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A NOVEL TEXTURE-BASED ALGORITHM FOR LOCALIZING VEHICLE LICENSE PLATES

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ABSTRACT

License plates localization is an important task for the recognition of Vehicle License Plates (VLP). To deal with this issue, a number of approaches have been proposed. These include texture-based, morphology-based and boundary line-based approaches. In this paper, we present a new texture-based algorithm to detect and localize license plates in images. Yet, focus will be laid on Moroccan VLP. Analysis has actually revealed that the proposed algorithm achieves high accuracy in plate localization. For evaluation purposes, various images taken from different distances and in different angles were used. The experimental results show that our system can efficiently detect and localize the VLP in images. Indeed, the recall/precision curve of the proposed method proves that 84.21% precision rate is obtained for recall rate value equals 80%, while the value of the standard measure of quality is equal to 82.05%.

Keywords: *Text detection, Texture analysis, Descriptors, Vehicle License Plate Localization (VLPL).*

1. INTRODUCTION

Recently, the need for Vehicle License Plate Recognition (VLPR) has increased very significantly. This need is very much motivated given that many security and road traffic applications are based on VLPR. However, it is so difficult to efficiently detect license plates from cluttered and various background [1] because of the interference of characters, variant illumination [2], and distance from the camera to vehicles [3], etc.

Each VLPR system consists of two tasks: Vehicle License Plate Localization (VLPL); where the algorithm determines candidate license plate regions [2], and Vehicle License Plate Character Recognition (VLPCR) that identifies the license plate number of the vehicle [4]. These two problems are often addressed separately in the literature. In fact, the plate detection and location present the most important and the most computationally intensive task because the whole image should usually be processed in order to detect the plate. Thus, in this paper we focus on the VLPL problem.

Different approaches are available in the literature. They can be grouped as color based approaches [5, 6, 7], Fuzzy logic approaches [8], generic programming approaches [9], and Neural Network ones [10]. In [11], the problem from an initially color-based standpoint is approached. In particular, the authors perform mean-shift segmentation, and subsequently use edge-density and rectangularity criteria to choose license plate candidates from the original segmentation output regions. Bayoumi et al. [12] made use of edge density and background color to locate Egyptian VLP. Their system depended on the characteristics of plate numbers. They applied projection functions to extract the license plate, and utilized a neural network in order to recognize the different digits, symbols and letters. Besides, authors of [13] made some intuitive rules to describe the license plates and gave some membership functions for fuzzy sets e.g. 'bright', 'dark', 'bright' and 'dark sequence', 'texture', 'yellowness' to get the horizontal and vertical plate positions. The proposed algorithm in Dlagnekov et al. [14] imposes the detection task as a boosting problem. The AdaBoost classifier selects the best performing weak classifier from a set of weak ones; each classifier is acting on a single feature, and, once trained, combines their respective votes. This classifier is then applied to sub-regions of an image being scanned for likely VLPL. An optimization based on a cascade of classifiers, using

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the false positive and false negative rates, helps to accelerate the scanning process.

In this paper, we propose a new texture-based approach to localize Moroccan VLPs. Our proposal consists of four basic processing steps: First, we improve the quality of the image. Next, we select the textured regions that will be segmented. Then, the license plate is localized using geometric rules and finally bounding boxes are placed. These steps are detailed in Section 2. The experimental results are given in Section 3 while the conclusion is drawn in Section 4.

2. TEXTURE BASED VLPL ALGORITHM

Considering text as a whole entity, it has enough features to be detectable as a texture; vehicle license plate characters have distinct textural characteristics that distinguish them from the background. In this section, we present the four basic steps of our proposed vehicle license plate localization algorithm.

2.1. Image Preprocessing

In order to improve the quality of the image and the successful rate of the VLP detection module, the input image is initially processed. First, we convert the image into a grey-scale one. Second, we use median filter to remove salt-and-peeper noise from it. Thus, the gray value of a pixel is replaced by the median of its eight neighbors' values. Then, the contrast is enhanced to increase the contrast between characters and background of the license plate. We apply the following equation on each pixel to form the corresponding output image I'.

$$I'(i,j,k) = 255 * \frac{I(i,j,k) - \min(k)}{\max(k) - \min(k)} \qquad (1)$$

Where (i,j) is the space coordinate of a pixel, $I'(i,j)$ (resp. $I(i,j)$ represents the output pixel (resp. the input pixel), 255 indicates the maximum gray level in the enhanced image, and $\min$ (resp. $\max$) represents the minimum (resp. the maximum) intensity value in the current grey-scale image.

2.2. Texture Analysis

The main idea of our method is that characters have distinct textual properties that discriminate them from the background. So license plates are present in textured regions of an image. The goal of this algorithm step is to extract texture regions and filter out smooth ones. To this end, we decompose an image into N Macro Blocks (MB); the size of the MB is set to 64x64 (size that works well with all test images). For each MB we compute the average edge intensity. Let $MB(X,Y)$ denote the MB at location (X,Y) in an image. The edge intensity of the $MB(X,Y)$ calculated by:

$$MBI(X,Y) = \sum_{(i,j)\in MB(X,Y)} V(i,j) \qquad (2)$$

Where V(i,j) represents the magnitude of the intensity gradient I(i,j) at location (i,j), using finite extent convolution masks to estimate the partial derivative. With:

$$V(i,j) = \sqrt{\left(\frac{dI(i,j)}{dx}\right)^2 + \left(\frac{dI(i,j)}{dy}\right)^2} \qquad (3)$$

A MB at (X,Y) is classified as textured region if $MB(X,Y) > T_v$, otherwise it is classified as smooth region. The T_v is determined by:

$$T_v = \beta \sum_{MB(X,Y)\in I} \frac{MBI(X,Y)}{N} \qquad (4)$$

Where β is the weighting factor, its value has been experimentally set to 0.75.

2.3. Texture Region Segmentation

In addition to license characters, most images contain graphics and objects, Thus, the image has to be segmented to identify VLP character regions.

2.3.1. Multi-segment decomposition image

Here, a standard Expectation Maximization (EM) algorithm is used to segment components from textured regions. We classify pixels into K classes, so we get K segmented images. The image intensities are modeled in terms of the combination of K simple random process representing regions with similar gray levels.

We consider that a class follows normal distribution:

$$f(x/\theta_k) = \frac{p_k}{\sqrt{2\pi\sigma_k}} e^{-\frac{(x-\mu_k)^2}{2\sigma_k}} \qquad (5)$$

With:

x : the vector of pixels

k : the class number

p_k : vector of a priori probability of the class k

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$\theta_k = (\mu_k, \sigma_k)$: a mixture of distributions

μ_k : vector of class means

σ_k : vector of class variances

The K individual processes are combined into a probabilistic mixture model, according to:

$$f(X) = \sum_{k=1}^{K} \pi_k f(x/\theta_k) \qquad (6)$$

The EM algorithm is decomposed into 3 steps:

The initialization step of EM algorithm:

Here, we initialize the different parameters that are a priori probabilities, means, and variances of each class k. The parameters are given by the next equations:

$$p_k = \frac{1}{K} \qquad (7)$$

$$\mu_k = m * \frac{k}{K+1} \qquad (8)$$

$$\sigma_k = m \qquad (9)$$

With K is a number of classes and m is the maximum gray pixel value in the image.

The expectation step of EM algorithm:

We assign pixel to the class that fits it best using the magnitude of intensity gradient, and we calculate the expected value of the log likelihood function given by:

$$L = \sum_{i=1}^{n} \log f(X)$$

$$\ldots = \sum_{i=1}^{n} \log \sum_{k=1}^{K} f(x_i/\theta_k) \qquad (10)$$

$$L = \prod_{i=1}^{n} \sum_{k=1}^{K} f(x_i/\theta_k)$$

With x_i in the pixel belonging to the class k.

The maximization step of EM algorithm:

We compute (μ_k, σ_k, P_k) that maximize the expected log likelihood found on the expectation step. These parameters are then used to determine the distribution of pixels in the next expectation step.

After classifying pixels into K classes, a binary image (mask) is generated for each class label. In our application, the value of K is experimentally set to 3. The clusters correspond to: patterns belonging to characters, uniform regions, and boundaries of uniform regions.

2.3.2. Choice of the mask

To select the most interesting mask, we use some characteristics of Moroccan license plates which are:

- The plate is composed of five digits (1-99 999) defining the number of vehicle registration, an incremented letter of the Arabic alphabet in the middle, relative to the registration number and the identifier of the prefecture that delivered the plate (from 1 to 72). So the Moroccan VLP contains at least, two numbers and one letter, and in maximum seven numbers and one Arabic alphabet.
- Characters are monochrome, they are written using white or black color. So they will appear on the same mask obtained at the segmentation step.

Figure 1 shows some examples of Moroccan VLPs.

Figure 1: Some Moroccan VLPs.

Based on the given Moroccan VLP characteristics, the mask containing plate characters must verify:

- Number of components must be greater than 3 and less than 10. Why 10? Because in addition to the 8 characters, we can detect the 'slash' that separates the numbers and the Arabic alphabet.
- The absolute value of the angle between two component neighbors centroids must verifies the next equation:

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$$-\frac{\pi}{7} \leq \alpha \leq \frac{\pi}{7} \qquad (11)$$

2.4. Vehicle License Plate Localization

Our next purpose consists in analyzing the components of the mask to localize the license plate. Thus, we have to group regions that belong to a VLP and satisfy:

- An Arabic alphabet does not exceed one hole, and the maximum holes of numbers is equal to 2 (case of the number 8). So in our approach, we set the maximum of holes to 3 because of noises.
- Candidates that have height (H) and width (W) ratio satisfied pre-defined constraints:

$$0.1 < \frac{W}{H} < 2 \qquad 50 < W * H \qquad (11)$$

- Two candidates' neighbors verify:

$$0.5 \leq \frac{H_i}{H_j} \leq 2 \qquad (12)$$

$$dist(x_i - x_j) \leq 0.2 \max(H_i, H_j) \qquad (13)$$

$$dist(y_i - y_j) \leq 2 \max(W_i, W_j) \qquad (14)$$

Where (x_i, y_i, W_i, H_i) and (x_j, y_j, W_j, H_j) are two neighboring blocks, and $dist(x - y)$ is the distance between x and y while $\max(x, y)$ is the maximum function of x and y.

Figure 2 shows an example of the input (color image) and the outputs of the different steps of our proposed VLPL algorithm.

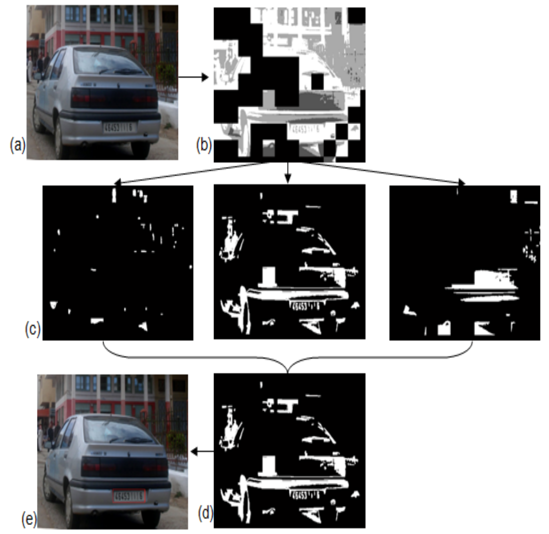

Figure 2: (A) The Input Image, (B) The Multi-Segment Decomposition Image, (C) The Three Masks, (D) The Choice Of The Mask, And (E) The Result Of The VLPL Approach.

3. EXPERIMENTAL RESULTS

We consider a database containing 100 images, where pictures are taken at various lighting condition and poses, taken from different places during day time, and contained in complex background (parking area, road side, and traffic scene).

We propose to evaluate the performances of our proposal compared to those of the approach of Matas et al. [15]. The latter is also based on the detection of connected components and followed by a machine learning method to select the characters of license plate regions.

Figure 3: Some Examples Of Vehicle License Plate Detection Process Outputs. (Top) The Results Of The New Proposed Approach, And (Down) Those Of The Method Given By [15].

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Figure 3 shows some examples of detected vehicle license plates on some images of our database; where the license plates are circled by red boxes. In fact, this figure presents the outputs of our global system dealing with the VLP detection and localization problem, as well as those of the method given by [15]. It presents some images with bad quality as well. Here the VLP are more efficiently localized when the new approach is used.

Traditionally, object detection algorithms are evaluated using techniques developed for information retrieval systems. More specifically, two metrics: Precision (P) and Recall (R) are commonly used, since they intuitively convey the quality of the results.

$$\text{Recall} = \frac{\text{No. of correctly retrieved items}}{\text{No. of relevant items in the database}} \qquad (15)$$

$$\text{Precision} = \frac{\text{No. of correctly retrieved items}}{\text{Total no. of retrieved items}} \qquad (16)$$

In order to have a single performance value for the ranking of methods, the harmonic mean of precision and recall has been introduced by the information retrieval community [16]. Its advantage is that the minimum of the two performance values is emphasized:

$$F = \frac{2 * RP}{R + P} \qquad (17)$$

Let us note TVLPLA the new proposed approach. Figure 4 shows the Recall/Precision curve of TVLPLA (red curve) compared to the one of the method given in [15] (green curve). Besides, Table1, summarized the values of the measures P, R and F.

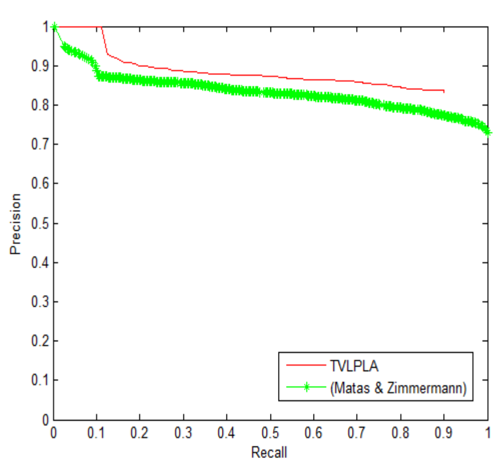

Figure 4: Recall/Precision curves of the proposed method and the Matas et al. [15] one.

Table 1: Some Performances Of The Two Compared Methods

Method	P	R	F
TVLPLA	84.21%	80%	82.05%
Matas et al. [15]	83.44%	50.12%	62.62%

The last figure and the table clearly show that the new approach offers best precisions for all recall values and best quality value. Therefore, we can conclude that the proposed method is a robust and effective approach to detect Moroccan VLPs in complex images.

4. CONCLUSION

In this paper, a new system that automatically detects and localizes Moroccan vehicle license plates has been presented. Detection and localization is based on images taken in a wide variety of conditions such as lighting, poses and background. Our algorithm has been proposed based on a multi-segment decomposition image of textured regions in an image and using geometric rules to identify vehicle license plates. Several points have been detailed such as the texture analysis and the EM segmentation.

Experimental results have proven that our method is efficient in localizing Moroccan vehicle license plates. The algorithm can be extended to take into consideration vehicle license plates of other countries.

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