License Plate Detection Using Neural Networks

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Abstract. This work presents a new method for license plate detection using neural networks in gray scale images. The method proposes a multiple classification strategy based on a Multilayer Perceptron. It consists of many classifications of one image using several shifted window grids. If a pixel belongs or not to the licence plate is determined by the most frequent answer given by the different classifications. The result becomes more precise by means of morphological operations and heuristic rules related to shape and size of the license plate zone. The whole method detects the license plates precisely with a low error rate under non-controlled environments.

1 Introduction

The license plate recognition (LPR) is a complex matter widely written about. The problem itself is how to recognize license plate characters of a front or rear image of a vehicle. In general, the LPR system has the following parts: the acquisition of the image, the image preprocessing, the detection of the license plate, the segmentation and the characters recognition [1].

The focus of this paper is the detection step, in other words, determining the zone where the license plate is. In the literature many techniques for this step have been reported. A segmentation method based on thresholds is proposed in [2]. Usage of Fuzzy Logic is shown in [3]. Edge detection by means of gradient and morphological techniques are presented in [4]. The image scanning using adaptive windows, considering heuristics of statistical descriptors is proposed in [1]. The horizontal and vertical projection is presented in [5]. The line detection using the Hough transformation is proposed in [6]. Learning techniques and Neural Networks have also been studied in this problem. Methods based on backpropagation networks are presented in [7,8,9], the use of Support Vector Machines is proposed in [10], and the Pulse Coupled Neural Network in [11].

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We propose for the license plate detection problem a strategy of multiple classification based on a Multilayer Perceptron (MLP)[1]. Some descriptors of texture and contrast are considered [12]. The image is scanned classifying windows partially shifted. This means that the image is many times classified. According to the window used a group of pixels would belong to the license plate or to the rest of the image. The nature of the group of pixels is defined by the most frequent answer given by the different classifications.

Our set of images has 350 samples[2]. The quantity of the samples is in size range reported in the related works [9]. The paper structure is the following: the adopted zone descriptors are described in section 2. Section 3 presents the idea of multiple classification. Section 4 explains the steps of the method for license plate detection. Section 5 shows the results, and section 6 presents conclusions and projections of our research.

2 Adopted Descriptors for License Plate Characterization

In order to characterize the region of the license plate, the adopted descriptors are: the mean value (m) , the standard deviation (σ), a measure of smoothing (R), the third statistical moment (μ_3), a measure of uniformity (U) and the entropy (e). The expressions of this descriptors are the following:

$$m = \sum_{i=0}^{L-1} z_i p(z_i) \ , \ \sigma = \sqrt{\sum_{i=0}^{L-1} (z_i - m)^2 p(z_i)}$$

$$R = 1 - \frac{1}{1+\sigma^2} \ , \ \mu_3 = \sum_{i=0}^{L-1} (z_i - m)^3 p(z_i)$$

$$U = \sum_{i=0}^{L-1} p^2(z_i) \ , \ e = - \sum_{i=0}^{L-1} p(z_i) \log_2 p(z_i)$$

where z_i is an aleatory variable that indicates the image intensity, $p(z_i)$ is the histogram, L the quantity intensity levels, and m the intensity media value.

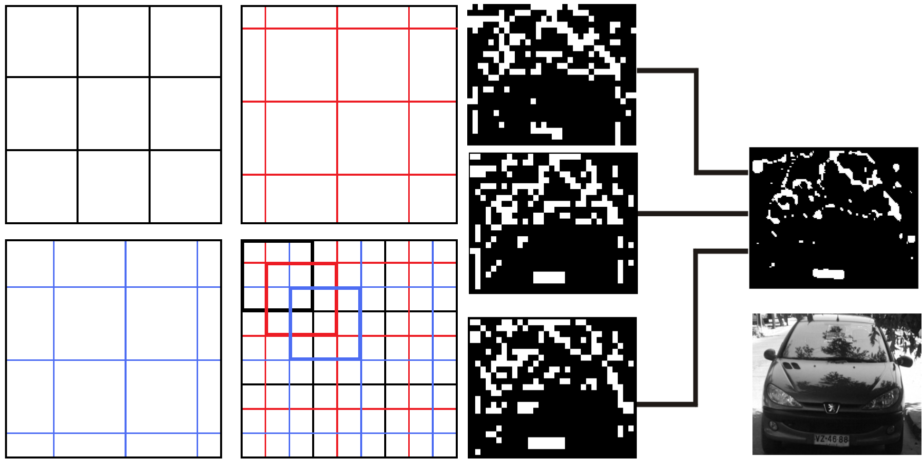
The previous descriptors to measure the contrast or homogeneity are based on the variance computation. To improve the input information of the classifier, we propose using a contrast descriptor $C = z_{min}/z_{max}$, where z_{min} and z_{max} are the minimum and maximum values respectively of the analyzed area. This descriptor is easily computed, and it is perfectly adapted to the processing in real time.

3 The Multiple Classification Idea

Multiple classification means that an image can be analyzed more than once. We train a neural classifier to determine if a window of the image corresponds

[1] This work is fully supported by TUTELKAN.

[2] The set of images is available from www.lfdp-iprg.net



(a) (b)

Fig. 1. Multiple classification

or not to a license plate zone. Many classifications of the image are done with several window grids which are partially shifted. The result of the classification with the grids are multiple binary images. If a pixel belongs to the license plate is determined by the most frequent answer given by all the binary images.

Figure 1 shows the procedure previously described considering 3 window grids. Figure 1(a) shows the grids and the superposition of them. Figure 1(b) shows the resulting 3 binary images, and the image fusion using the most frequent response criteria.

4 Proposed Method for License Plate Localization

Our method to localize the license plate is composed by the following steps:

4.1 Acquisition and Preprocessing

The acquisition is done with a digital camera. The image is supposed to have enough light to see the license plate. The image is converted from RGB to HSV model, and the channel V is selected to work with.

4.2 Training of the Neural Classifier

The classifier has 7 inputs that correspond to the zone descriptors mentioned in section 2, and it has one output 0 or 1 depending whether the window analyzed belongs or not to a zone of the license plate.

A MLP classifier has been chosen because this network is a universal function estimator [13]. The network is trained with the Bayesian Regularization method described in [14]. This method was chosen because it gives a criteria to determine the numbers of neurons of the hidden layer, and also includes a regularization strategy that permits an appropriate generalization.

To build the training set 70 of the 350 images are chosen, the other ones to test the network. For each image of the training set, 40 samples of license plates, and 40 samples of the background have been considered.

4.3 The Classification of the Image

The group of 7 descriptors mentioned in section 2 are calculated for each window of the image. Many classifications are done, each one of them with a different window grid. An odd number of grids is used to know if the pixel belongs to the license plate depending on the majority.

4.4 Improving the Classification

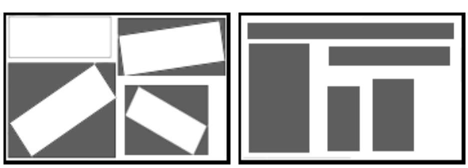
The result of the classification step is a binary image that has classification errors. To avoid this a procedure is applied, it includes erosion, segmentation based on shape and size, and image dilation.

The erosion step of the image is done with different structuring elements, in our approach with vertical lines and horizontal lines and circles [12]. The idea is to eliminate pixels of the objects in the image without affecting the license plate.

The segmentation step is based on the following principle. According to the capture angle the license plates are not necessarily placed horizontally. If the rectangle containing the license plate is considered, it can be pointed out that that is wider than taller. To mesure this property, it is proposed the ratio of length and width of the rectangle (r). As each country has its own license plate measures, the r value can be adjusted. Figure 2(a) shows examples of rectangles related to license plates, and figure 2(b) examples of objets not related to license plates. Our case has r between 0.20 and 0.80.

The choosing of the structuring elements for the erosion allows a great reduction of the zone of the objects that are not license plates. It is reasonable to suppose that after the erosion the license plate is the biggest object.

Finally, an image dilation is done with one circle as a structuring element. The idea is to recover the lost area caused by the erosion.



(a) (b)

Fig. 2. Rectangle shapes that containing license plate and others objects

5 Results

The acquisition step is presented in figure 3(a) and (b). Figure 3(a) shows the initial color image, and figure 3(b) the gray scale image using channel V of the HSV model.

The multiple classification step is shown in figure 3(c) and (h). After the training process we have been obtained a little network of 3 neurons in the hidden layer for this step. In our experimentations, we have used images of 320 $\times$ 240 pixels, 5 grids to do the classification, the size of the windows is 10 $\times$ 10 pixels, and the grids are symmetrically shifted. The images 1 to 5 in this sequence are the results of the classification of each grid, and the final image shows the fusion of them with the majority criteria. It can be seen that after the fusion the license plate zone is shown alone (gray zone in figure 3(h)), what can not be seen in each grid classification. This images demonstrate the importance of the multiple classification process.

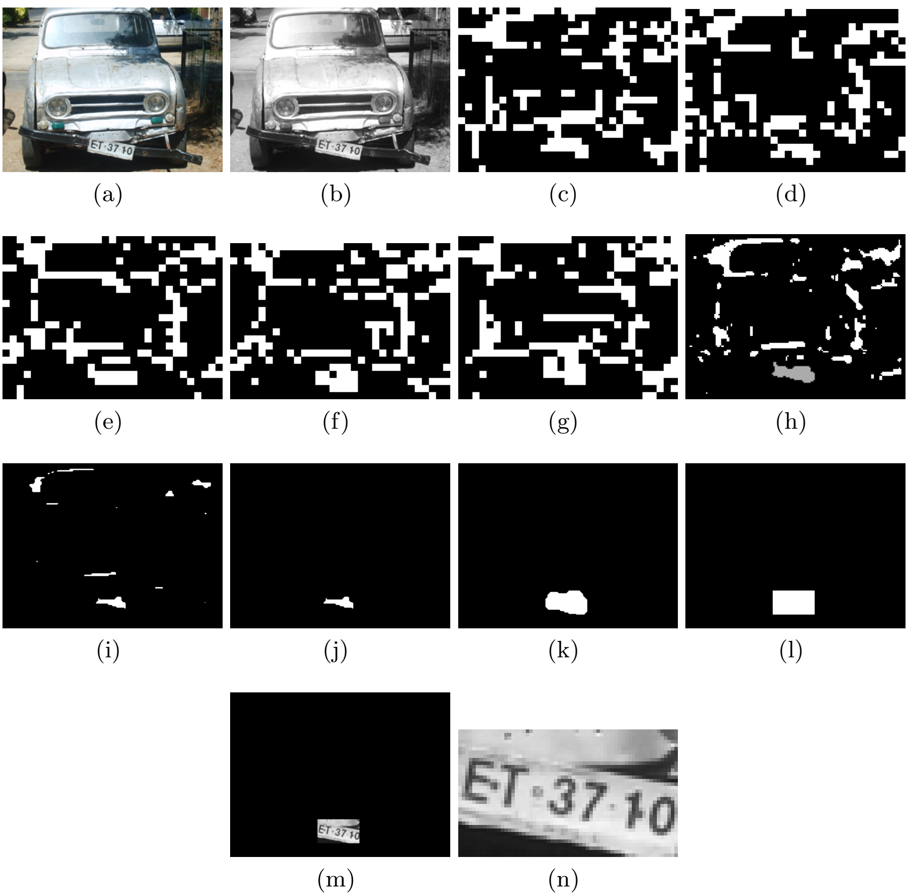


Fig. 3. Example of the localization process

As seen in figure 3(h), there are many zones that are wrongly considered as part of the license plate. The step of improving the classification aims to eliminate these errors. This step is shown in figures 3(i-l). The erosion is shown in figure 3(i), where an important decreasing of regions wrongly classified is seen. The structuring elements adopted are vertical lines (6×1 pixels), horizontal lines (1×15 pixels) and circles (radius 2 pixels). Figure 3(j) shows the effectiveness of the heuristics rules related to shape and size mentioned in section 4.4 , where the elimination of classification errors still remained after the usage of the erosion is observed. Figure 3(k) and 3(l) show the dilation of the image, and the smaller rectangle containing the license plate zone, respectively. The final results are showed in figures 3(m-n). Figure 3(m) shows the detected rectangle, and the license plate region inside it. Figure 3(n) is a zoom of the localized rectangle. In the final image, it is seen that our method finds exactly where the license plate zone is.

Figure 4 shows some general results of our method. The figure has two groups. The upper group presents right detections, and the lower one shows wrong

Fig. 4. Obtained results of our method

detections. From our images set of 350 license plates, our method has 95 % of effectiveness and 5% of wrong results. These percentages are similar to those reported by other methods, despite the simplicity of the used descriptors. In this sense, it is possible to increase the effectiveness percentage improving the quality of the descriptors. With respect to the time needed in this case, it is important to mention that the approach proposed is a little slower than the others methods implementing one neural network (we make several classifications). Nevertheless the times obtained by our approach are adapted for real-time applications.

6 Conclusions and Future Works

This paper has presented a new method for localizing license plates based on a MLP. Many classifications of the image are done, and the kind of pixel is selected according to majority. To improve results we use a sequence of steps based on morphological operations, and heuristics rules related to shape and size of the license plates.

The multiple classification helps to get better results when segmentating the license plate. It is observed that image fusion helps to identify the region of the license plate from others objects.

The kind of adopted erosions permit effectively to reduce the area of the classification errors, without affecting the license plate zone. The heuristics rules of shape and size help to clarify the prior knowledge about the license plate measures. This permitted to get a high percentage of hint, similar to related works presented by others authors.

The projections of this work are many. We can mention the inclusion of new descriptors to enhance the license plates detection, and the improving of the classification strategy to increase the hint percentage of our method.

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