Car License Plate Extraction from Video Stream in Complex Environment

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Abstract. The recognition of car license plates has a variety of applications ranging from surveillance, to access and traffic control, to law enforcement. Today a number of algorithms have been developed to extract car license plate numbers from imaging data. In general there two class of systems, one operating on triggered high speed cameras, employed in speed limit enforcement, and one based on video cameras mainly used in various surveillance systems (car-park access, gate monitoring, etc). A complete automatic plate recognition system, consists of two main processing phases: the extraction of the plate region from the full image; *optical character recognition* (OCR) to identify the license plate number. This paper focuses on dynamic multi-method image analysis for the extraction of car license plate regions, from live video streams. Three algorithms have been deviced, implemented and tested on city roads, to automatically extract sub-images containing car plates only. The first criterion is based on the ratio between the height and width of the plate, which has, for each type of plate, a standard value; the second criterion is based on the eccentricity of the image on the two dimensions, i.e. the projection histogram of plate number pixels onto the reference axes of the image; the third criterion is based on the intensity histogram of the image. For each criterion a likelihood is defined, which reaches its maximum when the tested sub-image is close to the standard value for the type of plate considered. The tuning of the methods has been carried on several video streams taken during travel on busy city roads. The results for the overall recognition rate on single frames is around 65%, whereas the multi-frame recognition rate is around 85%. The significant value for the performance of the method is the latter, as typically a license plate is visible in 5-10 frames. Based on three parameters ranking, the same system can potentially distinguish and identify a wide range of license plate types.

1 Introduction

Car license plate automatic recognition has an ever-increasing importance in many fields of application. Law enforcement has gained greatly from the availability of systems able to detect autonomously suspicious car plate numbers. There are also a large number of examples in surveillance, for premises monitoring, gate access control, car parking automatic management, etc. Differently from usual *optical*

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character recognition (OCR) applications (e.g. documents archiving, postal code reading, etc), which occur in controlled environments and lighting conditions, the recognition of car plates is generally applied to imaging data collected in highly complex sceneries [1,2]. In general such a system has to operate day and night, with varying visibility conditions, analyzing images containing a large number of unwanted objects of different nature (e.g. buildings, traffic signs, people, etc). In addition the scene to be analyzed may contain more than one car [1,3,5].

The most important phase of car plate recognition is the extraction of the plate region from the full scene frames. Subsequently OCR is applied, being this technology in a mature state and quite reliable. Of course the reliability of OCR algorithms rely on good quality images, not containing noise coming from unwanted information [4].

This paper reports a novel car plate extraction method, based on three independent feature matching criteria. In order to tackle the problem three parameters have been identified as representative of a particular license plate type: the ratio between height and width of the plate; the number of rows and columns where the characters are located; the ratio between the plate number area and the plate background area. The standard values of all the three features, defined for each car plate type, are compared with the values computed for each sub-image analyzed, to construct a likelihood ranking. The ranking gives an indication of how likely it is that a sub-image contains a car plate and only a car plate of a particular type (e.g. national, foreign, front or back, etc).

Experiments have been conducted on 34.5 minutes of video streams, recorded on high traffic city roads. The data has been divided into two subsets, one used for training of the system, the second one for testing. A total of 25 car plates have been considered for training and a total of 40 car plates have been used during the performance tests. Video streams where recorded on a standard digital camcorder, with full PAL resolution at framerate, using MPEG2 compression.

The developed system can recognize car plates in a variety of lighting conditions and a broad range of sub-image sizes, starting from 70x20 pixels (corresponding to less than 2% of the frame area).

2 Image Segmentation

The car plate recognition process requires a first step of image segmentation, to extract homogeneous regions within single frames. This is a necessary phase that partitions the acquired image into several sub-images, to be taken into account as candidate car plates.

In this paper a gradient based segmentation algorithm has been employed, which uses the Canny [6] method to extract edges from imaging data. A thresholding procedure is then used to remove dark areas of the image, given that plates show usually high values of intensity. This process results in a binary image where white pixels are the ones corresponding to brighter areas in the original frame. After thresholding and edge extraction a *seeded region growing* (SRG) [7] strategy is used to identify uniform image areas. A typical result of a complete segmentation for a frame captured during experiments is shown in Fig. 1. The top left image (a) shows the original data, the top right image (b) the threshold result, the bottom left image the edge detection output (c), the bottom right image (d) the segmentation result.

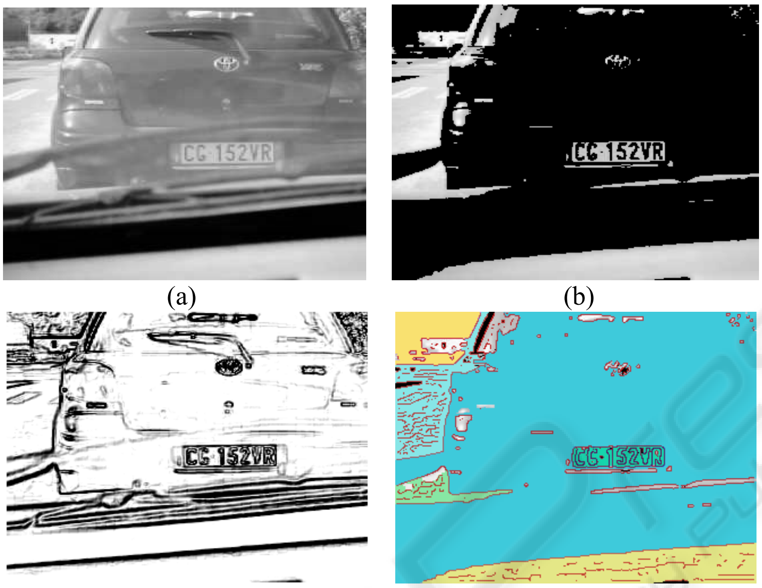


Figure 1. Example of image segmentation. Top left original image (a); top right thresholded image (b); bottom left edge detection result (c); bottom right segmentation output (d).

Once the image frame is segmented into homogeneous regions - solid colors in Fig 1. (d) - the subsequent feature extraction procedure starts, to identify amongst candidate areas of the image, the ones corresponding to car license plates. A detail of the feature recognition strategies is reported in the following section.

3 Feature Extraction

The second step towards the definition of a car plate type is to identify univocal features representing it. What is known about car plates is that they have a rectangular shape, they contain a certain number of characters with a specified font and size, distributed over a fixed number of rows and columns. The above features constitute a reliable indication of a specific car license plate type, exception made for customized car plates. An additional feature useful for identification is the background/foreground colors, which is some cases can be different from white/black.

Starting from the above definition of what constitutes a car plate, three identifying features have been defined: the ratio between height and width of a plate; the number of rows and columns over which the plate digits distribute, which are described by the projection eccentricity; the ratio between the areas covered in the plate by digits and the area of background, defined through the intensity histogram.

A brief description of the methods used to implement the feature extraction for the three criteria above mentioned is reported in the following.

Aspect ratio

Given a particular type of car plate, to be identified, its height and width are measured and their ratio is computed to give a dimensionless characteristic number. The absolute value of the difference between the height/width ratio measured on each sub-image, and the characteristic number is defined as ΔR. From all ΔR measured on the training set of images, a maximum value is obtained ΔR_{max}. A parameter is then defined that gives a measure of how close to the actual value the aspect ratio of each sub-image is, with respect to a specific plate type:

$$D_a = 1 - \Delta R \; / \, \Delta R_{max}$$

Digit distribution

A second identifying feature is the location of characters included in the car plate. Two integer numbers can be defined as the number of rows Nr and the number of columns Nc over which characters align in the plate. In our case all digits and letters spread across a single row and 7 columns, giving the following values for Nr = 1, Nc = 7 (see Fig. 2). Using the eccentricity projection of digit pixels, an histogram can be constructed, where peaks correspond to individual characters and valleys correspond to the separation between adjacent characters. To obtain Nr and Nc the eccentricity histograms have to be processed and the number of peaks and valleys extracted. For this purpose a threshold value is applied to the smoothed histograms, as a fraction of the average value of each histogram, this to construct a binary vector. Then the number of transitions from zero to one in the binary vector is counted.

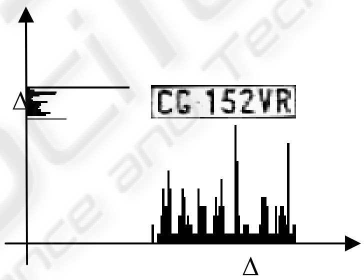


Figure 2. Italian license plate example, with its eccentricity histograms reported in the x, y axes.

Once Nr and Nc are computed for a sub-image, they are compared to the actual values for the specific car plate type considered, and the absolute value of the differences ΔNr and ΔNc extracted. From the training set of data, the maximum values of these quantities are derived, ΔNr_{max} and ΔNc_{max}. Two parameters can be defined, giving a measure of how close to the actual case the distribution of characters in a given sub-image is:

$$D_r = 1 - \Delta Nr \; / \, \Delta Nr_{max}$$

$$D_c = 1 - \Delta Nc \ / \Delta Nc_{max}$$

Coverage ratio

Given a particular license plate type, which corresponds to a fixed background color and a distribution of digits with specific font type and size, the coverage ratio of is confined in a fixed range. In order to account for variations of the coverage related to varying character sequences and to allow for noisy data, a characteristic intensity histogram can be constructed from experimental training data.

This characteristic histogram is a representation of the "average" value for the coverage ratio. To construct such an average histogram the sub-images containing license plates are extracted manually from the data and their histograms computed. The result of averaging over all 25 sample license plate is shown in Fig. 3. It is noticeable as the histogram shows a broad distribution of dark pixels, present in lower number, and a more peaked bright pixel distribution, corresponding to the plate background.

From the analysis of the histogram shape it is evident that the two pixel classes are present in the images, digits and background, which spread over a rather wide range of intensities. This is mainly due to the changing environmental conditions during experiments and data acquisition noise.

Figure 3. Average intensity histogram computed on experimental sample Italian license plate images.

The intensity histogram for a single plate candidate sub-image is derived, stretched to cover the dynamic range of the average histogram (see above), with which is then compared. From the comparison a metric distance is extracted as the sum of the absolute value of the differences computed over all intensities, to obtain the *coverage ratio* difference ΔCR. The maximum value of ΔCR is computed on the training set of data giving ΔCR_{max}. A parameter can then be defined, which gives a measure of how close to the actual scenario the coverage of characters with respect to the background of a candidate plate sub-image is:

$$D_{cr} = 1 - \Delta CR_{max} \ / \Delta CR_{max}$$

4 Classification Methods

The recognition process starts from the segmented image as input and proceeds to compute the features of each sub-image identified, in order to compare them with the standard values defined for a specific car plate type.

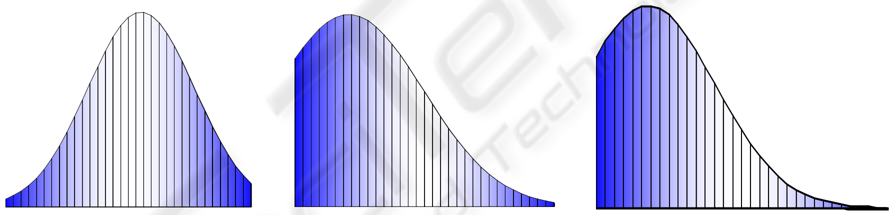
Each of the four parameters defined in the previous section, D_a, D_r, D_c and D_{cr} has values ranging from zero to one. The latter corresponding to the perfect correspondence of the analyzed sub-image to the specific plate type considered.

Once the four feature values for a sub-image are extracted they have to be turned into homogeneous parameters and combined into a single *recognition score*. To achieve this the training car plate set is analyzed to construct statistical distributions of each feature.

The distribution widths are used to define the weight of each feature in the combined *recognition score*. When data distribute over a wide range it means that the corresponding feature has a low discriminating capability, thus it should not contribute substantially to the recognition process.

In the present case, however, all the feature normalized distributions show comparable widths and they are, as a consequence, all significant in the recognition process. For the case of Italian license plates the parameter D_r has been neglected because of the single row digit distribution characterizing the standard plate.

Data are shown in Fig. 4 for the training set used during the calibration of the system. Fig. 4 refers to the *aspect ratio* D_a distribution (a), *digit distribution* on columns D_c (b), *coverage ratio* D_{cr} (c).



(a) (b) (c)

Figure 4. Distributions of values for the three features used in the recognition process (see text).

From the training set of images and the above distributions, with mean and variance reported in Table 1, the following formula is defined for the *recognition score R*:

$$R = \alpha D_a + \beta D_r + \gamma D_c + \delta D_{cr}$$

with

$$\alpha + \beta + \gamma + \delta = 1$$

5 Experimental results

Apart from the training set a total of 34.5 min of video streams have been analyzed. From this data 2362 single sub-images have been extracted, according to the procedure described in section 2. All sub-images have been processed according to the algorithm presented in sections 3 and 4, giving an overall recognition performance of 65% on single frames and of 85% on sequences of 5 frames. In Table 1 a summary of the experimental results are presented.

Table 1. Results of the plate classification experiments.

Video stream	*Environmental conditions*	*# of actual plates*	*Average # of frames/plate*	*Recog. rate on single frame*	*Recog. rate on sequences*
movie1.avi	daylight	13	54	72%	90%
movie2.avi	daylight	16	48	74%	91%
movie3.avi	night	11	49	54%	65%

The lower performance of the algorithm, observed in data collected at night, is due both to the lower visibility of the car plates and to the slow and noisy response of the camera.

The values for the weights of the feature parameters in defined section 4 have been, for the experiments conducted on the collected video streams, of $\alpha = 0.07$, $\beta = 0$, $\gamma = 0.75$ and $\delta = 0.18$. The parameter β has value zero because the car license plate type analyzed has only one row of characters, thus it does not have a relevant influence on the recognition process.

The obtain the final classification the *recognition score R* parameter has been thresholded to 0.5 – i.e. all sub-images with a computed value of *R* higher than 0.5 are considered car plate images. This is consistent with the assumption that the parameter *R* is an indirect measure of the probability that a sub-image represents a car plate. In this view when the value of *R* is higher the ½, there more than 50% chance that the sub-image is the one containing only the car plate.

Table 2 shows some examples of recognized car license plates, together with the corresponding values of *recognition score R.*

Table 2. Example recognized car license plates

License plate sub-image	*R*
	0.68
	0.52
	0.54

6 Conclusion

This paper describes a novel method for car license plate automatic extraction from video streams. Experiments were presented for a set of 34.5 min of video data, showing a good performance for the recognition of car plate locations within outdoor sceneries. The algorithm allows the analysis of both single frames and sequences, the latter giving a greatly improved performance. This is extremely useful for a great deal of applications of the method, where single plate are visible in sequences of successive video frames.

The system can be trained to recognize a variety of plate types, and can be extended to do multi-type recognition, through a ranking procedure on the single recognition parameter defined *R*.

Another possible extension of the method, able to track plates on image sequences, is in the field of motion dynamics, extremely useful, for example, in speed limit enforcement applications.

Though preliminary, the results shown here are promising for the definition of a robust method for car plate recognition.

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