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Two-stage HOG/SVM for license plate detection and recognition

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ABSTRACT

Automatic license plate recognition (ALPR) is one of the technologies used in intelligent transport systems (ITS) to read vehicle license plates automatically. The extracted information has various potential applications, including but not limited to an electronic payment gateway, a system for paying parking fees, road surveillance, and managing traffic flow. In this paper, we propose an efficient method to detect and identify the Algerian license plate (LP). This method consists of a two-stage algorithm that combines the histogram of oriented gradients (HOG) with the support vector machine (SVM) classifier. The purpose of the first stage of HOG/SVM is the detection of the LP, while the recognition of the digits is accomplished by the second stage of HOG/SVM. As first contribution, a dataset of standard Algerian LP not available elsewhere is built (DZLP dataset), The second is a proposal of a very efficient pre-processing step for LP detection and digit recognition. Experimental results show that the proposed approach yields very high license plate and average digits recognition rates, which of 97.5% and 99.46%, respectively.

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1. INTRODUCTION

One of the main objectives of the automatic license plate detection and recognition (ALPDR) of vehicles is to identify vehicles responsible for traffic violations, as well as suspect and wanted vehicles, to reduce the number of violations and road accidents. The purpose of ALPDR is to identify the vehicle's license plate (LP) from a photo taken by video surveillance devices. For this purpose, the image representing the license plate must be detected, isolated, segmented into digits, and identified, before it can be used by other parts of the system without human intervention. Several works have been done in this field, but the non-standardization of the LP format, where each country adopts its own standard, has prevented the development of a universal method that meets all standards. This motivated us to develop an ALPDR method adapted to the Algerian LP standard.

ALPDR has become a very interesting research area that attracts the attention of many researchers, and that has been widely used in different fields, such as traffic control. It has helped a lot to reduce the number of traffic violations and accidents, as it represents a very effective tool for tracking vehicles in transport systems, as well as for identifying and locating suspicious vehicles. Several works on ALPDR have been done during this decade where several methods and techniques have been proposed. The first class of these techniques is based on the color, the texture, the morphology, or the detection of contours [1]-[8]. The second class is qualified advanced techniques based on learning and artificial intelligence [9]-[17]. The organization of the rest of this paper is as follows: section 2 is devoted to a detailed description of the steps of the proposed ALPDR method. The obtained results are presented and discussed in section 3. Finally, in section four, we draw some conclusions.

2. METHOD

To identify an LP, firstly, we extract the LP from the image using the standard Algerian LP features and the histogram of oriented gradients (HOG)/support vector machine (SVM) algorithm. Secondly, we isolate the digits, then another HOG/SVM based algorithm stage is used to classify them. In the first part of this section, we present the standard of the Algerian LP, specifically described by the particular color and shape. In the second part, we describe our proposed method, thus we will introduce the detection principle and the pruning technique to eliminate false LP candidates.

2.1. Algerian's standard of LP

2.1.1. The shape

According to the Algerian standard, an LP must have a rectangular shape of dimension approximately $(52 \times 11)cm^2$. It should be composed of 3 groups of digits separated by a space, and the digits of each group must be spaced by 1.5 cm. The first group is composed of five to six digits, which correspond to the vehicle file number. The second group is composed of 3 digits: the first digit (the hundreds) identifies the type of vehicle (1 for light, 2 for heavy, 3 for commercial cars, 4 for buses, 5 for a semi-trailer tractor, 6 for tractors, 7 for machinery, 8 for trailers, and 9 for motorcycles), the two following digits refer to the first year of circulation of the vehicle. The third group is composed of 2 digits that identify the wilayah of registration (from 01 to 58). For example, 31 corresponds to the wilayah of Oran. All the numbers have the same height of 6.5 cm but the width varies from one number to another and generally, it is between 2 and 3.5 cm.

2.1.2. The color

Beside to the shape, the color is the second relevant parameter in the Algerian LP standard. This standard requires a white background with black numbers on the front, and a yellow background with black numbers on the back, as shown in Figure 1. From this color condition, we can say that detecting the back License Plate is the same as detecting a homogeneous yellow zone.

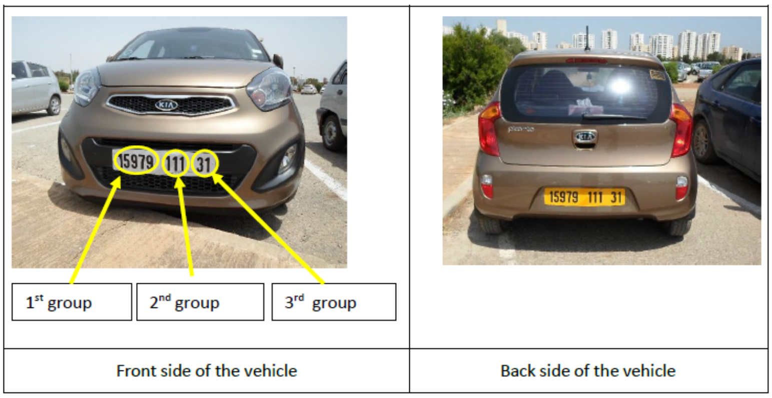


Figure 1. Shape and color of the Algerian LP (front and back)

2.2. License plate extraction

2.2.1. License plate detection

The extraction of the LP from the image consists of two steps. In the first step, all the yellow rectangular regions in the image are detected. These regions represent the potential LP candidates. Then, in the second step, these candidates are pruned to eliminate the false LP.

Taking advantage of the Algerian LP characteristics, especially from the back side of the vehicle, detecting LP begins by detecting a uniform area of rectangular shape and yellow color see in Figure 1.

It is known that the yellow color is better detected in the YC_bC_r color standard than in the RGB standard. To calculate the normalized values of the components YC_bC_r of an image from the RGB components, which vary from 0 to 255, we use the (1) [18].

$$\begin{pmatrix} Y \\ C_b \\ C_r \end{pmatrix} = \begin{pmatrix} 0.299 & 0.587 & 0.114 \\ -0.16874 & -0.33126 & 0.5 \\ 0.5 & -0.41869 & -0.008131 \end{pmatrix} \begin{pmatrix} R \\ G \\ B \end{pmatrix} \quad (1)$$

After converting the image from RGB to YC_bC_r, we will focus only on C_b and C_r, because Y (black and white) does not give us the color information. The pixels that belong to the yellow color range will be segmented in white and the other pixels in black.

After hard work, it has been shown, that the yellow pixel color that belongs in the LP verifies the (2) conditions.

$$(|C_b| > 0.15) \; and \; (|C_r| > 0.05) \quad (2)$$

The segmentation of the image in black and white using raw thresholding does not allow to have homogeneous (uniform) candidate areas, which makes isolating the license plate as a single uniform area impossible as illustrated in the experimental results section. To overcome this problem, morphological filters are applied. Morphology is used, in particular in image analysis, to study objects according to their shape, size, relations with their neighborhood (in particular topological), texture, and gray levels or color, and can be situated at different levels of image processing (filtering, segmentation, measurements, and texture analysis) and thus provides tools for pattern recognition.

After applying morphological filters to the black-and-white segmented image, we obtain homogeneous areas segmented in white that represent any area colored in yellow in the original image, and a background segmented in black that represents areas with all different colors. We then proceed to a refinement step, which eliminates any area that can not be a license plate, either in terms of shape or size. The remaining areas are considered as potential LP candidates, that will be pruned to keep only the real LP, if there is one.

2.2.2. Pruning of the LP candidates

In this step, the HOG/SVM algorithm is used to classify the candidate area as LP or non-LP (NLP). The candidate area classified as LP will be used at the recognition step, while the NLP area is eliminated. The HOG algorithm is a tool introduced by Dalal and Triggs [19]. It defines in a region the proportions of pixels whose gradient orientation belongs to a certain interval. These proportions characterize the shape present in this region. The information is more characteristic if the HOGs are taken on images of several location units. It can then be used as a shape descriptor [19], [20].

Classification is the development of a decision rule that transforms the attributes characterizing the shapes into class membership (passage from the coding space to the decision space). Before a decision model can be integrated into a recognition system, two steps must be completed: the learning step and the testing step [19]-[24]. The object is classified as a LP or NLP by using a conventional SVM-based window classifier, as shown in Figures 2-3. To find the optimal configuration of the parameters of the HOG/SVM classifier, we followed a procedure that will be explained in the section on experimental results. Figure 3, presents a flowchart summarizing the different stages of LP extraction, from the original image to the final extraction of the LP.

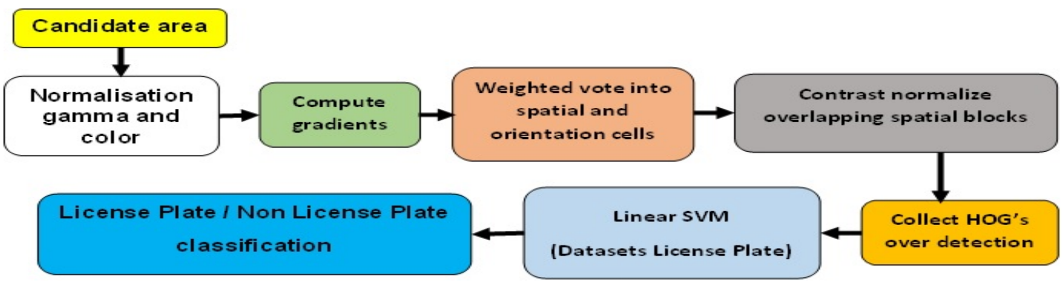


Figure 2. The HOG/SVM classification algorithm

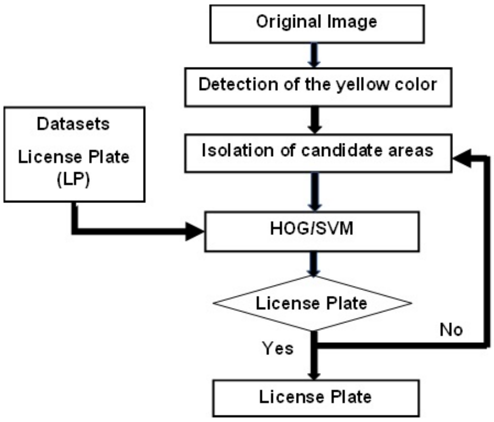


Figure 3. License plate extraction

2.3. Isolation and recognition of digits

After isolating the license plate, we must proceed to the isolation and recognition of each digit of the three groups that make up the plate. For this purpose, we use the HOG algorithm as a descriptor and SVM as a classifier. Since each digit of the license plate can take a value from 0 to 9, we must learn our network all the digits from 0 to 9.

2.3.1. Digit isolation

To isolate the LP area's digits from the segmented black-and-white image, we must go through the calculation of two horizontal and vertical histograms. The first (horizontal) gives us information on the interval of the lines that contain the digits while the second (vertical) gives us the position (column) of each digit in the selected LP area. Figure 4 shows the segmentation and the two vertical and horizontal histograms of a positively classified candidate area LP. From this figure, we can see the borders of each digit in the vertical histogram (columns), while all characters have the same horizontal borders (lines). To improve the LP classification and to achieve good isolation of digits, we must perform the three following PP.

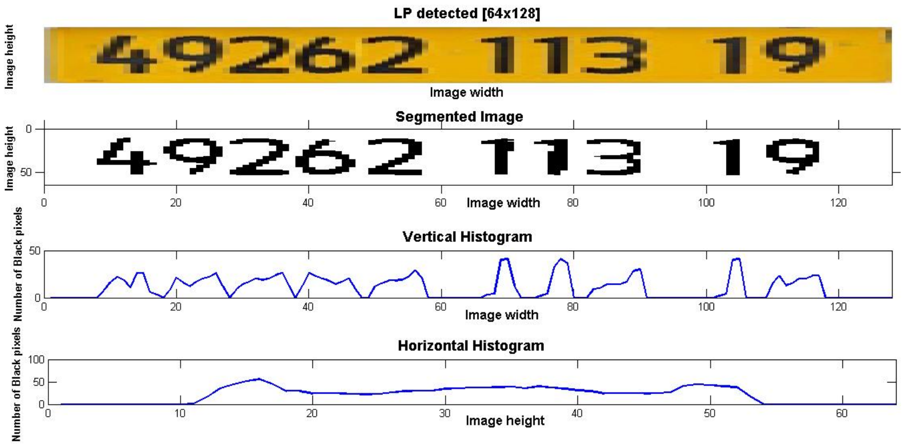


Figure 4. Horizontal and vertical histograms of a license plate

Shadow elimination: we noticed that setting the threshold of the segmentation of the plate in black and white to a fixed value does not always give good results. This situation can occur for example, if the plates include a part of shadow or the intensity of yellow is very bright. This directly affects both histograms. Affecting the horizontal histogram makes impossible the isolation of the characters. To remedy this problem, we considered a variable threshold that is adapted to the intensity of each uniform section.

Elimination of the vehicle color from the candidate area: Generally, if the candidate area is extracted with the presence of the vehicle color towards the edges, the calculation of the vertical and horizontal histograms will be erroneous. This situation makes the isolation of characters impossible. In this case, we propose to go through a PP where the color of the vehicle is eliminated from the candidate area, making a second split of the area where we keep only the plate part. It shows that the presence of an extra part in the LP candidate that does not belong to the real LP. The presence of the vehicle color in the candidate area leads to false histograms, making it impossible to isolate the digits part. On the other hand, after eliminating these undesirable colors, the horizontal and vertical histograms become correct, and consequently, the isolation of the digits becomes very easy.

License plate inclination correction: sometimes the image is captured with a certain angle of inclination leading to a plate that is not parallel to the horizontal plane. Figure 5 illustrates the issue of license plate inclination correction. Sometimes, the image is captured with a certain angle of inclination leading to a plate that is not parallel to the horizontal plane. In Figure 5, both left (Figure 5(a)) and right (Figure 5(b)) inclinations of the LP are shown. This results in a candidate area where the plate represents only a certain percentage of the total area, and the greater the angle, the smaller the percentage of the LP in the original image. This directly affects the calculation of both vertical and horizontal histograms, which makes the task of isolating the characters impossible. To correct this angle, it is sufficient to determine the angle of inclination θ and then rotate either the original image or the plate area by this angle. To achieve this, we follow the method proposed in [25]. Let us consider a section A, whose moments of inertia in the plane XOY I_x, I_y, and I_{xy} are known. We propose to calculate the moments of inertia of the section A in the plane UOV, which makes an angle θ with the plane XOY see Figure 6.

(a) (b)

Figure 5. License plate inclination (a) left inclination and (b) right inclination

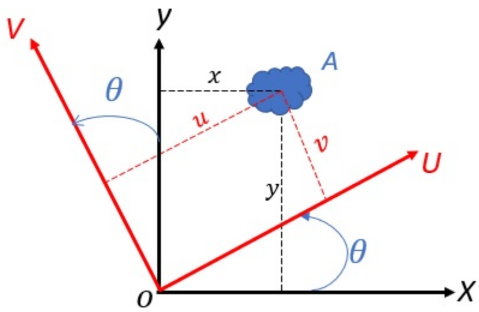


Figure 6. Axis rotation [25]

The static moments S_x and S_y of a section relative OX and OY axis see Figure 6 are given by the following expressions, respectively:

$$S_x = \int_A x dA \tag{3}$$

$$S_y = \int_A y dA \tag{4}$$

The moment of inertia or quadratic moment of a section is defined as the degree of resistance of this section to applied external forces, taking into account the shape of this section. The coordinates of the center of gravity are:

$$x_g = \frac{S_y}{\int_A dA} \tag{5}$$

$$y_g = \frac{S_x}{\int_A dA} \tag{6}$$

Let us define, the integrals:

$$I_x = \int_A y^2 \, dA \tag{7}$$

$$I_y = \int_A x^2 \, dA \tag{8}$$

$$I_{xy} = \int_A xy \, dA \tag{9}$$

The quantities I_x and I_y are called moments of inertia of section A relative to the OX and OY axes respectively, while I_{xy} is called the centrifugal moment or product of inertia of section A relative to the XOY system. From Figure 6, we can calculate the angle of inclination θ using in the (10):

$$tan(2\theta) = \frac{I_{xy}}{I_x - I_y} \Rightarrow \theta = \frac{1}{2} arctan\left(\frac{I_{xy}}{I_x - I_y}\right) \tag{10}$$

So to correct the angle of inclination of the LP, it is enough to determine the angle of inclination θ of the LP relative to the horizontal axis and rotate the LP according to this angle.

2.3.2. Digits recognition (classification)

After isolating the digits that compose the LP, we need to classify them. Our proposed method is based on the HOG/SVM algorithm to perform this classification. Figure 7 represents a flowchart of digits isolation and recognition. So, we need to create ten HOG/SVM networks that correspond to the digits recognition from 0 to 9. Therefore, we need a database for each digit.

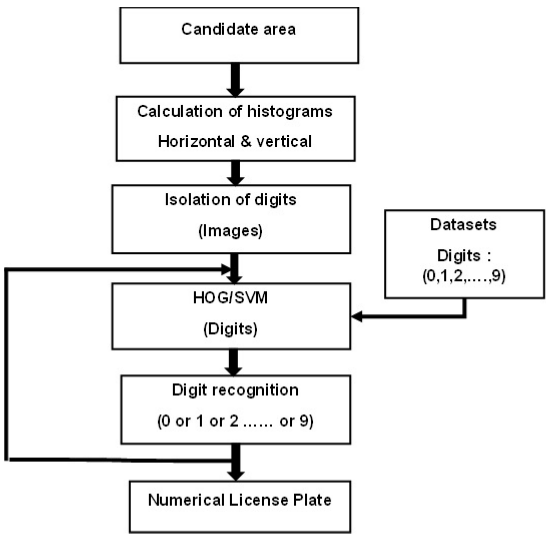


Figure 7. Digits isolation and recognition

To identify the HOG descriptor size of each candidate area, corresponding to each digit, we adopt the same rule, that the height is equal to twice the width, which corresponds exactly to the image size considered

in the works [19], [20], where the author presents an optimal architecture (Bins×Cell×Block×Overlapping), to compute the HOG descriptor for a better recognition of persons. The following values were chosen for the different parameters Image size [64×128], 09 bins, cell of 08×08 pixels, a block of 02×02 cells with an overlap of 02 cells between the adjacent blocks. The global rate of detection and recognition of the LP is calculated using probabilistic reasoning. First, let us define the following events:
- LPD: the LP is correctly detected.
- LPR: the LP is correctly recognized.
- D_n: the n^{th} digit is correctly recognized.
- LPDR: the LP is correctly detected and correctly recognized.

We suppose that the LP is composed of n digits, such as $8 \leq n \leq 12$, according to the Algerian standard. We have:

$$\mathrm{Prob}(LPR \mid LPD) = \mathrm{Prob}(D_1 \cap D_2 \cap D_3 \cap ...... \cap D_n) \tag{11}$$

Assuming that, the digits are independent, the probability in (11) becomes:

$$\mathrm{Prob}(LPR \mid LPD) = \prod_{k=1}^{n} \mathrm{Prob}(D_k) \tag{12}$$

It follows that:

$$\mathrm{Prob}(LPD \cap LPR) = \mathrm{Prob}(LPD) \times \mathrm{Prob}(LPR \mid LPD) = \mathrm{Prob}(LPD) \times \prod_{k=1}^{n} \mathrm{Prob}(D_k) \tag{13}$$

Where, we are assimilating $\mathrm{Prob}(LPD)$ to the detection rate of the LP, and $\mathrm{Prob}(D_n)$ to the recognition rate of the n^{th} digit.

3. RESULTS AND DISCUSSION

As we mentioned before, the feasibility of our algorithm relies on learning, which is based on an extensive dataset. Before the evaluating performances of the proposed method, we begin by describing the datasets we have used. After hard work of setting the datasets for LP and digits, a statistical analysis will be done to the optimal parameters for our method, based on the work presented in papers [19], [20]. After eliminating the NLP candidate and once the LP is detected, we use the vertical and horizontal histograms to isolate the digits. To improve the effectiveness of our method, a statistical analysis will be done at the end of this section.

3.1. Datasets

3.1.1. Dataset of LP (DZLP dataset)

Given that there is no universal standard of license plates in the world, and that our country, Algeria, adopts its standard, we had to build our dataset of LP (DZLP dataset). Our dataset consists of 820 images, divided into two classes: 410 of which are positive (LP) and 410 negative (NLP). Figure 8 represents some positive and negative examples of the constructed dataset. A positive image is an image, which corresponds to a real LP. A negative image is an image with a rectangular shape and a yellow color, that does not correspond to a license plate.

To find an optimal configuration of the parameters (size of the images, the architecture of the networks, size of blocks, cells, bins, and overlapping), we adopted the following procedure. In the learning step of LP extraction, we considered several sizes for the input image, while respecting the rectangular shape. Secondly, for the negative images of the database, we also considered two cases. In the first case (Dataset1). The negative images are yellow color images taken randomly, whereas in the second case (Dataset2), the negative images are taken as the false LP candidate areas, provided by the LP detection procedure, that do not contain a real LP.

3.1.2. Dataset of digits

To build our digit databases, 120 positive and 120 negative images, for each digit are considered. The image size is chosen by taking into account the rule that the height of the number must be twice its width. In Figure 9, we present some examples of the positive and negative images of the different digits.

Figure 8. DZLP dataset exemples

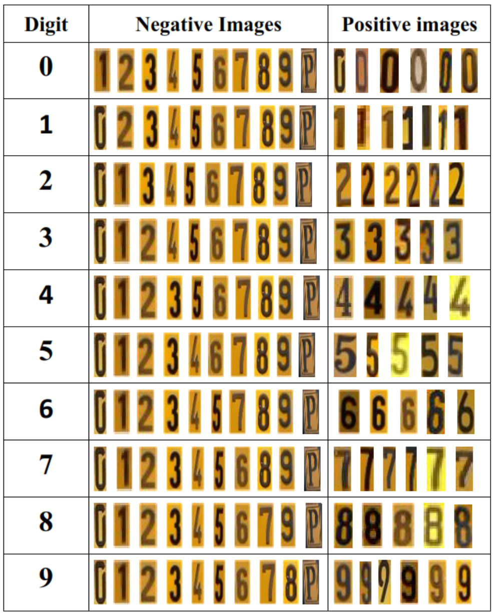


Figure 9. Examples of digits dataset

3.2. LP extraction results

As explained in section 2, to extract an LP, we first detect all LP candidate zones, using yellow color detection, morphological filters, and refinement see Figure 10. The Figure 10(a) shows the original image, while the Figure 10(b) shows the final detection. It can be stated that the application of morphological filters gave us very good detection results, whose candidate zone is a homogeneous white area, which facilitates the isolation phase. On the other hand, the refinement allowed us to eliminate all the homogeneous areas of yellow color, which do not have the rectangular shape of the license plate, or which represent a low aspect ratio compared to the original image of LP. Figure 11, presents one result of correct LP extraction (detection of LP), where Figure 11(a) represents the input image, and Figure 11(b) represents the extraction of the candidate area.

We tried several rectangular sizes and architectures (Cell-Block-Bin) to have the best recognition rate. So that the descriptors are of the same size, we have resized to a rectangular shape a size that corresponds to the rectangular shape of the LP. Table 1, presents the results obtained from two sizes that have given the best results: 64×128 and 64×320. These results were obtained using a test database that consists of 493 positive and 507 negative images. To study the robustness of our application, this database was chosen to a complex incorporating images with some complications, including blurred positive images, images with a badly isolated plate area (badly framed), and others with a plate tilt, and in the negative part, we considered images that look like a LP. Figure 12 shows some examples of these complex images that have been misclassified.

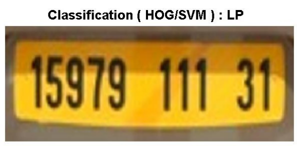
The results show that the architecture: cell of (08×08) pixels, block of (02×02) cells, bins of 09 angles, an image size of (64×128), with a database of 1,000 images gave the best recognition rate 96.6% see Table 1. Concerning the classification, we found that a license plate is badly classified in the following three cases: blurred image, image taken with a certain angle of inclination, and image with a large percentage of the vehicle color. Hence the pre-processing step allowed us to improve the recognition rate. The problem of a blurred image remains a very strong limit of the recognition algorithms, the efficient solution that we recommend to avoid this problem is to take photos in good conditions. It should be noted that the best result presented in Table 1, is obtained after applying the three steps of pre-processing. Without pre-processing the best LP recognition score that we could obtain is about 76.1% only.

(a)

(b)

Figure 10. LP candidates detection (a) original image and (b) final detection

(a)



(b)

Figure 11. P detection (a) input image and (b) extraction and classification of the candidate area

Table 1. Confusion matrix for different HOG architectures

HOG descriptor architecture	TP	FP	TN	FN	Detection rate
C(8×8)B(2×2)Bin4, Image size(64×320), Dataset1	358	104	403	135	76.1%
C(8×8)B(2×2)Bin6, Image size(64×320), Dataset1	474	95	415	16	88.9%
C(8×8)B(2×2)Bin9, Image size(64×320), Dataset1	468	33	474	25	94.2%
C(8×8)B(3×3))Bin9, Image size(64×320), Dataset1	443	48	459	50	90.2%
C(8×8)B(3×3)Bin6, Image size(64×320), Dataset1	460	145	362	33	82.2%
C(4×4)B(2×2)Bin, Image size(64×320), Dataset1	443	03	504	50	94.7%
C(4×4)B(3×3)Bin6, Image size(64×320), Dataset1	464	18	489	29	95.3%
C(6×6)B(2×2)Bin9, Image size(64×320), Dataset1	397	58	449	96	84.6%
C(8×8)B(2×2)Bin9, Image size(64×128), Dataset1	466	13	494	27	96.0%
C(8×8)B(2×2)Bin9, Image size(64×128), Dataset2	481	41	466	12	94.7%
C(4×4)B(3×3)Bin6, Image size(64×128), Dataset2	483	34	473	10	95.6%
C(8×8)B(2×2)Bin9, Image size(64×128), Dataset2	483	24	483	10	96.6%
C(8×8)B(2×2)Bin9, Image size(64×128), Dataset2 and PP	492	24	483	1	97.5%

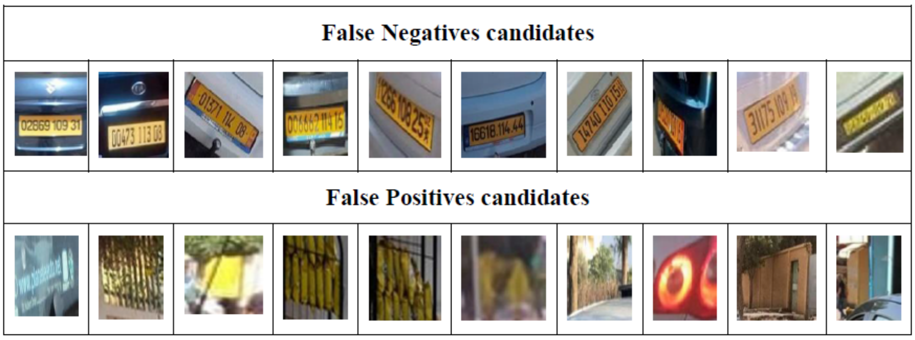
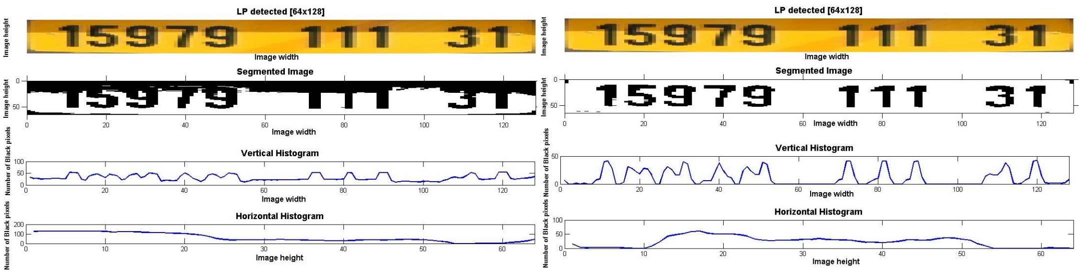


Figure 12. Some examples of badly classified LP

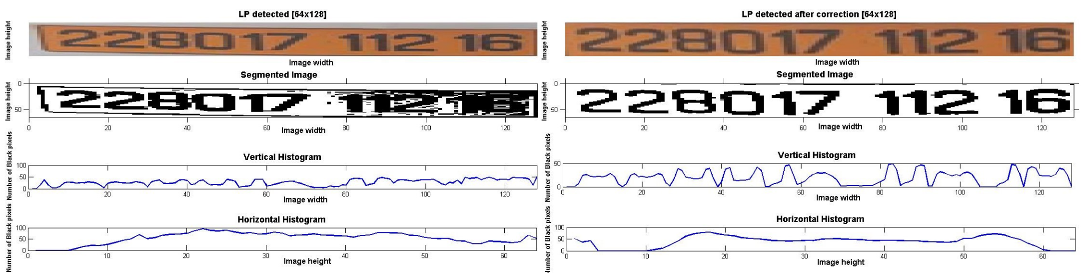
3.2.1. Pre-processing results

As stated before, the shadow can reduce drastically the performances of LP detection, Figure 13 represents the results with a fixed threshold see Figure 13(a) and a variable one see Figure 13(b). It is clear that for a fixed threshold, by using a horizontal histogram, we will lose completely the edges of all digits, and also, we can't separate those digits by the vertical histogram. The construction of the vertical and horizontal histograms, depends strongly on the color of the LP detected, which must be a yellow background with black digits; the presence of any other color impacts the appearance of the two histograms, which makes it impossible to isolate the digits. Figure 14 illustrates the two histograms, horizontal and vertical, before see Figure 14(a) and after see Figure 14(b) the elimination of the color of the vehicle in the candidate area.



(a) (b)

Figure 13. Shadow elimination (a) fixed threshold and (b) variable threshold



(a) (b)

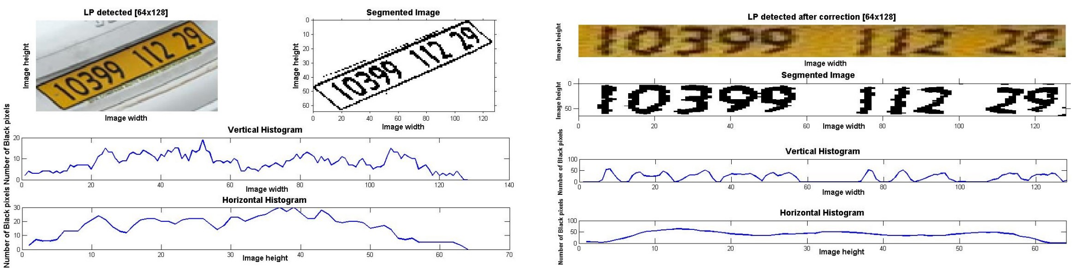
Figure 14. Elimination of the vehicle color (a) before elimination and (b) after elimination

Due to acquisition constraint conditions, several images are usually subject to tilting. Thus, to make our algorithm more realistic, we have added an angle correction block, see Table 2. This key step allow as to calculate histograms in both directions, hence a good digits separation.

Table 2. License plate angle correction

Original image	LP (before angle correction)	Angle correction	LP (after angle correction)
			
			

Figure 15 presents a comparison between the horizontal and vertical histograms before see Figure 15(a) and after see Figure 15(b) the tilt angle correction. After doing this pre-processing, we recalculated the statistics with the same architecture that gave the best recognition rate (image size (64×128), cell (08×08) pixels, block (02×02) cell, 09 bins and overlap of 02 cells between two adjacent blocks, and dataset2). The obtained results show that we could correct nine of the ten remaining images, we enhanced the recognition rate by 0.9% more, which gives a final recognition rate of (96.6+0.9)% which gives 97.5%. The pre-processing is a very important step before the calculation of the vertical and horizontal histograms, which are in turn very important for the step of the isolation of the digits.



(a) (b)

Figure 15. Tilt angle correction (a) before correction and (b) after correction

3.3. Digits recognition results

At this stage, we assume that the LP was correctly extracted and the digits that compose it were well isolated. We considered a test database constructed of 500 images. So, for each digit, we have 50 positive images and the remaining 450 are considered negative images. The recognition of the license plate is the same as the recognition of the digits that make it, so the recognition rate of the license plate is also the recognition rate of the digits. After testing the 500 images of the test database, with the 10 networks that correspond to the ten digits from 0 to 9, we obtained the following confusion matrix, see in Table 3. The average rate calculated from Table 3 is 99.46%, which is a very good average recognition rate. Generally, if the plate is badly extracted (bad isolation), it directly affects the histogram, which in turn will give a wrong classification. We mention that our algorithm gives a very high recognition rate for the positive images (Near 100%).

The results show the great importance of pre-processing, without pre-processing one never reaches these recognition rates neither for the license plate nor for the digits. In Table 4, we present some results of the LP detection (image form), digits isolation, and LP recognition (digital form). Since the recognition rate is not the same for all digits, the recognition rate of the license plate changes from one plate to another, because it depends on the recognition rates of the digits that constitute it. The global results obtained from the two parts:

detection and recognition of LP, show that if the LP is well isolated, with a well-applied pre-processing, it leads to a very good isolation rate and a very good recognition rate of the digits as well.

Table 3. Confusion matrix for numbers recognition

Number	TP	FP	TN	FN	Recognition rate
Zero	50	03	447	00	99.4%
One	49	00	450	01	99.8%
Two	49	04	446	01	99%
Three	50	00	450	00	100%
Four	50	00	450	00	100%
Five	47	00	450	03	99.4%
Six	50	03	447	00	99.4%
Seven	50	01	449	00	99.8%
Eight	50	08	442	00	98.4%
Nine	50	03	447	00	99.4%

Table 4. LP detection and recognition

Detected LP (image form)	Digits isolation	LP recognition (digital form)
		1597911131
		0570619931
		4926211319
		0054112013
		0834610717
		0763719010

4. CONCLUSION

In this work, we have presented an automatic system for the identification of an Algerian license plate from a captured image. This system consists of three steps. First, the LP is extracted from the image, then its digits are isolated, to be recognized by the classifier. In both steps one and three the HOG/SVM algorithms are used. Beforehand some pre-processing, which includes: Shadow elimination, vehicle color removal from the LP candidate areas, and correction of the inclination angle, is applied to help pruning the LP candidate regions by the HOG/SVM classifier and to facilitate the digits isolation. Algeria has its standard license plate. Since no public database of these license plates is available, we had to build our proprietary database (DZLP dataset), for the performance evaluation of the proposed system. The Algerian standard specifies that the numbers on the back plate should be drawn in black on a yellow background. We have exploited this specification to perform detection of the license plate candidate. To keep only the candidate that corresponds to the true license plate, we apply morphological filtering, refinement, based on the shape and aspect ratio of the license plate, and pre-processing to the license plate candidate regions, before pruning them using a HOG/SVM algorithm that discriminates between a true and false license plate. Once the license plate is extracted we compute its horizontal and vertical histograms that we use to isolate its composing digits, which are recognized afterward, using a HOG/SVM classifier, to identify the license plate. It should be emphasized that the proposed pre-processing has proved to be very useful both for the license plate extraction and the digits isolation. Thanks to the application of this pre-processing, we reached very high license plate and average digits recognition rates, which were 97.5% and 99.46%, respectively.

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