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Saudi Arabia License Plate Detection based on ANN and Objects Analysis

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Abstract

This paper proposes an algorithm to detect the license plate (LP). The road images are analyzed which often contain vehicle license plate to be detected. Low-quality images due to severe lighting conditions, vehicle motion, weather conditions, variable distance, LP styles and complex background are the most popular problems which are to be considered. In order to overcome these problems, the proposed algorithm is utilized. Firstly, the contrast of the vehicle is increased to facilitate the detection of LP. Then, the edges of the vehicle are extracted and the most of the background and noise edges according to a predefined threshold are removed. The next step is to construct objects using morphological operations and analyze these objects using orientation and width-to-height ratio. Finally, Artificial Neural Network (ANN) is used for decision making about these objects. The DWT is adopted to represent the objects to decide whether the candidate object is a LP or not. An optimization process is performed on the ANN parameters to enhance the detection rate. The experimental results have been demonstrated the robustness and high efficiency of the proposed algorithm in term of the detection rate of vehicle license plates. Moreover, a comparison has been carried out with the most related algorithms to show the superiority of the proposed algorithm.

Keywords: License Plate Detection (LPD), License Plate Extraction, Neural Networks, DWT.

INTRODUCTION

License plate detection (LPD) is an important stage in vehicle license plate recognition(LPR) for automated transport system. Automatic license plate recognition (ALPR) has many applications such as in traffic flow control, automatic parking systems, automatic bridge systems, and radar based speed control. The advantage of the license plate recognition system is the ability to operate without the need of installing extra equipment on the vehicle. A license plate recognition system has basically three modules for: (a) Localization of the plate region using the image of the vehicle (this step is also called license plate detection or extraction), (b) character (letters or numbers) plate recognition. Automatic License Plate Recognition (ALPR) has found numerous applications in various areas. It can be used for automatically identifying vehicles in a vehicle park, for vehicle access control in a restricted area and for detecting and verifying stolen vehicles. License plate detection is a crucial step in a LPR system for automated transport system.

License plate detection is the most important and difficult task in the LPD recognition systems because the images always have low contrast, blurring and dirty plates. The most common solutions for LPD include techniques based on Prewitt edge detection, Canny edge detection and gray stretch [1, 2]. In [1], they proposed a method to locate a license plate based on improved Prewitt arithmetic operator. The first step was to apply the improved Prewitt operator to the image under processing. They selected a vertical and horizontal method based on characteristics to position the lower and upper edges. Their method accuracy achieved 96.75% with 0.2 sec for positioning time. In [2], the authors presented a method to position the license plate. They analyzed the information of edges, which contain a lot of edges and texture information. They used only the vertical edges with rectangular window to extract the license plate. The results indicated that the license plates can be located using their method with high recognition rate. The authors in [3], introduced an artificial neural networks for license plate recognition. They determined the dimensions of license plate for the captured images as 220×50 pixels. They used Canny edge detection operator to detect the characters inside the plate, following by blob coloring method to separate the characters. The overall recognition rate of their method was 95.36%. Other techniques for color images based segmentation for blue white plate. Vehicle license plate detection technique based on color segmentation was proposed in [4]. They used the characteristics of the license plate information such as color and shape for detection. They proved that using the color segmentation method gave more accurate detection rate than using method depending on gray scale license plate images. In [5] the authors represented license plate recognition system which could be divided into three steps: 1- plate localization, 2- characters detection, and 3- characters recognition. They used Otsu's threshold method to locate the plate. Probabilistic Neural Networks are used for characters recognition. The recognition rate of their system can achieve 91%. Other techniques had converted the image to another color system. Kaushik Deb et al. [6] proposed an approach to extract license plate of a road image which contains vehicles. They utilized a sliding concentric window to segment the region of interest. Then HIS color model is used for color verification of the adopted region. Their approach was able to estimate the rotation angle of the plate and utilized ANN for Korean plate characters recognition. They achieved high recognition rate for of Korean Alphanumeric Characters. In [7], the authors introduced a real-time license plate recognition system. They used the color characteristics to detect the plate regions. By utilizing the probability distribution they could set the plate. Their system can remove any environmental interference with 88.71% recognition rate. In [8], the authors proposed a method for license plate recognition. In their method, the multi-style license plates were represented with quantitative parameters, which were managed by a relevant algorithm. Their method obtained an overall success rate of 90.1%. Moreover, there are a lot of techniques to detect the license plate using various procedures [9-15]. The aim of this work is to combine the accuracy and low execution time in the detection process of the license plates. To avoid missing detection of the license plate, the proposed algorithm increases the contrast of the candidate regions, especially for poor quality images. The proposed algorithm, based on a combination of measured edges, morphological operations and optimization of ANN, is able to overcome most detection problems and achieve a high detection rate.

The rest of the paper is organized as follows. Section 2 describes briefly the problem definition. Section 3 presents in details the proposed algorithm. Section 4 demonstrates the experimental results. Finally, the conclusion remarks are drawn in section 5.

PROBLEM DEFINITION

Many factors can affect the accuracy and efficiency of license plate detection. For example, license plate style may differ from one country to another or it may differ in the same country. There are many common recognition problems between most countries such as there is no database for vehicle license plates, the absence of a standard style for plates, poor weather conditions, varying the distance and angle between the vehicle and the cameras. In addition, some drivers do not keep the plates in the right place, and may there is more than one plate in the front of the vehicle or in the back.

Variation in lighting conditions during day &night makes the detection a challenge for any license plate recognition system. The variation of lighting conditions affect the colors of the captured image which creates several problems for system such as color based segmentation.

The main target of this work is to detect the license plate of Saudi Arabia. Figure 1 shows an example of Saudi Arabia license plate which contains Arabic letters. Saudi Arabia has many license plate styles and all the plates have a white color background, which makes the recognition process too difficult depending on the colors, especially with vehicles painted white.

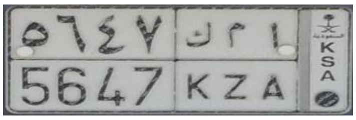

Figure 1: An example of a vehicle of Saudi Arabia license plate was introduced in 2007 [16]

The image segmentation is one of the most important techniques of image processing. A segmentation technique is able to partition an image into parts, called segments. It is inefficient and time consuming to process the whole image. So, image segmentation is used to segment the image into parts for further processing. There are many image segmentation techniques which based on certain image features like pixel intensity value, color texture, etc. All segmentation techniques can be partitioned from two basic techniques of segmentation; region-based and edge-based techniques. In this paper, two region based segmentation techniques such as pixel intensity threshold and K-means clustering are utilized for license plate detection, but the proposed algorithm is based on edge techniques.

Also, it is difficult to segment the image into color regions using K-means or using pixel intensity threshold because in some conditions the reflection of light at noon makes a vehicle painted gray like a vehicle painted white. Hence, it is recommended to isolate the background before starting the license plate extraction process. It means that it is needed first to detect vehicle before starting license plate detection processing steps. Figures 2 and 3 show segmentation process using pixel intensity threshold and segmentation using K-means clustering for five and ten colors, respectively. By visual inspection, it can be seen that the license plate cannot be segmented using these techniques, which confirms the importance of using the isolation step before starting of the segmentation process.

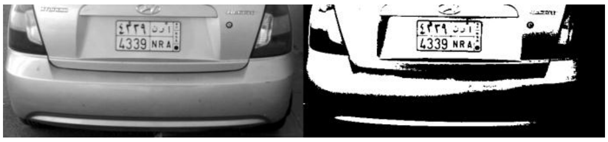

Figure 2: Segmentation process using pixel intensity threshold

Figure 3: Image labeled by Clusters (five colors) using K-means (left) and Image labeled by Clusters (ten colors) using K-means (right)

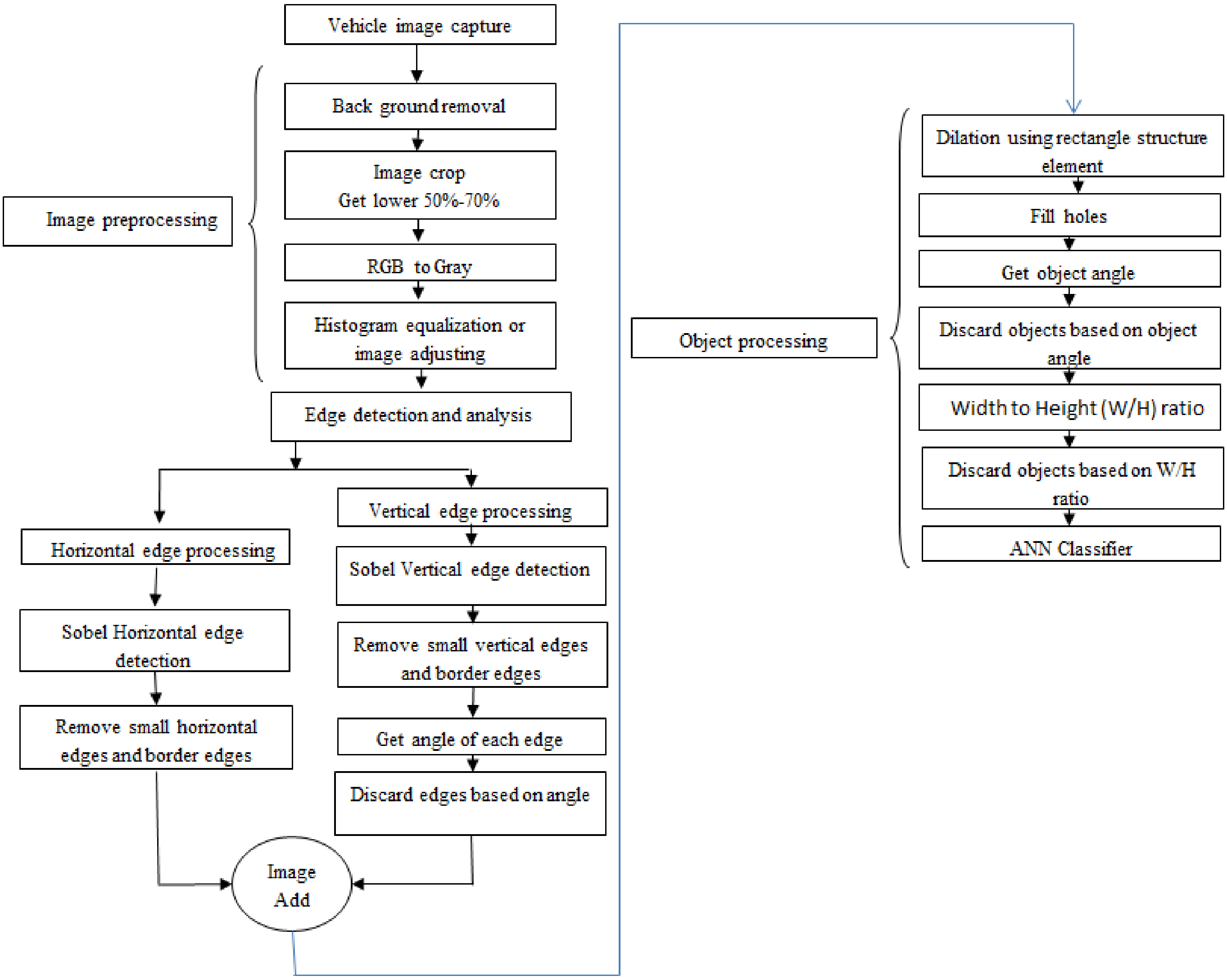

Figure 4: The proposed algorithm

THE PROPOSED TECHNIQUE

In this section the proposed algorithm will be explained then applied to the Saudi Arabia license plate. The proposed algorithm has four basic steps: 1- image preprocessing, 2- edge detection and analysis, 3- object analysis and 4- The ANN classifier. Figure 4 summaries the proposed algorithm.

Image preprocessing

Image preprocessing consists of three steps as follows:

1-Background removal. 2-Image cropping and conversion of a RGB color image into a gray scale image. 3-Histogram equalization.

Background Removal or Vehicle Detection

The background removal means removing any details in an image which maintains only the vehicle inside the image. This step aims to improve the recognition process by decreasing the edges and objects inside the image under process. This step can be easily performed by several methods such as choosing a monochrome or fixed background. For video processing, the foreground is detected from moving vehicles by Gaussian mixture model (GMM) [17]. In [17], the first frames are used to initialize GMM. Another approach in [18, 19] which used the GMM with Kalman filter to detect the foreground. The removing of the background was carried out by using the vertical and horizontal edges, but the performance was unsatisfactory. Also, there is a method for vehicle detection by capturing two images of the same place one with vehicle placed and the other without the vehicle. Then, background subtraction process is utilized to extract the vehicle from the captured images [20]. In [21], the authors proved that the existence of the background may decrease the system efficiency. Deep learning is an efficient machine learning technique that automatically learns image features required for detection tasks. Also, the Faster R-CNN algorithm is a deep learning technique depends on region proposal algorithms to hypothesize object locations [22], which can be used for vehicle detection.

Training Faster R-CNN algorithm consists of four steps. The first two steps train the region proposal and detection networks used in Faster R-CNN. The final two steps combine the networks from the first two steps such that a single network is created for detection. The ability to detect and track vehicles using computer vision techniques is required for many autonomous driving applications, such as for forward collision warning, adaptive cruise control, automated lane keeping and license plate detection. Here, we have removed the image background manually to simplify the operation. Figure 5 shows the background removal step.

Figure 5: Background removal

Image cropping and conversion of a RGB color image into a gray scale image

The untreated original RGB true-color image contains 24-bit true color chart. This is a large amount of color information. It not only occupies large computer storage space but also can decrease the speed of the algorithm. So the original color images need to be resized and converted to a smaller size with 8 bit grayscale for smaller storage space and speed up the algorithm. Then, convert the color image into a greyscale image which contains only the brightness information, according to the following equation.

$$f = 0.11\times B+0.59\times G+0.3\times R \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

where: f is the grayscale image, B is the blue component in the color image, G is the green component in the color image and R is the red component in the color image.

In [11], they have been reported that some of the posters on the glass of the vehicle lead to errors in the detection and recognition processes, because posters have the same form of the plates. Therefore, by removing the upper half of the image that contains the glass, which increases the recognition. Other study [23], depend on scanning vehicle image by rows and counting the number of vertical edges in each row to determine region of interest (ROI) which have maximum number of vertical edges.

The license plate is always located at the bottom of the vehicle. So, after removing the background, make sure the vehicle is only in the image, the dimensions of the image are almost same as the dimensions of the vehicle. We can crop the image and investigate only the lower half which we ensure that license plate is located. This process will reduce the effort, time and the false detection rate. Region of interest is determined here according to the fact that LP is located at the bottom of the vehicle. Figure 6 revels the image cropping and grayscale processes.

Figure 6: From left to right: Resized image, cropped image and gray scale image

Histogram Equalization

The histogram equalization stretches the color range of an image for more contrast. This manipulation yields an image with higher Contrast than the original. The process is based on the creation of a transfer function that maps the old intensity values to new intensity values. To increase the contrast of the gray scale captured image, histogram equalization is used for low contrast images only. As shown in figure 7, the histogram equalized is applied to the image to increase the contrast. The figure indicates much better contrast that avoids missing plate edge detection.

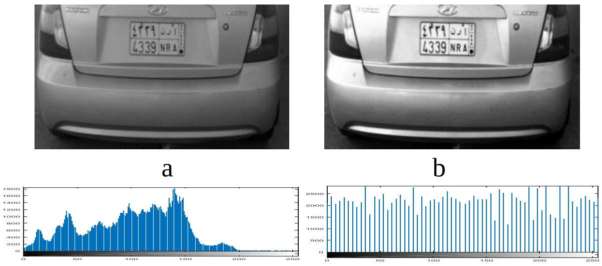

Figure 7a) original image and
b) Image after histogram equalization

Edge detection and analysis

The second step of the proposed algorithm is to find the edges to be analyzed (as shown in figure 8). Firstly the vertical edges are detected and enhanced. Secondly, the horizontal edges are detected and enhanced. The edge detection is consecutively performed because they have different thresholds. So we have two basic sub-steps vertical edge processing and horizontal edge processing.

Figure 8: Sobel edge for original image (left)and image after equalization (right)

Vertical edge processing

The front of the vehicle has many horizontal edges and fortunately, most of the vertical edges belong to the license plate or the lanterns lighting. Therefore, many techniques based on vertical edges can be applied to locate the plate.

In [24], they looked for the existence of a cross shape to locate the LP. However this technique has a problem with rotated LP. Sobel operator edge detector is one of the most widely used operators for computing gradients of an image. It uses two masks in a 3× 3 region to compute the partial derivatives of the central pixel on x-direction and y-direction respectively. The two masks are:

Sx =

-1	0	1
-2	0	-2
-1	0	1

Sy =

-1	-2	-1
0	0	0
1	2	1

By testing, we have found that the Sobel and Prewitt operators are the best edge detector which gives promising results with most of the used samples. Finally, by testing the whole algorithm, Sobel operator gives the best results.

To remove the small vertical edges and border edges, we have performed many experiments to find the most appropriate height of the vertical edge of an LP in an image with a size of 500×500. It is found that the height equals 25 pixels. It means that the suitable threshold is about 5% of the image height. This step may be called noise removal. Figure 9 illustrates the vertical edge detection step.

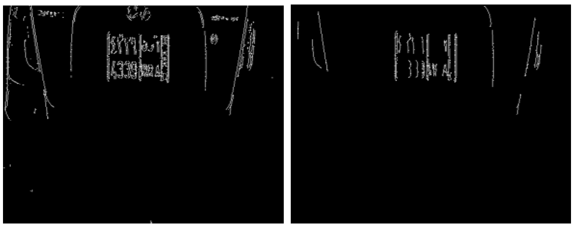

Figure 9: Vertical edge detection using Sobel operator (left) and Vertical edge after noise removal(right)

Now measuring of edge orientation is required to decide which edge belongs to the LP or decide to exclude it. Orientation is a scalar that specifies the angle between the x-axis and the major axis of the ellipse, which has the same second-moments as the region. The value varies from -90 to 90 degrees.

Figure10 illustrates the axes and orientation of an ellipse. The left side of the figure shows an image region and its corresponding ellipse. The right side shows the same ellipse with the solid blue lines representing the axes, the red dots are the foci, and the orientation is the angle between the horizontal dotted line and the major axis [25].

Each 8-connected pixels are considered as one edge, the orientation of vertical edges is computed and excludes edges which its orientation exceeds a certain threshold. It is known that the orientation of vertical edges equals 90° and an error of ±10° is accepted. So, the absolute value of orientation less than 80° will be excluded. Figure 11 illustrates vertical edge detection step based on orientation value.

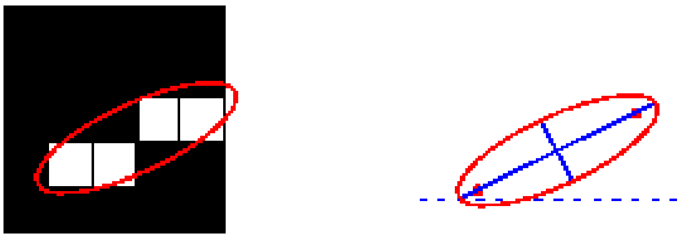

Figure 10: The orientation

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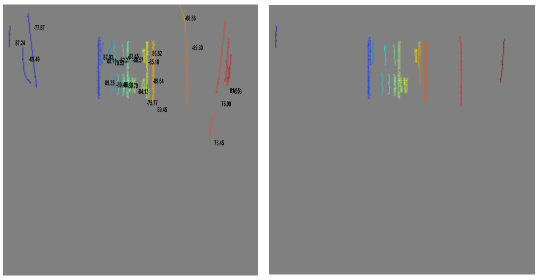

Figure 11: Vertical edges labeled with orientation value (left) and Vertical edges after excluding based on orientation threshold (right)

Horizontal Edge Processing

The vertical edge detection is followed by horizontal edge detection. The horizontal edges are detected using Sobel horizontal edge operator and the edges that have lengths smaller than certain threshold are removed. The threshold value used in this paper is 30 pixels. Figure 12 reveals the horizontal edge operation. It is visually clear that the horizontal edges of the LP appear very well.

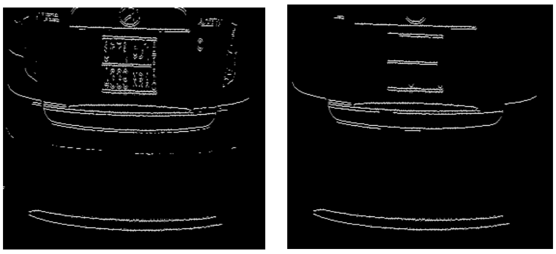

Figure 12: horizontal edges (left) and horizontal edges after noise removal (right)

Object analysis

The vertical and horizontal edges are collected to construct objects where the LP is expected to be one of them. Some operations such as morphological operations are applied to construct an image of objects for easy LP detection process. These processes are explained as follows:

Dilation and fill holes morphological operations

Morphological operations such as dilation and fill holes are applied to the objects to analyze the object shape to decide whether a region is an LP or not. Figure 13 reveals the two morphological operations.

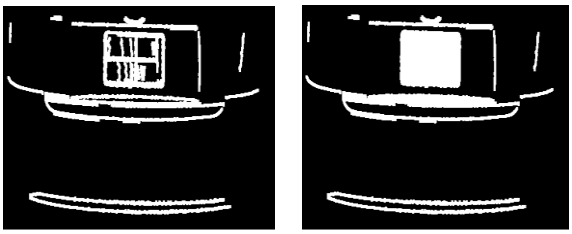

Figure 13: dilation using 4×4 square structure element (left) and filling holes to construct objects (right)

Next, measuring the orientation angle of each object is utilized to examine its suitability to be a vehicle license plate. The orientation is the angle between a horizontal line and major axis. So, the angle should be zero degrees with some acceptable error. In this work, 25° is used as a threshold. Hence, every object with an angle more than 25° will be removed. Figure 14 shows the objects removal operation while retaining the candidate objects to be a license plate of the vehicle.

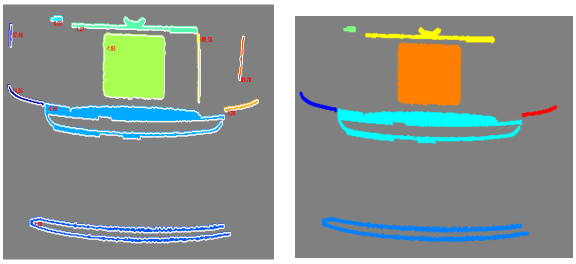

Figure 14: objects labeled with orientation angle (left) and after exclusion (right)

The property that the proposed algorithm depends on is the aspect ratio (width/height) of the object. The aspect ratio of a plate is approximately 2:1 based on its shape. The major axis length is a scalar that specifies the length (in pixels) of the major axis of the ellipse that has the same normalized second central moments as the region. Minor axis length is a scalar that specifies the length (in pixels) of the minor axis of the ellipse that has the same normalized second central moments as the region [25]. In order not to miss any candidate object may be an LP, aspect ratio less than 4:1 is selected. Figure 15 shows the aspect ratio of each object and the objects after applying the threshold. To examine the effectiveness of last steps, Table 1 demonstrates the number of objects per image (include at least one object to be the LP) in the dataset against the percentage of the number of images with the detected objects. The table indicates that the proposed algorithm gives promising results with accuracy rate 98.67%.

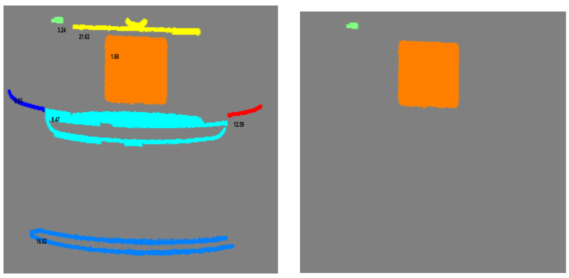

Figure 15: Objects labeled with W/H ratio (left) and Objects after threshold (right)

Table 1: Number of detected objects in an image to the percentage of images with the detected objects in the dataset

Number of objects per image in the dataset	Percentage of number of images with the detected objects(%)
0 object	1.3158%
1 object include LP	39.4737%
2 object include LP	42.1053%
3 object include LP	2.6316%
4 object include LP	7.8947%
More than 4 include LP	6.5789%
Accuracy rate	98.6842%

ANN Classifier

At this step, it is the time to decide whether an object is LP or not. The Artificial Neural Networks (ANN) is adopted for its ability to classify an object based on inherent learning. Discrete wavelet transform (DWT) may help in representing the image in a form to make feature extraction process easier and more accurate. The outputs of DWT are decomposed into four quadrants with different interpretations, which are called the approximation coefficients matrix cA, and details coefficients matrices cH, cV, and cD (horizontal, vertical, and diagonal respectively).

We will test which mother function and details coefficient give the best detection rate. Also, we will use Principal Component Analysis (PCA) for optimization and reduction features.

Multilayer topologies are capable of learning non-linear decision boundaries, a fact which increases the versatility of neural networks to solve real-world. ANN with Multi-Layer Perceptron (MLP) is adopted. MLP consists of three layers; input layer, hidden layer and output layer. Number of neurons in input layer is varying according to the number of used details coefficient.

Table 2: The general specification of the proposed ANN

Training function	**Trains or trainscg or traingdm or trainrp or trainb or trainc**	**Network Goal**	**0.001**
Data division	Random	Train ratio	70%
Performance	MSE(Mean Square Error)	validation ratio	15%
No. of epochs	1000	Test ratio	15%
No. of hidden neurons	Variable 80:130	No. of neurons in output layer	1
Input layer data	DWT vertical or horizontal or diagonal coefficient taken from different DWT mother functions.	No. of neurons in input layer	Variable according to DWT mother function used.
Optimization technique	Principal Component Analysis (PCA)	DWT families/ mother functions	DMeyer, Symlets, Daubechies, Haar, Coiflets, ReverseBior.
Simulation tool	MATLAB	Hardware used for processing	Toshiba Satellite core I5,4GB RAM ,Windows 10.

The results of the ANN depends on the used number of neurons in the hidden layer and the used training function (i.e., sequential weight/bias). In the next section, we investigate the better choice of these parameters. Also, optimization of the number of used neurons in input and hidden layer is carried out. A single neuron at the output layer is used. Table 2, proposes the general specification of the proposed ANN.

EXPERIMENTAL RESULTS

Constraints and Data Collection

Most of the existing license plate detection algorithms are restricted by various controlled conditions such as fixed backgrounds, known color, or designated ranges of the distance between cameras and vehicles. Some constraints are taken into consideration such as:

a) All images are captured during the day.

b) Image of the vehicle is captured with variable angles.

c) Vehicle is stationary when the image is taken.

d) Image background is removed manually before processing or uses fixed background.

e) Dataset does not include trucks.

f) Captured mages at night have not been tested.

g) Only current Saudi Arabia license plates are examined.

The current license plates have the following characteristics:

a) The plate size is 32cm × 16cm.

b) The ratio of width to length is 2:1.

c) The plate is divided into 5 sections; Arabic letters, Hindi numbers, Latin letters, Arabic

numbers and vehicle type section which is color coded and includes the name and logo of Saudi Arabia.

d) There are 4 color codes; white is for private vehicles, yellow is for transport vehicles, blue is for commercial vehicles and green is for diplomatic vehicles.

e) Size of letters is 36 × 21mm and size of numbers is 55 × 26mm.

Results and Discussions

The strategy of the proposed algorithm is based on optimization of ANN for the detection process. Firstly, we test three different DWT coefficients (horizontal, vertical, and diagonal) and compare the performance (mean square error) and regression of the designed ANN. Figures 16 and 17 show the relation between performance and regression with the number of the hidden neurons for DWT: horizontal, vertical, diagonal coefficients. It is clear that horizontal coefficients give the best results which mean lowest performance (MSE) and highest regression. Table 3 summarizes the results. DWT horizontal coefficients give the max regression 99.03% and min MSE 0.0029.

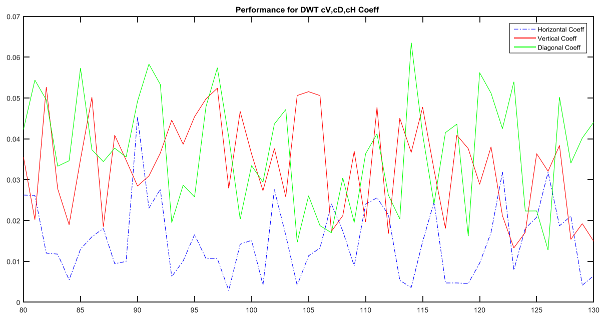

Fig. 16 The relation between number of hidden neurons and MSE for DWT coefficients. Horizontal coefficients (blue dot dash line) give the best results.

Table 4: Comparison between the DWT families

Coeff/train fun	Wavelet families	MAX regression	MSE	No. of hidden neuron	No of neurons in Input layer	Time Elapsed
Horizontal/trains/No hidden 80:130	Daubechies 'DB1'	99.05%	0.0029	100	125	357.66254 5 seconds
Horizontal/trains/No hidden 80:130	Symlets 'Sym3'	96.92%	0.0091	126	127	356.26560 4 seconds
Horizontal/trains/No hidden 80:130	Coiflets 'Coif2'	96.27%	0.0110	108	130	359.51120 3 seconds
Horizontal/trains/No hidden 80:130	Haar 'haar'	99.45%	0.0017	126	125	354.16599 4 seconds
Horizontal/trains/No hidden 80:130	Discrete Meyer 'demy'	99.90%	2.8146e-04	111	175	359.38364 9 seconds
Horizontal/trains/No hidden 80:130	ReverseBiorthogonal 'Rbio2.4'	96.93%	0.0091	121	129	355.09032 2 seconds

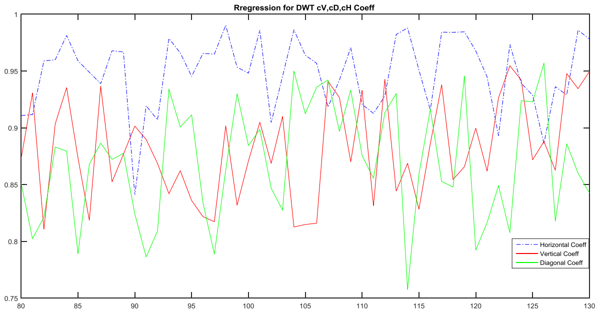

Figure 17: The relation between number of hidden neurons & Regression for DWT coefficients. Horizontal coefficients (blue dot dash line) give the best results.

Table 3: Comparison between DWT coefficients

Train fun=trains, Topology=MLP, No. of hidden neurons =80:130		
Coefficients	**MAX REGRESSION**	**MSE**
DWT/Haar/Horizontal Coeff.	99.03%	0.0029
DWT/Haar/Vertical Coeff.	95.46%	0.0133
DWT/Haar/Diagonal Coeff.	95.70%	0.0128

Next, we will examine the ANN using different DWT families such as Haar, symlets, Coiflets, etc. Table 4, shows a comparison between DWT families. It is clear that the 'demy' family gives max regression 99.90% and min performance 2.8146 e^{-04} at 111 neuron of the hidden layer. The relation between ANN performance and number of hidden neurons is illustrated in figures 18 and 19.

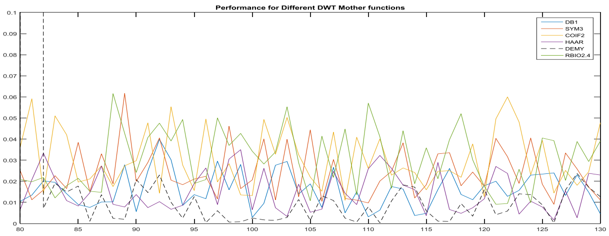

Figure 18: The relation between number of hidden neurons &MSE for different DWT families. Demy gives the best results

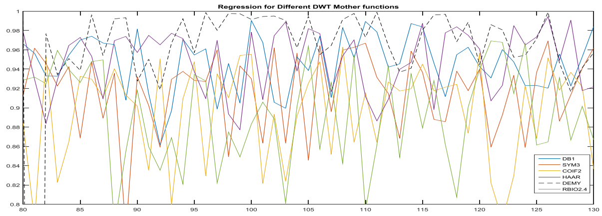

Figure 19: The relation between number of hidden neurons & Regression for different DWT families. Demy gives the best results.

It is too difficult to expect which training algorithm will be the fastest and accurate for a given problem. It depends on many factors, including the complexity of the problem, the number of data points in the training set, the number of weights and biases in the network, the error goal, and whether the network is being used for pattern recognition (discriminant analysis) or function approximation.

Table 5: Comparison between DWT families

Common Specifications	**Training Algorithm**	**Max Over All Regression**	**MSE**	**No. of Hidden Neurons**	**Over All Execution Time**
Discrete Meyer Wavelet Family Horizontal Coefficients only. PCA for Feature Reduction Random Weight/Bias initialization. 105 neurons in input layer	Sequential weight/bias 'trains'	99.93 %	2.1808e-04	125	537.126082 sec
	Scaled Conjugate Gradient 'trainscg'	97.08%	0.0094	120	46.325877 sec
	Gradient descent with momentum backpropagation 'traingdm'	74.51 %	0.1405	97	38.954022 sec
	Batch training with weight and bias learning rules 'trainb'	78.03 %	0.1146	82	41.179374
	Cyclical order weight/bias training ' trainc'	98.41 %	0.0055	87	5397.301047
	Random order incremental training	92.38 %	0.0244	106	107.795021

Number of neurons at hidden layer is variable (80:130) Single output neuron Performance=MSE	with learning functions 'trainr'				
	Resilient Backpropagation 'trainrp'	82.21%	0.0517	111	36.787127
	Variable Learning Rate Backpropagation 'traingdx'	89.37%	0.0321	119	40.226540

We test some of the common ANN training algorithms to determine which one gives the best classification with min performance and maximum regression. Although Leven berg-Marquardt training algorithm (trainlm) is able to obtain lower mean square errors than any of the other training algorithm, but in our case, we have excluded it because it needs large execution time. Also, the BFGS Quasi-Newton (trainbfg) needs large execution time. Sequential weight/bias training algorithm (trains) gives the maximum overall regression 99.93% with mean square error of 2.1808e^{-04} when using 125 neurons at the hidden layer. We have run the proposed algorithm 51 times for each training algorithm. In each time, the number of neurons at the hidden layer is varied from 80 to 130 to obtain the best regression and MSE. The overall execution time for sequential weight/bias is 537.126082 sec. This means that the execution time needed for one case (at 125 neurons at hidden layer) is approximately 537.126082 /51=10.51 sec. Resilient Back propagation (trainrp) achieves the best overall execution time (36.787127 sec) but it have low overall regression (82.21%). All training algorithms are tested for 175 and 105 neurons in the input layer and they give close results. Table 5, shows a comparison between the DWT families with 105 neurons for input layer. Figures 20 and 21 show the mean square error (MSE) versus the number of neurons at hidden layer for four best training algorithms and the overall regression versus the number of neurons at hidden layer respectively. It is clear that sequential weight/bias training (trains) has a stable performance and regression with a variable number of neurons in the hidden layer.

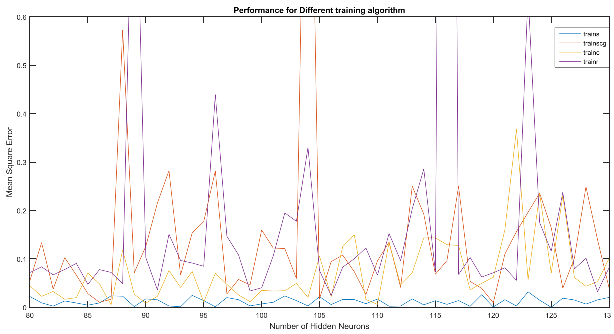

Figure 20: The number of hidden neurons &MSE for different training algorithm trans gives the best results.

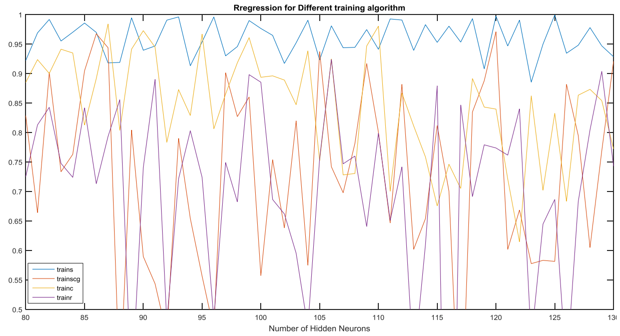

Figure 21: The number of hidden neurons &regression for different training algorithm .trans gives the best results.

Finally, the effect of changing the number of neurons in input layer on MSE and regression is investigated. The number of neurons in the input and hidden layers is variable. We have investigated for a minimum number of neurons at theses layers with maintaining the best regression and MSE. Table 6, shows that the results are very close to each other. When we compare the second result with the third result, we find that input neurons are reduced by 5 neurons but the hidden neurons are increased by 8 neurons which mean that the third result has neurons more than the second result. Also, regression and MSE is approximately equal.

Table 6: Comparison of the used number of neurons in input and hidden layers

Topology=MLP, trains algorithm, demy Family, single output neuron, number of neurons at hidden layer is variable (80:130) Number of neurons at input layer is variable (100:175)				
No. of neurons at Input layer	**No. of neurons at Hidden layer**	**Max Over All Regression**	**MSE**	**Overall Processing Time(s)**
175	111	99.90%	2.8146e-04	437.21
110	117	99.87%	3.9024e-04	⋮
105	125	99.93 %	2.1808e-04	379.62

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We have compared the performance of the ANN with DWT against DCT to find out what is the best transformation for LP detection. Table 7, indicates that the results are too close to each other, which means that the two transformations are suitable for LP detection.

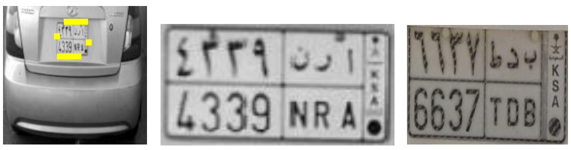
Table 7: Comparison between DWT and DCT

Topology=MLP, trains algorithm, DCT features, single o/p neuron, number of neurons at hidden layer is variable (80:130) Number of neurons at input layer is variable (100:250)				
Number of neurons at Input layer	**Number of neurons at Hidden layer**	**Max Over All Regression**	**MSE**	**Overall Processing Time**
105	127	99.86	4.261e-04	396.96
250	109	99.85	4.3062e-04	386.39

To prove the superiority of the proposed algorithm, a comparison has been carried out with the most related algorithms. Table 8, reveal the superiority of the proposed algorithm. Figure 22 shows some results of successful and wrong detection of LP.

Table 8: A Comparison with related algorithms.

Author	**LP style**	**Success rate**	**Reference**
Saleh Basalamah	New (Saudi Arabia)	76%	[24]
Muhammad Sarfraz	Old (Saudi Arabia)	96.22%	[21]
The proposed algorithm	New (Saudi Arabia)	98.68	



a) Successful detection of LP

b) Wrong detection of LP

Figure 22: Some results of the proposed algorithm

CONCLUSION

This work aims to overcome most of the problems faced by detection of license plates (LP) in Saudi Arabia such as the color of the plate (in KSA most vehicles and plates have the same color), image background and posters on the glass. The captured image is firstly preprocessed to improve the contrast. Then, the edge detection and morphological operations are applied to the improved image. The obtained objects are analyzed regarding the aspect ratio and orientation to exclude the non-match objects. To decide whether the candidate object is an LP or not, the ANN is employed. The input to the ANN is the DWT of the candidate objects for best feature extraction to ensure good classification. An optimization is performed for the designed ANN to examine the parameters that affect the performance of the ANN. The experimental results show that the horizontal coefficients, Demy family, and the trains training algorithm give the best for the detection rate. As a proof, a comparison with the most related algorithms reveals the superiority of the proposed algorithm with high detection rate 98.68%.

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