)	Character recogition	Run time (sec)	Method - P:plate localization R: recognetion classifier	Test images	year	TOOL	Computer speed/RAM	Database	classifier	Language	Note
UTSA	93%(O)	99%	5	P:screw intensity and Edge detection along with plate dimention R:SVM	238	2010	MATLAB R08A	2.4gHz,3G	3 sets for contry, city and numbers	SVM	Arabic	Images tested on our system
[11]*	96%(o)	97%	5	P: Edge detection R:NN		2008	MATLAB 7.0	Not Reported	one template per character		Arabic	simmiler images tested using there approach as we implemented it
[13]	99%	98%	3	Inclined plates	949	2000	Visual C++ 6.0	Not Reported	Not Reported	PNN:probabilistic neural network	Englesh	result reported in there systemand verified in our system using simmeler images
[23]*	89% (p)	96%	not reported	edge detection and graytheshold	65	2005	MATLAB	Not Reported	Not Reported	3 layer neural network	Arabic	implemented there ialgorithm
[42]	95%(o)	95%(o)	2	P: multiple interlacing method R:NN	400	2005	C++	and image processing board DT2868		neural network pattern	Farsi	reported results
[22]	Not Reported	97.50%		P: 2NN filter :R:NN	200	1999	Not Reported	Not Reported	2 sets parked and moving training sets		Korean vehicle	reported results
[41]	88%	92%	30		22	2005	C++	1.8-GHz Pentium IV		lane classification algorithm	Englesh	text from vedo (car plate vedo)
[39]	86(o)%	96.50%	276(ms)	P: Connected component R:2 PNN	1334	2000	Visual C++ 6.0	Not Reported	one set	Neural Network	Englesh	reported results

Some of the reasons why our system did not get a very high plate localization is due to the edges of the plate being affected by neighboring pixel features of the vehicles, so that identification of the object boundaries proved to be problematic. To eliminate this problem, the morphological opening step is used. This step has the side-effect of chopping up the boundary of the license plate and making it impossible to select it as a region of interest.

Other factors playing a big role are the variations in contrast levels and the sharpness of the edges in the images. These make the task of applying a threshold to the edge image to convert it to a binary image difficult to do reliably for all cases.

5. Conclusion

This paper developed an Arabic license plate recognition system that is insensitive to character size, font, shape and orientation. Sidestepping these issues and using 3 small training sets resulted in an extremely high accuracy rate. The proposed system is based on a combination of enhancement, license plate localization, morphological processing, and feature vector extraction using the Haar transform. Localizing the plates and segmentation is done through identifying the location of screws using pattern matching, plate aspect ratio, and background and text color after binarizing the image. Then by applying a coordinate system, the area is masked with respect to each screw position. The proposed system uses efficient classification of alphanumeric features based on license plate organization. It is flexible and allows for additional refinement if needed to elevate an already exceptional success rate. Experimental results are outlined here for license plates from two different Arab countries and show an average of a 99% successful license for number recognition for different images captured in a complex outdoor environment. The result run times are shorter when compared to many conventional and state-of-the-art methods.

The Arabic LPR system has its own unique issues. In addition to not having many publications, there are two main problems. One problem is unique to Arabic LP and the other is a common problem similar to image degradation, contrast and blurry images. In this research we developed a system that solves many issues related to Arabic LP but future work is needed to deal with different kinds of vehicles with governmental and special plate designs. To increase the speed of the system, other programming languages might be used such as: C++ or Java. Also, the LPR system can be written in verilog and installed in a custom-burned PLC (Programmable Logic Controllers) or even an FPGA to get extremely fast performance.

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