Car License Plates Extraction and Recognition Based on Connected Components Analysis and HMM Decoding

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Car License Plates Extraction and Recognition based on Connected Components Analysis and HMM Decoding*

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Abstract. A system for finding and recognizing car license plates is presented. The finding of the plates is based on the analysis of connected components of four different binarizations of the image. No assumptions are made about illumination and camera angle, and only mild assumptions regarding the size of the plate in the image are made. Recognition is performed by means of Hidden Markov Models. Experiments on a database of Spanish number plates show the feasibility of the proposed approach.

1 Introduction

Car License Plate Recognition (CLPR) has a wide variety of applications [1, 2], such as control of parking lots, borders or traffic, recovery of stolen cars, etc. Many of the current CLPR systems work under controlled light settings and assume that the plate is horizontal and/or perpendicular to the camera direction. We present a CLPR system that makes no assumptions about illumination and it makes only mild assumptions about the position of the camera and the relative size of the plate in the image. Figure 1 shows some typical images from our database.

Two different problems are faced when building a CLPR system: (1) License plate extraction: finding the area of the image that corresponds to the plate; and (2) recognizing the characters in the plate.

In our approach, the license plate extraction phase produces an ordered series of regions of interest (ROI). These regions are found by analyzing the connected components of four different binarizations of the image. Character recognition is performed on each ROI by means of a Hidden Markov Model (HMM) decoding system. The recognition yields a string of characters and an estimation of the probability, according to the HMMs, that those are the characters present in the text in the ROI. This value is used to rescore the ROIs and to select the one that really corresponds to the license plate.

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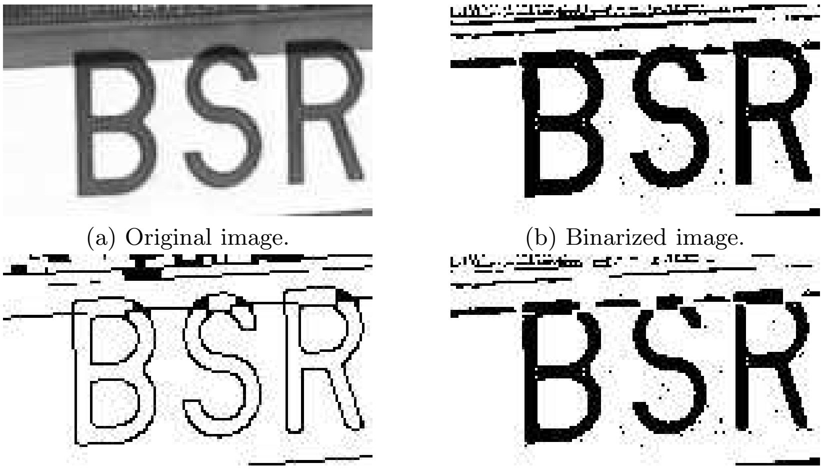
Fig. 1. Sample pictures of Spanish license plates in the database.

The paper is structured as follows: the next two sections explain the license plates extraction and recognition procedures, respectively; after that, we present experimental results of both stages and the whole system on a database of Spanish license plates; finally, we comment some conclusions and future work.

2 License Plates Extraction

The aim of this phase is to find a set of quadrangles that can be considered promising regions for holding a plate. Note that the plate cannot be assumed to have a rectangular position due to the perspective distortion introduced by the angle of the camera with respect to the car. For the same reason, the plate is not assumed to be horizontal. These regions (which we call ROI, for Regions Of Interest) are searched for by analyzing the connected components of a binarization of the image. This analysis looks for regions in which the components have certain properties such as being of similar height, having an aspect ratio in some range, and being roughly aligned.

The analysis of connected components is performed four times, each one using a different binarization. Similar plate candidates coming from different binarizations are combined and their scores are readjusted. Up to three candidates are selected by score. For each surviving plate candidate, a ROI is returned consisting of the minimum area quadrilateral fitting the bounding boxes of the connected components it contains.



(a) Original image. (b) Binarized image. (c) Edges. (d) Binarized image with edges deleted.

Fig. 2. Effect of removing edges from the binarized image: the characters of the plate are separated from one another.

In the following description we assume that the pictures are gray level images containing the frontal or rear side of a single vehicle. Plate width is assumed to be between 25% and 75% of the image width, which in our case is 800 pixels. Different sizes would need to change the values presented. No assumptions are made about the angle of the camera with respect to the vehicle. As mentioned above, this causes distortions in the image.

2.1 Binarization of the image

Global thresholding is not appropriate in our case because the ROI usually is a small portion of the image and there can be large lighting differences in a scene. Therefore, we use a local thresholding technique: for each pixel, the threshold is computed by substracting a constant c to the mean gray level in an $n \times n$ window centered in the pixel. There is no single setting of n and c that has proven useful in all images of our training set. Thus, we use three different settings: $(n = 20, c = 2)$, $(n = 20, c = 6)$, and $(n = 9, c = 6)$.

In some plates, shadows due to direct sunlight may link several characters (Figures 2 (a) and 2 (b)). To overcome this undesirable effect, a fourth binary image is produced by applying an edge detector to the original image (Figure 2 (c)) and removing the edges from the binary image obtained with parameters $(n = 9, c = 6)$. This is expected to disconnect the characters that were linked by the shadow (Figure 2 (d)).

2.2 Connected Component Analysis

Once the image is binarized, the process of analyzing the connected components for finding ROIs consists of the following steps: (a) connected components detection and filtering; (b) ROIs finding; and (c) ROIs scoring.

Connected Components Detection and Filtering The binarized image is decomposed into 4-neighbours connected components. A filter removes small components (containing less than 100 pixels) and keeps those components whose width, height, and aspect ratio fall between some limits (25 and 140 for the height, 5 and 80 for the width, and 0.4 and 14 for the aspect ratio).

A possible problem with this filter is that it may miss some components corresponding to characters in the plate. However, note that this is only a problem when it affects to the leftmost and rightmost characters. Furthermore, we have seen experimentally that it is very unlikely that this happens on all four binarizations.

ROIs Finding Once the connected components have been filtered the process of ROIs extraction begins. The aim of this process is to find sets of connected components containing at least four connected components of similar size and whose bounding box centers can be roughly fitted by a straight line. Only maximal sets are considered: *i.e.* if one such set is properly included in another, the first one is ignored. On the other hand, the sets need not be disjoint: a connected component can belong to more than one.

A simple analysis of the ROIs is performed in order to remove those components that lie too far away from the others. Figure 3 shows the ROIs found in the images of Figure 1.

ROIs Scoring Each region of interest is scored attending to its number of connected components, overlapping of bounding boxes, and slope. The scores are defined so that higher scores are worst. The actual criteria are:

- The difference between the width of the candidate and the sum of the widths of the bounding boxes of the components is the basis score.
- If the number of components is below six or above eight, a penalty is added for each component of the difference with six (if it is below) and eight (if it is above).
- For each pair of components, the score is increased by the percentage of overlap between the corresponding bounding boxes.
- Finally, the score is increased with a multiple of the absolute value of slope of the line joining the centers of the components.

3 License Plates Recognition

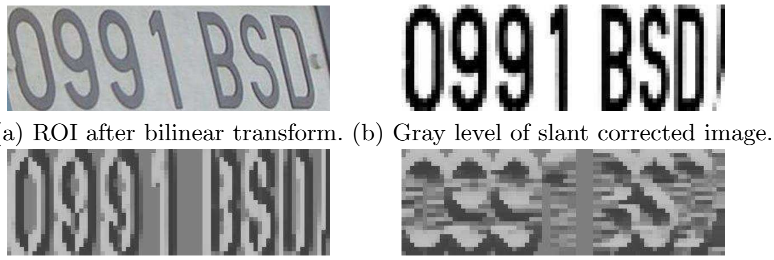
We use Hidden Markov Models (HMM) as the basis model for our recognition engine. HMMs have been successfully used in speech recognition for a long time

Fig. 3. ROIs found in the pictures of Figure 1.

and more recently they have been applied to OCR tasks. The recognition begins with a preprocessing and a parameterization of the ROIs detected in the previous phase.

Preprocessing The quadrilateral ROIs of the gray level image are mapped into rectangles by means of a bilinear transform (see Figure 4 (a)). These regions are supposed to contain only the plate, so a better binarization can be performed on them. We use a new local thresholding with a larger window. After binarization, a new connected component analysis removes noise. The slant of the surviving connected components is corrected and each component is rescaled to a standard height of 100 pixels.

Parameterization We use a parameterization based on the one presented in [4]. The image is divided into a grid of $20 \times N$ cells, where N is proportional to the width of the ROI. In each cell the average gray level and horizontal and vertical derivatives are computed. The gray level is a weighted average of the gray levels of a 5×5 cells neighbourhood, the weights following a gaussian distribution (see Figure 4 (b)). The same neighbourhood is used in the computation of the derivatives. The horizontal derivative is defined as the slope of the line fitting the average gray level in each row (see Figure 4 (c)). The vertical derivative is defined analogously (see Figure 4 (d)). With this process, the parameterization the ROI consists in N vectors of dimension 3×20.



(a) ROI after bilinear transform. (b) Gray level of slant corrected image.

(c) Horizontal derivative of (b). (d) Vertical derivative of (b).

Fig. 4. Preprocess and parameterization for the HMMs.

Hidden Markov Models An HMMs was trained for each character. Each model has a Bakis topology [3]: each state has three output arcs, one to itself, and one to each of the two following states. After some experiments performed on training images, the total number of states per character was fixed to 12, each one with a mixture of 128 Gaussian distributions. The models were trained on manually segmented images with the Hidden Markov Models Toolkit (HTK) [6].

Language Model A standard practice in speech recognition [3] is to restrict the possible sequences by means of a *language model*. This is responsible for assigning an *a priori* probability to the different sequences. In our case, the valid Spanish license plates were encoded in a regular grammar. This is straightforward as there are currently two models of plate codes: (1) one or two letters that identify a province, four digits and one or two letters; (2) four digits and three consonants. In this first approach, all productions with the same left side were assigned the same probability.

4 Experiments

We have carried out some experiments with a corpus consisting of 468 images taken with a conventional digital camera (ftp://acrata.act.uji.es/pub/MATRICS). The images were resized to a standard width of 800 pixels. In the images, the width of the plate, after rescaling, lies between 25% and 75% of the width of the image (in pixels, between 200 and 600).

The images were divided in a group of 418 images for training and 50 images for test. The training images correspond to 341 vehicles (for some vehicles both the frontal and rear plates were taken) and the test images correspond to 43 vehicles. Care was taken to avoid the overlapping between the vehicles in the training and the test sets.

To ease the training procedures, the plates were transcribed and the bounding boxes of each character and plate were manually obtained.

Fig. 5. Highest scored ROIs in test pictures after the mapping to rectangles.

4.1 Extraction Experiments

To evaluate the performance of the ROIs detection method, we have measured the number of times that the highest scored ROI matches the plate region on the test data. This happened in 45 of the 50 test plates. If the best three ROIS are considered, 49 plate regions are correctly identified. In all cases, the best ROI contained a significant part of the plate region. The result of the bilinear transforms of the best ROIs is presented in Figure 5.

4.2 Recognition Experiments

HMMs parameters were estimated using a manual segmentation of the training images. In order to assess the HMMs, a first experiment was conducted on the manually segmented images of the test data. 94% of the plates were correctly recognized. A character accuracy rate of 98.1% was obtained. The errors were due to problems on overexposed and blurry images.

4.3 Global System Experiments

The ROIs obtained in the plates extraction stage were fed into the HMMs based recognizer. The average log-probability per column was used to rescore the ROIs and their associate license plate transcriptions. In this case, 88% of the plates were correctly recognized. In a additional 4% of the plates, a correct transcription was found for one ROI, but the combined score chose a wrong ROI, i.e. a better rescoring would have increased the recognition rate up to 92%. The

ROI and HMMs scoring did not help to select the correct transcriptions in two misclassified plates, but the HMM recognizer correctly produced a transcription for their corresponding ROIs. The character accuracy rate was 95.7%.

5 Conclusions and Future Work

We have presented some preliminary results with a license plate extraction and recognition system based on connected components analysis and HMMs decoding. The results show the feasibility of this approach.

From the experimental results we can conclude that, although the ROI detector performance is very high, an improvement of the rescoring of ROIs is needed: the decrease in plate recognition from 94% (manual segmentation) to 88% is attributable to the fact that only in 90% of the cases the plate region corresponds to the first ROI. When all regions are taken into account, the recognition rate goes up to 92%, which corresponds to the 98% of times that plate region was one of the three best ROIs.

The HMMs produce near to 100% of correct characters on well parameterized regions of interest: the few decoding errors are due to extremely low quality images (severe overexposure) and inaccuracies in ROIs detection.

In the future we plan to improve the extraction by means of texture analysis such as the one proposed in [5]. Preliminary experiments with textures have shown that its results are not as good as the analysis of connected components, but it could be used to guide that analysis. We also plan to estimate the width of the strokes in the digits in order to improve the analysis of the connected components. This could be also employed to estimate the size of structural elements for applying morphological operators [1]. Another line of work is the recognition of plates in sequences of images from video streams, where movement information can be helpful to detect regions of interest.

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