Learning Color Transitions to Extract Senegalese License Plates

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Abstract. Automatic License Plate Recognition (ALPR) is gaining increasing attention. Indeed it offers a wide range of applications such as automatic toll, parking payment and the control of the compliance with traffic laws.

The detection and extraction of the license plate is the most important step of an ALPR task as it determines the speed and robustness of the system. In this work, we deal with the issue of detecting and extracting senegalese license plates from car images.

Our method is based on the learning of the color transitions specific to the license plate. Then it uses vectors of features to describe textures of the different regions of the image. From these vectors, an analysis of the probability distribution allows to find the license plate region and to extract it.

Our experimentation on a dataset of 182 car images shows the effectiveness of our method which achieves a detection accuracy around 92%.

Keywords: License plate extraction · Artificial neural networks · ALPR · Color transition

1 Introduction

Government policies are increasingly oriented towards intelligent transport systems (ITS) for a better management of road traffic in major urban centers. These systems enable safer, better coordinated and "smarter" use of transport networks through the use of traffic information. Among the most popular solutions, Automatic License Plate Recognition (ALPR) is gaining more and more attention [11,14].

While making it possible to strengthen compliance with traffic laws with the use of surveillance cameras, ALPR also makes it possible to automate traffic control and payment for services such as tolls and parking [8]. Thus it offers a wide range of applications.

However, ALPR is usually computationally intensive, especially when the input image needs to be processed as a whole. In practice, license plate recognition is done in four steps as illustrated in Fig. 1.

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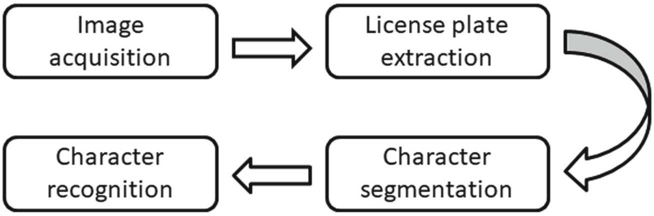


Fig. 1. ALPR processing steps

First, an input image from a video sequence is given to the system. The latter processes the image in its entirety in order to detect the position of the plate and extract it. Once the plate is extracted, it is segmented into characters and then an optical character recognition (OCR) algorithm is then performed for each segmented character to determine the corresponding letter or number.

The detection and extraction of the license plate region is the most important step, nay the most difficult, as it determines the speed and robustness of the system. Several studies and researches have been devoted to this step. Thus different methods have been proposed like edge detection, morphological operations and features selection such as color [13].

In this paper, we are interested in the detection and extraction of senegalese license plates. Indeed, senegalese government has been working for more than a year to standardize senegalese license plates. But to our knowledge, there is currently no solution for automatic recognition of new senegalese license plates, although this could greatly improve the urban mobility by strengthening compliance with traffic laws.

We aim to build a "lightweight" ALPR adapted to operate under limited capacity devices by consuming less power while operating quickly and accurately. Our proposal relies on two neural networks to learn the specific color transitions inside new senegalese license plates. With this capability, we are able to handle input images of various scenes and under different lighting conditions with sufficient training data. The experiments we carried out on a dataset of 182 images containing cars with senegalese license plates demonstrate the effectiveness of our technique.

The remainder of this article is organized as follows. In Sect. 2, we present works related to automatic detection of license plates in an image, in particular those based on the analysis of edges and the features of the license plate region such as its foreground and background colors. In Sect. 3 we detail our proposed license plate detection method based on the analysis of color transitions. We expose its functioning and explain how it proceeds to locate a vehicle license plate and extract it. Then in Sect. 4 we show our experimental results. Finally, in Sect. 5 we conclude this paper and present some future works.

2 Related Works

The most important step of an ALPR task is the license plate extraction as it allows the segmentation and character recognition steps to be done correctly. The extraction step takes as input a car image and returns as output a region of the image that contains the potential license plate.

As the license plate can exist anywhere in the image, all the pixels of the image have to be considered. But processing every pixel in the image may lead to an expensive processing time. Instead, most ALPR systems rely to the custom license plate features derived from its format and characters. Therefore they can process only the pixels that have these features.

The colors of the license plate are one of the used features since the colors of license plates are legislated in many countries. Likewise, the rectangular shape of the license plate boundary is another feature that can be considered. The license plate texture known as the color change between the characters foreground and the license plate background can also be used. Finally, several features can be combined to locate the license plate.

In the following sub-sections, we present a summary of some methods used to detect license plates in order to extract it.

2.1 License Plate Extraction Using Edge Detection

Considering that every license plate is rectangular and has a known aspect ratio, it can be extracted by finding all possible rectangles in the image.

Edge detection methods are commonly used to find the rectangles. First, Sobel filter is applied to the input image for edge detection, then Hough Transformation is applied to identify the straight lines in the image.

Once the edges retrieved and some morphological steps that eliminate unwanted edges done, the license plate rectangle is located by using geometric techniques for detecting edges that form a rectangle. Then the rectangles that have the same aspect ratio than the license plate are considered as candidates.

Edge detection methods are simple and fast with a good extraction rate under various illumination conditions. However, they need the continuity of the edges and they are highly sensitive to unwanted edges. Therefore they are not suitable to be used with blurry and complex images [1,4,13].

2.2 License Plate Extraction Using Texture Features

Many countries have legislated the colors of their license plates with very contrasting colors. Texture-based methods are based on the hypothesis that the presence of characters in the license plate should result in a significant color difference between the plate and its characters. Hence, the license plates are viewed as irregularities in the texture of the image. Therefore, the abrupt changes in the local features are the potential license plate. Indeed, the color transition makes the plate region to have a high edge density.

All the texture-based methods are robust against license plate deformation and it is a key advantage of using these methods. Still, these methods involve complex computations and work poorly with complex backgrounds and different illumination conditions [1,4,13].

2.3 License Plate Extraction Using Color Features

Color-based methods rely on the fact that the color of a license plate is different from the background color of the car. More precisely, the color combination of the plate and its characters is unique and is nowhere found in the image other than in the plate region [5].

Some color-based methods classify all the pixels in the input image using HSB or RGB color model. They commonly use neural networks to classify the color of each pixel [13]. Then the highest color density region is taken as the license plate region. While some others focus on color transitions, they are referenced as color edge detectors. In contrary to the first methods, the latter offer more robustness as they can handle input images from various scenes and under different conditions [5].

Extracting license plate using color information has the advantage of detecting inclined and deformed plates but it is sensitive to illumination changes.

Besides, it makes wrong detections especially when some another part of the image have similar color than the license plate. To overcome this issue, statistical threshold can be adopted to select candidate regions.

Color-based methods are often combined with some other technique to achieve accurate results [4,13].

2.4 License Plate Extraction Using Character Features

License plate extraction methods based on locating its characters have also been proposed. These methods consider all regions with characters as possible license plate regions. They are robust and can achieve good results under different illumination conditions and viewpoints.

Due to the fact that they scan the whole image for the presence of characters, they are time-consuming and often prone to errors if there are other texts in the image [4,13].

2.5 Discussion

In order to effectively detect the license plate, many methods combine two or more features of the license plate. They are called hybrid extraction methods. Color feature and texture feature are frequently combined. Our proposal combines these two features in order to take advantage of their strengths while avoiding their weakness.

According to the recent development in computer vision approaches, most of the statistical methods have been replaced by deep learning neural networks due to their high accuracy in object detection. Embracing this fact, many studies in license plate detection have used different types of neural networks [3,13].

Several studies have used the state-of-the-art YOLO object detector for license plate detection [3,13]. They often use two separate CNNs for vehicle detection and license plate detection.

The accuracy of deep learning methods is slightly better than statistical methods, but they fail on the computational time aspect to be used in a real-time context with limited capacity devices. This explains why we prefer to use a multiple-ordinate neural network architecture rather than a deep one.

A complete review of all these techniques can be found in these surveys [1,2,6,13].

3 Learning Color Transitions to Extract Senegalese License Plates

The senegalese authorities have chosen to overhaul the vehicle registration system to fight fraud. Thus the new license plates are on a white background with black writing. A vertical blue stripe is positioned at the start of the plate and the numbering is done in seven alphanumeric positions. Figure 2 shows an example of new senegalese license plates.

Fig. 2. Senegalese license plate

The main idea of our proposal relies on the detection of some color transitions specific to senegalese license plates. Our approach uses a multiple ordinate neural network architecture (MONNA) made of two small neural networks followed by a recomposition unit which classifies each pixel of the image whether it belongs to the license plate region or not. Each of the two neural networks is a binary classifier implemented by a Multi-Layer Perceptrons (MLP) with a single hidden layer. Their outputs serve as entries of the recomposition unit which processes them to determine the class of each pixel of the image.

This way of doing things is not new [7]. Indeed the use of individual classifiers and simpler feature extractions allow to create relatively shallower models that allow significantly faster processing compared to some Deep learning techniques. Though this kind of model is relatively simple, they are currently the most accurate models for license plate detection [9,13].

Each of the two binary classifiers receives as input a sequence of five pixels that is to be classified as belonging or not to the license plate region.

Following this classification, each row of the image is represented by a statistical descriptor making it possible to calculate the probability that it covers the license plate region. From there, the position of the license plate can be easily determined by the distribution of the probabilities and then the license plate can be extracted. Let us notice here that we introduce a new probabality measure which is one of our main contributions as we will describe below.

In theory, all the pixels of the input image should be processed. However, to greatly reduce the cost of traveling through all of them, a vertical edges detection is applied in the preprocessing step to determine the pixels of interest (POI) to be processed. Only the POIs are processed as they indicate color transitions into the image. Each of POI is associated with the four pixels of the image which follow it in order to constitute a sequence of five pixels which is transmitted to the classifiers. These latter determine whether or not the sequence contains a color transition specific to the presence of the license plate. Figure 3 sums up the main steps of our license plate extraction method.

In the following sub-sections, we detail each of these steps and its task in the processing.

3.1 Image Preprocessing

As said before, a preprocessing step is carried out on the image before its submission to the classifiers. The objective of this step is to reduce the processing time of the classification by determining in advance the regions of the image which may contain a part of the plate.

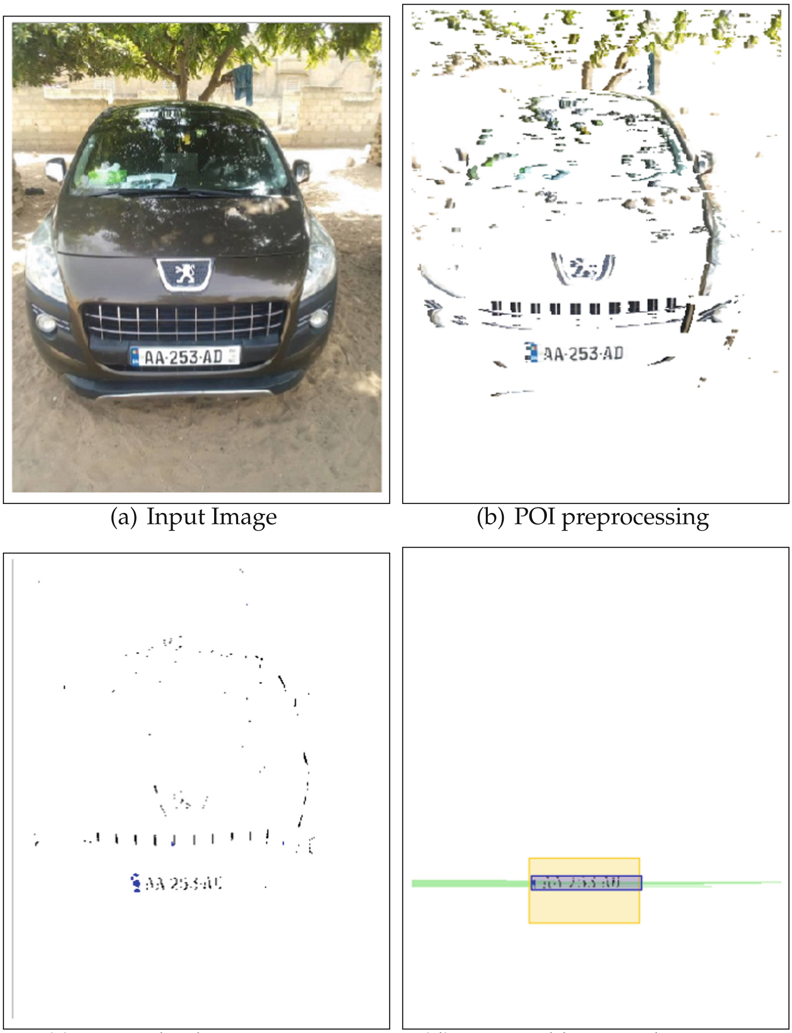
Beforehand, the image is grayscaled and its contrast enhanced by histogram equalization. This is the object of our first convolution on the image with the row vector $[0.3, 0.4, 0.3]$ as the kernel. Then a second convolution with the row vector $[1, -1]$ is applied to detect vertical edges making it possible to determine abrupt color transitions separating the foreground from the image background. Finally, Gaussian blurring followed by a dilation of the detected edge regions is done in order to prepare the sequences of five pixels on which the two binary classifiers must work. Figure 3(b) shows an overview of the obtained result at this phase.

Once completed, the resulting image is binarized with its black pixels representing the POIs to be considered. From this binary image, one can easily make the correspondence of its POIs with the pixels of the real input image. And thus find the same POIs in the input image. All the other pixels are ignored in the classification phase.

This preprocessing makes it possible to reduce the computational time of the classification phase of the pixels of the image by 85% on average.

3.2 POI Classification

In this step, the two binary classifiers work to find the regions of the image containing specific features of senegalese license plates. The use of the two classifiers allows us to break down the classification problem into two lesser complex sub-problems. The responses of the classifiers are processed by a recomposition unit.



(a) Input Image (b) POI preprocessing

(c) Located color transitions (d) Detected license plate region

Fig. 3. Steps of license plate detection (Color figure online)

The preprocessed image is submitted to the two binary classifiers. The first classifier classifies each sequences of five pixels and determines whether or not it corresponds to *blue-white* color transitions. While the second works on *black-white* color transitions. They learn from a training set of ten car images with different scenes and car body colors.

Blue-White Color Transition Classifier. We used a MLP with a single hidden layer of twenty neurons. The input layer has five neurons representing the sequences of five pixels to be taken as input. The output layer determines whether the sequence corresponds in a transition from blue to white color.

The color of each pixel in the image is represented in the RGB color model. Each neuron in the input layer is activated according to the ratio β of blue to red and green via the following formula:

$$\beta = \frac{B + B}{1 + R + G} \tag{1}$$

Black-White Color Transition Classifier. In parallel with the first classifier, the second one searches for black-white color transitions. It is also a MLP with a single hidden layer which is made up of twenty neurons but it has ten neurons in its input layer. Indeed, the pixels are taken in the HSB color model and two input neurons describe the saturation and brightness of each of the five pixels of the input sequences. Let us remind that the HSB color model is an alternative representation of the RGB color model and it is designed to better adapt with the way human vision perceives colors. Therefore it models how colors appear under light and is more suited than RGB color model to distinguish dark pixels from light ones corresponding to black-white color transitions.

3.3 Plate Area Feature Descriptors

Once the processing of the two classifiers is complete, their outputs are combined by the recomposition unit. Figure 3(c) points out the result obtained which is a sparse matrix whose values represent blue-white or black-white color transition positions.

Following the image filtering by the recomposition unit, a statistical analysis of the filtered image is carried out on each of the image rows. Thus each row is associated with a numerical vector descriptive of the successions of black-white color transition preceded by a blue-white color transition. The numerical vector reflects the coloring features specific to senegalese license plates found on the corresponding row. As a reminder, Fig. 2 shows a senegalese license plate example.

The first entry of the vector represents the position of the blue-white color transition preceding the list of black-white color transitions. In the absence of a blue-white color transition on the row, the vector remains empty. The following entries of the vector record teh positions on the row of the sequence of black-white color transitions following the blue-white one. The maximum size of the vector is fixed to 15 entries to store the position of the blue-white color transition in front of the fourteen positions of the black-white color transitions which compose the seven characters of the license plate.

3.4 Probability Measure of License Plate Presence

An array of vector descriptors representing all the rows of the image is made. The distribution of transition positions into the vectors allows to locate the region of the license plate. Table 1 gives an example of such a distribution corresponding to the rows of the license plate region in Fig. 3(d).

Table 1. Example of the distribution of color transition positions in the plate region

129	145	156	172	177	192	207	214	220				
127	145	156	172	177	191	208	214	220				
127	145	156	172	182	192	203	208	214	220			
127	141	145	152	157	171	183	193	198	203	208	214	220
127	141	146	152	157	170	183	194	203	208	214	220	
128	141	146	152	157	170	183	194	208	214	220		
129	146	157	169	183	194	208	214	220				
130	146	157	168	177	183	188	193	202	208	214	219	
124	140	147	152	158	167	182	193	202	218			
129	140	147	151	158								

For each of the vectors, we calculate the probability that it overlaps the license plate region on the interval of positions defined by the vector. We introduce a new probability measure that calculates the entropy of the dispersion of black and white colors over the interval. Then we associate it by multiplication with the Gini index' value of the inequality of the distances between the black-white color transition positions representing the locations of the characters on the plate. The combination of the values of entropy and Gini index makes it possible to easily find the most probable region where the plate is on the input image. We achieve it with the establishment of the histogram of the two combined values.

In Fig. 3(d), we illustrate the rows of the input image that most likely overlap the license plate region. They are colored with a green background color relatively to their probability values.

A similarity analysis of the neighborhood of the largest peak allows to calculate the height in pixels of the license plate region. As the ratio of the width and the height of senegalese license plates is around 3.75, we can deduce the width of the license plate if the latter is not tilted on the image. Otherwise, we apply a geometric transformation to correct tilt license plate. Such transformations are popular and widely presented in [10, 12].

4 Experimentation

We demonstrate in this section the effectiveness of our proposal. In the previous section, we explain its functioning. In this section, we describe how we did our experimental evaluation and we present the accuracy of our method to locate senegalese license plates in a car image.

4.1 Dataset

In our knowledge, there is no senegalese license plate dataset publickly available to researchers, thus we made our own dataset which contains 182 labeled car images with the bound of the senegalese license plate within the image. We collected the images from senegalese websites specializing in the sale of cars[1].

The images in the dataset have different sizes and are taken from different scenes. Furthermore, the cars in the images have various body colors.

4.2 Experimental Results

Our evaluation consisted to train our classifiers with a training set of ten cars with different car body colors in addition to different brightness and license plate skews. Then we submit the rest of the images for the test phase.

Our system extract for each image the license plate region which is compared to the real license plate region into the image. We achieve a detection accuracy around 92%.

Figure 4 shows a sample of detected license plates among the images of our test set.

Fig. 4. License plate detection

[1] The dataset is available at https://bit.ly/3rd0ofR.

5 Conclusion

In this paper, we presented a novel senegalese license plate extraction algorithm. We detailed its functioning and discussed how it extract license plate from an input image. The experiments we led points out the effectiveness of its detection. Therefore license plates can be accurately extracted.

As part of future work, we aim to collect a larger senegalese license plate dataset to better improve the accuracy of our detection by further training the binary classifiers. Next, we intend to compare our approach to others that are available in the literature.

Likewise, we aim to extend our method to detecting multiple license plates in a single image.

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