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An Efficient Method for License Plate Localization Using Multiple Statistical Features in a Multilayer Perceptron Neural Network

Mahdi Rezaei, Morteza Isehaghi
Faculty of Computer and Information Technology Engineering
Qazvin Branch, Islamic Azad University
Qazvin, Iran
rezaei@qiau.ac.ir, m.isehaghi@gmail.com

***Abstract*—Accurate license plate localization is the most important prerequisite in ANPR (Automatic Number Plate Recognition) systems. Majority of the existing algorithms use a single feature to obtain the license plate location which causes to potential false detections. In this article we propose a robust methodology using 16 statistical features while we still preserve real-time processing of the system which is a requirement for such applications. The proposed method uses a Vertical Projection technique and Discrete Fourier Transform (DFT) in order to extract multiple statistical features, as well as K-means clustering and multilayer perceptron neural network technique to identify the location of a license plate in an image. The method is compared with the state-of-the-art research in the field and the effectiveness of the method is evaluated for various types of license plates with different scripts.**

***Index Terms*—License Plate Localization, Vertical Projection, Statistical Features, MLP Neural Network**

I. Introduction

Automatic Number Plate Recognition(ANPR) or License Plate Recognition(LPR) has many applications such as traffic surveillance, stolen car detection, speed limit enforcements, parking lot control, or even border management [1]. A license plate includes a unique combination of digits and alphabets, and the License Plate Detection (LPD) or localization is the most important steps prior to LPR. Usually, the structure and coding of license plates within a country is unique; however, a robust LPD system should be able to detect and localize multi-language international license plates.

A typical LPR system acquires vehicle license plate information from a set of sample license plate images, as the training set, in order to learn some unique identity features associated within the plates [31]. The most crucial phase in an LPR is specifying the location of the license plate in the background car images. The wide variety of license plate types, complex environment and uneven illuminations make the license plate detection as a challenging computer vision task [37].

In this paper, we introduce a novel algorithm to detect location of license plates in a traffic scene. This is done by defining sixteen statistical features to ensure a highly accurate license plate localization. The rest of the paper is organized as follows: Section 2 reviews the literature in the field and discusses on related work. In Section 3 we provide our methodology in details. Section 4 evaluates the performance of the proposed method comparing with the state-of-the-art, and Section 5 concludes the paper.

II. Related Work

There are diversity of methods for license plate localization. Below, we review a list of the well-known and most cited works in the field. One of the typical approaches for license plate localization is the application of Haar-like features [29], [30]. These features consist of rectangular gray-scale masks which can be used in cascaded classifiers [14]; however, the method suffers from a high rate of false positives but extremely fast in which makes it a rather satisfactory approach for the real-time systems. Discrete Fourier Transform (DFT) and Fast Fourier Transform (FFT) are efficient algorithms used in signal processing. License plate numbers exhibit frequencies that make them feasible for spectral analysis through the Fourier transform. This can be considered as an acceptable feature, however, this as a single feature, would not be sufficient to obtain all properties of a license plate [1]. Plenty of texture information exist in plate region, specially in vertical edges [17]. Yingjun Wu and Chang Tan take advantage of texture features for extracting plate area in an image [2], [3], [20].

In most countries, the license plates come with a particular background color in one side of the plate which can be taken into account as color information of color features [22] for LPD applications. Based on the European Union (EU), the standard format of vehicle license plate has a blue section on the left side with the country code and EU circle of stars [38] (See Figure 1). Some researcher utilize color information for license plate localization [2], [3], [13]. However, color-based features can not be considered as robust features. In complex environment there may exists similar background colors that can be confused or mixed with the license plate color. Weijuan Wen employs Wavelet Transform to extract texture information of license plate [4]. The method extracts skew information, horizontally and vertically. Some other

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Fig. 1. Samples of EU vehicle registration plates

localization approaches are also done using machine learning algorithms. Machine learning algorithms are used for training from samples. One of this algorithms is Support Vector Machine (SVM). SVM is an statistical machine learning algorithm known as linear separator. Liu Yongchun and Yu Xiaohong developed an SVM-based method to detect plate area in a traffic scene [24]. Genetic algorithm (GA) is an optimization search method. As a great advantage, GA does not need to search the whole image area to detect a license plate. GA consists of various steps including generating initial population, defining fitness function, selection, crossover, and mutation. Zhao Ji-yin and Zheng Rui-rui (2008) used GA to locate license plates and achieved an accuracy of 97% [34]. In 2013 Halin et al. employed Naive Bayes classifier for plate localization. In their work, 144 license plate images was tested and showed the precision rate of 0.98% [25]. Nevertheless, the number of tested images was not sufficient to statistically validate the claimed accuracy. Cascade of Classifiers [15], Stereo Vision based features [32], [33], and Fuzzy logic Neural Networks [26], [28] are other alternative approaches.

Reviewing the related works, it can be observed that in most of the license plate localization techniques only a single feature is searched and utilized to acquire the license plate location. In next section, we develop a robust methodology using sixteen statistical features in a multilayer perceptron neural network to extract the license plate location.

III. Methodology

In this algorithm, we chose 300 images for training and 911 images for a test. The first step of our algorithm is image preparation. As the first step, all of color images were converted to gray-scale images. After that we divided the input images into rectangular grids, each grid equals to the largest size of the license plate size observed from the train dataset. Considering average plate size of 180 pixel by 40 pixel, and scanning every input images with a 10 pixel shifts from top to bottom and from left to right, this leads to a scanning grid including 21000 rectangles for a 1800 by 1200 pixel input image.

Since all the images are captured from a stationary camera with a fixed distance from the passing vehicles, we define a maximum plate size area as the region of the license plates.

In next step we calculate 6 basic signals followed by extraction of 16 features from those basic signals out of all 21000 rectangles in an input image. In preparation for feeding the inputs to our Neural Network, we mark up 300 plate locations as ground truth information. Then we train all the mentioned 21000 features with neural network and finally we apply a performance check on all 911 test images. Below we describe the proposed algorithm in more details:

A. *Preparation*

Figure 2 briefly illustrates the main phases of the algorithm. The first phase of the algorithm includes the following steps:

- Converting the original image in gray scale:

$$G = 0.29 * R + 0.58 * G + 0.11 * B \tag{1}$$

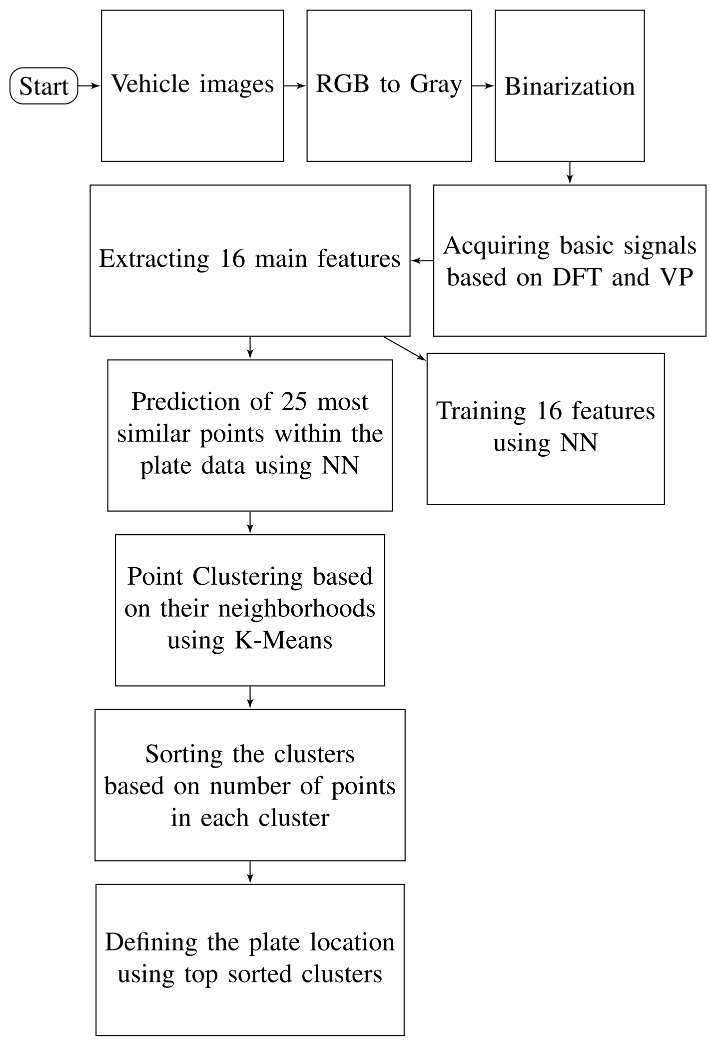

Fig. 2. Flow chart of the proposed algorithm

Fig. 3. Left to right: Original image, Gray scale image, Binarization

where R,G, and B are Red, Green and Blue components of the original image, respectively [1] (see Figure 3).

- Automatic thresholding to obtain a binary image.
  For this crucial stage, we use Gaussian adaptive thresholding [35] as follows:

$$f(n) = \begin{cases} 255 & \text{if src(x,y) > T(x,y)} \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

  Where T(x,y) is the threshold value which is calculated by the summation of the Gaussian window with the size of Size$_w$ * Size$_w$ applied to the neighbor pixels of the pint (x,y). We defined Size$_w$ equals to 33 value based on genetic algorithm variable optimization (See Section III-F). Later in Section 3.6 and in Figure 4 we compare the difference between simple global and adaptive thresholding.

- Extrema Patch Removal: Removing patches and segments that are much bigger or much smaller than the expected average segments' size within a plate region (i.e. average proportional size of digits and characters). This action removes most of the non-plate segments in the query image as shown in figure 5.

B. Feature Extraction

In this step, as discussed earlier, we scan the binary images using a 180 by 40 pixel sliding window, starting from top left corner, with a shift step of 10 pixels in each iteration of the scan. The 10-pixel shift step is applied horizontally and vertically. In each iteration, we evaluate some basic features for plate size window. The shift-step value (i.e. 10) is chosen based on genetic algorithm optimization results as per in section III-F.

The basic features include:

1 - VP (Vertical projection of plate size window): In general, the vertical projection of an image is a function of row coordinate. Thus we define the vertical projection of the image, $P(c)$, as follows:

$$P(c) = \sum_r f(r, c) \qquad \text{for all c.} \tag{3}$$

VP is a 1-Dimensional feature vector with a length of 180 pixels. Vertical projection is summation of all 40 vertical pixel values [36]. Figure 6 shows VP of a sample plate window.

2 - LVP (Half left vertical projection feature). The signal is obtained from half left signal of VP and its length is 90.

3 - RVP (Half right vertical projection feature).The signal is obtained from half right signal of VP and its length is 90.

4 - DFT, The fourth feature that we need is the discrete Fourier transform of VP and can be defined as:

$$DFT(u) = \frac{1}{N} \sum_{x=0}^{N-1} VP(x) e^{\frac{-i2\pi ux}{N}} \tag{4}$$

5 - DFTL (Discrete Fourier transform of LVP feature). It can also be defined in a similar way of DFT:

$$DFT(u) = \frac{1}{N} \sum_{x=0}^{N-1} LVP(x) e^{\frac{-i2\pi ux}{N}} \tag{5}$$

6 - DFTR is also DFT of RVP feature and it can be calculated similar to DFTL.

Using the above mentioned basic features, we propose 16 extended features as per Table 1 and 2:

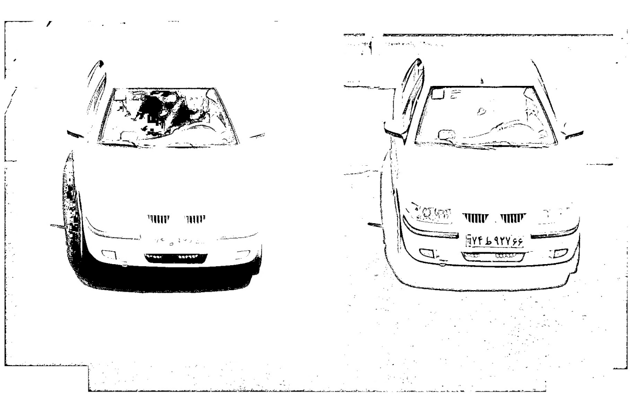

Fig. 4. Left: Simple global thresholding, Right: Adaptive thresholding

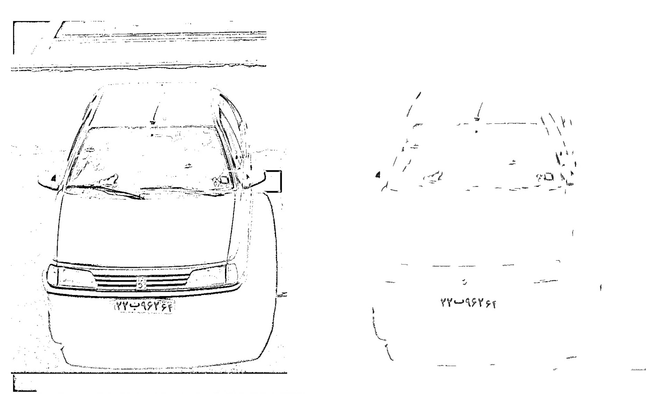

Fig. 5. Left to right, before and after removing non-plate segments

R	Title	Formula	Comment
1	Summation of vertical projection	$SVP = \sum_{i=0}^{180} VP(i)$	First feature is simple but effective.
2	Summation of half left vertical projection	$SLVP = \sum_{i=0}^{90} VP(i)$	....
3	Summation of half right vertical projection	$SRVP = \sum_{i=90}^{180} VP(i)$	is third feature.
4	Summation of horizontal discrete derivatives	$DD(r,c) = \lvert(f(r,c) - f(r,c-1))\rvert$ $DHDD = \sum_{r=0}^{40}\sum_{c=0}^{180} DD(r,c)$	, to calculate this feature fist we most calculate $DD(r)$ of the binary image $f(r,c)$.
5	Maximum amplitude of DFT	$MAD = max(DFT(f))$	, We consider the maximum amplitude of the discrete Fourier transform.
6	Maximum amplitude of DFTL	$MADL = max(DFTL(f))$	MADL , maximum amplitude of the discrete Fourier transform of left side of window .
7	Maximum amplitude of DFTR	$MADR = max(DFTR(f))$	MADR, maximum amplitude of the discrete Fourier transform of right side of window.
8	Maximum amplitude of VP	$MAV = max(VP(f))$	MAV, Maximum amplitude of the vertical projection.
9	Maximum amplitude of VPL	$MAVL = max(VPL(f))$	MAVL, Maximum amplitude of the left side of vertical projection.
10	Maximum amplitude of VPR	$MAVR = max(VPR(f))$	MAVR, Maximum amplitude of the right side of vertical projection
11	Frequency of maximum amplitude of DFT	$FMA = argmax(DFT(f))$	FMA, Frequency of maximum amplitude of the discrete Fourier transform
12	Frequency of maximum amplitude of DFTL	$FMAL = argmax(DFTR(f))$	FMAL, Frequency of maximum amplitude of the discrete Fourier transform of right side of window
13	Frequency of maximum amplitude of DFTR	$FMAR = argmax(DFTR(f))$	FMAR, Frequency of maximum amplitude of the discrete Fourier transform of right side of window
14	Summation of DFT	$SD = \sum_{i=0}^{180} DFT(i)$	SD , Summation of the discrete Fourier transform signal
15	Summation of DFTL	$SDL = \sum_{i=0}^{90} DFTL(i)$	SDL, Summation of the discrete Fourier transform of left side of window
16	Summation of DFTR	$SDR = \sum_{i=0}^{90} DFTR(i)$	SDR, Summation of the discrete Fourier transform of right side of window

TABLE I
FEATURES

Fig. 6. Vertical projection feature in a given license plate window

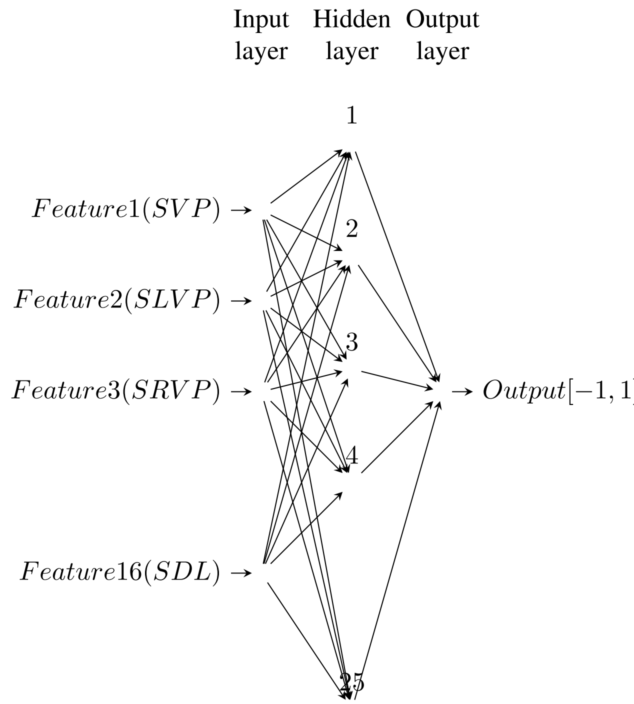

Fig. 7. Structure of the designed Neural Network for license plate localization

C. Training Phase

Now we have sixteen features for each iteration of scan and we use 300 images for training purpose. There are variety of training approaches, as mentioned in related work section. Choosing the most suitable approach depends on multiple factors such as complexity, speed, and type of data. We prefer multilayer perceptron (MLP). Multilayer perceptron as one of the most effective and well-known types of neural network.

The multilayer perceptron MLP is an aggregate liked neurons which connect an input vector to output. We feed sixteen features as input vectors and the output is a scalar value between -1 and 1 such that -1 represents no plate data and 1 represents the existence of the plate data. We also define a hidden layer as illustrated in the Figure 7. Choosing the number of nodes in the hidden layers is a challenging part in designing a neural network. We define an optimum number of hidden layer neurons based on genetic algorithm optimization results in section III-F.

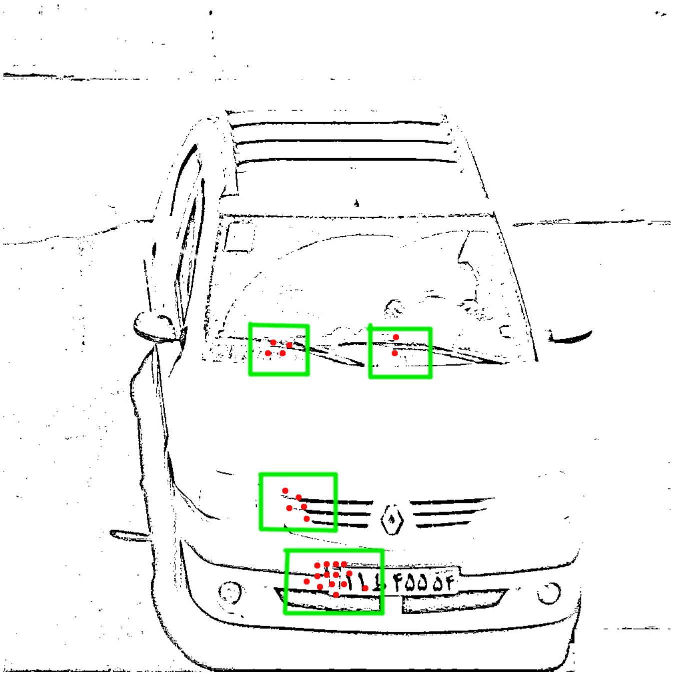

Fig. 8. 25 Selected plate location candidates (red points) and 4 identified cluster of grouped points (green rectangles)

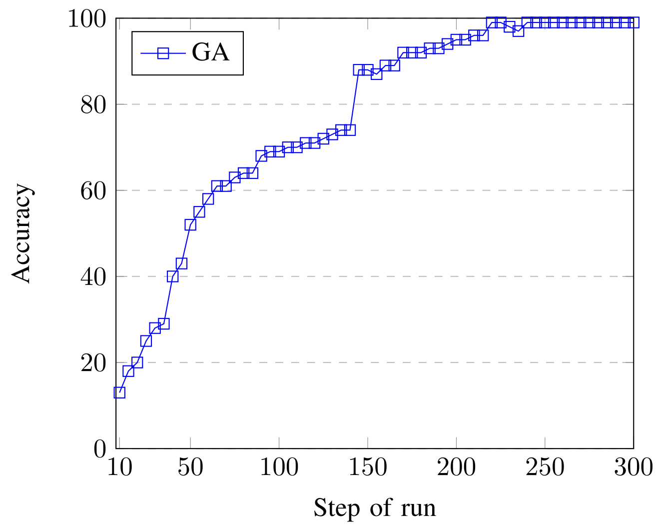

Fig. 9. Variable optimization by genetic algorithm

D. Prediction Phase

After the training phase, we proceed with the test and evaluation phase. For every input image we perform all the previous stages to extract features. Then in order for evaluating the input image, the obtained features are fed to the trained neural network. The output of the neural network will be a number between -1 and +1. After multiple iterations of image scan for various size of license plates, we keep 25 best candidate locations that have closer values to +1. The number 25 was the optimized number, selected by genetic algorithm optimization, as described in section III-F. These 25 points show the top-left corner of candidate plate locations with a higher possibility of the existence of a license plate in the area.

E. Clustering

In this stage, we initially divide those 25 points (obtained in previous step) into two clusters, using *k*-means clustering [1]. In any clusters, if we find two or more points with the Euclidean-distance of more than 90 pixels, the clustering process will be repeated to divide the current cluster into two new clusters. This step will be repeated until there is no clusters with the points with a distance of 90 pixels or more. *k*-means parameters and the threshold of 90 is obtained using the same genetic algorithm optimization solution described in Section III-F

As the next step, we sort the clusters based on the number of points in each cluster. Statistically, the sorted clusters shows the candidate plate regions with the highest likelihood of existence of a plate within the given region. Figure 8 shows 25 selected points and four identified clusters.

F. Variable Optimization Using Genetic Algorithm

As discussed earlier, there are some heterogeneous parameters in the proposed method that need to be taken into account for optimization:

- Number of nodes in the hidden layer of neural network.
- K-means clustering parameters.
- Number of most similar points to select a candidate plate region in an image.
- Size of steps to scan the image.
- Gaussian adaptive threshold parameter.

Since these parameters can vary in a wide range of values and they are dependent together, this makes it a non-trivial task to define optimum values. To achieve optimum values we considered a genetic algorithm based solution. First, we defined a limited range for all parameters and allowed a random population with six members. We run all algorithm steps include train and test with the input parameters of those six members and calculated the accuracy of this members, individually. The accuracy value of the members were calculated based on 973 ground truth license plates. After that, the fitness function selects two best members with highest accuracy. As the next step, we reproduce two new members by recombination of those two best members (from previous step). We also applied a mutation phase by applying a random change in one of the cells of the best members. All the above steps will continue with this six children to create new members. The genetic algorithm iterated for 300 times by taking about 27 hours for parameter optimization in a Core i7 PC platform. Figure 9 shows the final result.

IV. Experimental Results and Discussion

The proposed method was tested on 'Iran License Plate' dataset including 1211 gray-scale and color images with the size of 1920 x 1980 pixel which are captured from Iran's highways. A set of 300 images was used for training and we tested our method by the rest of 911 images. In our dataset two lanes of the highway is captured, therefore, there could be one or two cars in every image scene. The camera captures a depth of about 20 meters and according to the distance between cars and the camera, the car plate sizes can vary between a width of 100 and 200 pixels. Such a high variation in plates size causes a variation in features and make the recognition process harder. The dataset is very comprehensive and includes road scenes in various times of day and night. A set of 640 images are captured in night with a infrared light projection. Other 571 images are captured in the day light. Some images are noisy and some other are not. These variations makes image preparation even more difficult. The complex background is another property of the dataset. Non-plate numbers and text labels on the outer body of the car are other challenges that may lead to false positive license plate detections. Images were taken in the forward direction, the camera is aligned with the road central lane, therefore no significant angels to incoming cars. Figure 10 shows some samples of 'Iran License Plate' dataset.

TABLE II
ACCURACY OF THE PROPOSED METHOD

Number of images in the dataset	1211
Number of images used for training	300
Number of test images	911
Number of ground truth plates in test images	973
Number of true positives	965
Number of false positives	39
False negative	8
Precision Rate	$\frac{965}{965+39} = 96.1\%$
Recall Rate	$\frac{965}{965*8} = 99.1\%$

After train and test algorithm with optimized parameters we achieve 965 true positive detection out of 973 plates plus 39 false positives and 8 false negatives among 911 input images. Precision rate and recall rate are calculated based on the number of true positives, false positives, and false negatives. Table II and Table III presents the obtains accuracy of the proposed method and a comparison with other well-known and state-of-the-art methodologies. In variable optimization

Fig. 10. Samples of 'Iran Licence Plate' dataset

TABLE III
EXPERIMENTAL RESULT: COMPARING THE ACCURACY OF THE DEVELOPED METHOD WITH STATE-OF-THE-ART TECHNIQUES

Method	# of images	Success	Accuracy	Reference
Proposed algorithm	973	965	99.1%	
DFT-based method	332	323	97.1%	[1]
Color Features based method	500	491	98.2%	[12]
Projection method + GA	100	97	97%	[16]

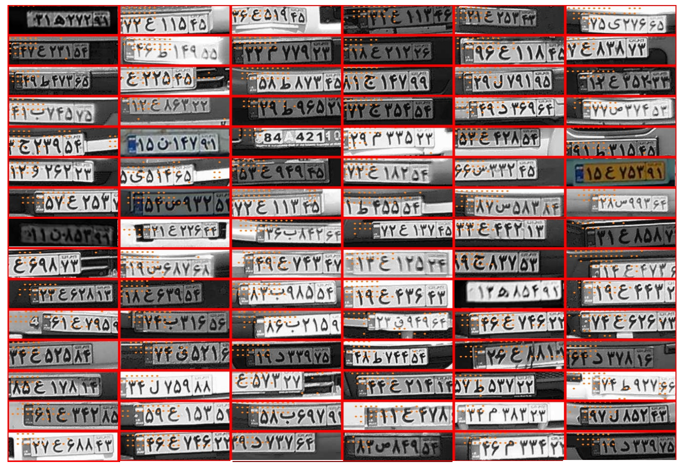

Fig. 11. Some samples out of 965 true positive detections

Fig. 12. Some samples out of 39 false positive detections

Fig. 13. Vertical projection of European License Plate

step and fitness function development of the genetic algorithm we only use number of true positives as the reference for calculating the accuracy of the model, therefore the algorithm is optimized to get maximum true positives. Figure 11 shows some sample true positive detections and Figure 12 shows some samples of false positive detections.

This algorithm is implemented with C++ and OpenCV. The experiments were performed on a PC platform with 8 GB of memory and an 8-core 2.4 GHz CPU, under Ubuntu OS.

V. Conclusion

As per the experimental results we obtained a robust results for day and night conditions; however, due to the nature of the optimization algorithm, we may expect a higher recall rate and lower precision rate. Development of a better fitness function that can lead to a more optimum parameter values and higher precision rates can be considered as future work. Compared with other License plate localization methods such as Haar-like feature based algorithm, color-based processing methods, or edge detection based systems, the proposed algorithm can detect the license plates with more accurate sizes, positions, in more complex backgrounds. As the final note, Iran License Plate follows the European standard in terms of width and height (see Figure 13); hence, the developed algorithm can perfectly work for European License Plate localization, as well.

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