License Plate Character Segmentation Based on the Gabor Transform and Vector Quantization

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Abstract. This paper presents a novel algorithm for license plate detection and license plate character segmentation problems by using the Gabor transform in detection and local vector quantization in segmentation. As of our knowledge this is the first application of Gabor filters to license plate segmentation problem. Even though much of the research efforts are devoted to the edge or global thresholding-based approaches, it is more practical and efficient to analyze the image in certain directions and scales utilizing the Gabor transform instead of error-prone edge detection or thresholding. Gabor filter response only gives a rough estimate of the plate boundary. Then binary split tree is used for vector quantization in order to extract the exact boundary and segment the plate region into disjoint characters which become ready for the optical character recognition.

1 Introduction

Applications such as traffic measurement and management, traffic surveillance, car park automation require successful license plate recognition (LPR) system. A typical LPR system is comprised of two parts: license plate detection (LPD) and license plate character segmentation (LPS), each targets different aims. LPD aims at detecting the presence of any plate in an image, while LPS aims at extracting the actual boundary and segmenting the license plate into characters which are sent to optical character recognition. There are several factors which have a negative influence on the results of any LPD and LPS system including weather conditions, lightning conditions, physical damages in the license plate.

There have been a number of studies in LPD. Most LPD algorithms are based either on edge detection or on thresholding. Edge detection and thresholding are both used to convert the color or gray-level image into binary image. The binary image is then analyzed by searching the histograms obtained by taking vertical or horizontal

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projections along the image. Inherent nature of license plates causes specific transition characteristics on these histograms. In [1], gradient magnitude and their local variance in an image are computed. Then, regions with a high edge magnitude and high edge variance are identified as license plate regions. In another study [2], the straight lines are detected using Hough transform and horizontally parallel lines are grouped as candidate plate regions assuming that the lines in the real scene are preserved also in the captured image. Since the proposed methods are generally color or shape-based, they fail at detecting various license plates with varying colors and shapes. This is due to the fact that license plates are actually textures. The other one detects the license plate "signature" as it is presented in [3].

LPS prepares the license plate to optical character recognition. The aim is to segment the characters that appear in the plate. Proposed methods generally use the same approach as used in LPD. In [4], a relatively new neural network architecture called fuzzy ARTMAP is used together with edge detector filters. In [5], to segment the characters in the number plate image, they search for valleys in the vertical projection of the binary image.

We have developed a computer vision system that detects license plates and segments license plate into characters in an image by using the Gabor transform in detection and vector quantization [6][7] in segmentation. The overall system is depicted in Fig.1.

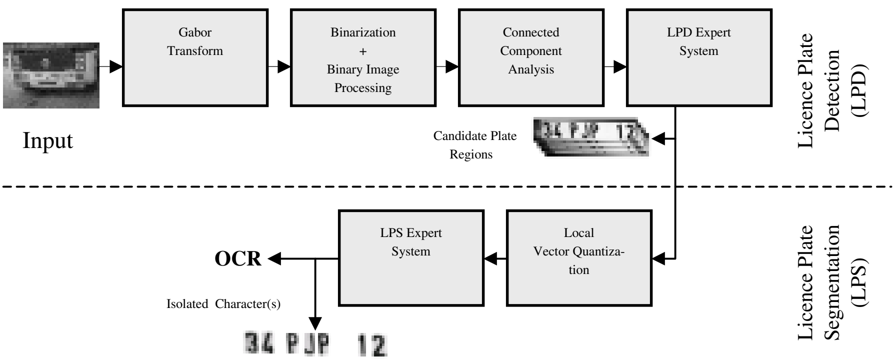


Fig. 1. Overview of the license plate detection and license plate character segmentation.

The output of the system is the bounding box for the license plates detected and their segmented characters. The paper is organized as follows: Section 2 examines Gabor transform and its application to license plate detection. Section 3 presents license plate character segmentation and introduces an expert system to filter out the segmentation results and apply a priori information if there is available any. Results of the methods described in this paper are presented in Section 4. Finally future works and conclusions are given in Section 5.

2 License Plate Detection

Gabor filters have been one of the major tools for texture analysis. This technique has the advantage of analyzing texture in an unlimited number of directions and scales. Physiological studies have found simple cells, in human visual cortex, that are selectively tuned to orientation as well as to spatial frequency. The Gabor filters are local spatial bandpass filters that achieve the theoretical limit for conjoint resolution of information in the 2D spatial and 2D frequency domains.

An input image $I(x,y), x, y \in \Omega$, where Ω is the set of image points, is convolved with a 2D Gabor function $g(x,y), x, y \in \Omega$, to obtain a Gabor feature image $r(x,y)$ as follows:

$$r(x,y) = \iint_{\Omega} I(\xi,\eta) g(x-\xi, y-\eta) d\xi d\eta \tag{1}$$

We use the following family of Gabor functions;

$$g_{\lambda,\theta}(x,y) = e^{-\frac{\left(x'^2+y'^2\right)}{\sigma^2}} \cos\left(2\pi \frac{x'}{\lambda}\right) \tag{2}$$

$$x' = x\cos\theta + y\sin\theta$$
$$y' = -x\sin\theta + y\cos\theta$$

The standard deviation σ of the Gaussian factor determines the effective size of the surrounding of a pixel in which weighted summation takes place. The parameter λ is the wavelength and $1/\lambda$ is the spatial frequency of the harmonic factor $\cos(2\pi x'/\lambda)$. The ratio σ/λ determines the spatial frequency bandwidth of the Gabor filters. The angle parameter θ specifies the orientation of the normal to the parallel positive and negative lobes of the Gabor filters.

The filter responses that result from the convolution with Gabor filters are directly used as license plate detector. Three different scales and 4 directions are used, resulting in a 12 Gabor filters. Fig.2. shows an intensity image and its Gabor filter response ($r(x,y)$). High values in the image $r(x,y)$ indicate probable plate regions. In order to segment these regions, first we have utilized thresholding algorithm and obtained a binary image. Then morphological dilation operator is applied to the binary image in order to merge nearby regions. Finally we extract plate regions simply by applying eight-connected blob coloring. The results of the detection by the given method are shown in Fig.3. where each region is painted with different color.

Fig. 2. Original images and normalized the Gabor filter responses.

3 License Plate Character Segmentation

Although Gabor filter performs well at detection, its segmentation performance is poor. We apply nonlinear vector quantization to eliminate the false alarms and segment the license plate characters to its exact boundary. Vector quantization is a process to assign pixel values in one of a finite number of vectors. First step in vector quantization is the decomposition of vector set. In binary split tree approach, these vectors are determined in such a way that the quantization error is minimized.

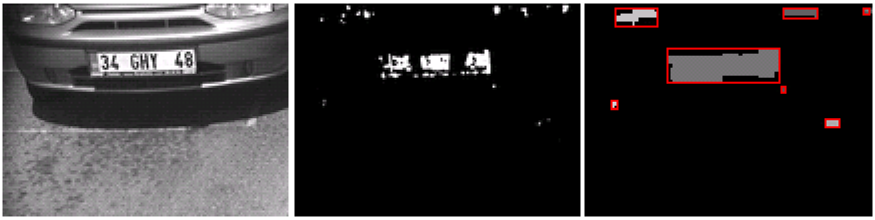
$$E = \sum_{n \in Q} \sum_{s \in C_n} \| I_s - q_n \|^2 \tag{3}$$

where $\{q_n\}$ is the set of quantization vectors and C_n is the set of pixels assigned to the vector q_n. Initially all pixels belong to the same class whose vector is the average of the image. Then the class is divided into two sub classes denoted by C_{2n} and C_{2n+1}. The vectors associated with these sub classes are chosen based on the second order statistics within the class

$$\begin{aligned} R_n &= \sum_{s \in C_n} I_s I_s^T \\ m_n &= \sum_{s \in C_n} I_s \\ K_n &= |C_n| \end{aligned} \tag{4}$$

Quantization vector (q_n) is assumed to be equal to the class mean:

$$q_n = \frac{m_n}{K_n} \tag{5}$$



(a) (b) (c)

Fig. 3. (a) Original Image, (b) Thresholded (Otsu) filter response, (c) Candidate plate regions each labeled with different color.

Class covariance matrix is given as

$$\tilde{R}_n = R_n - \frac{1}{K_n} m_n m_n^T . \tag{6}$$

When a class (C_n) is decided to divide into two classes, new class vectors (q_{2n}, q_{2n+1}) are computed. This computation requires the calculation of unit vector e_n which minimizes the expression.

$$\sum_{s \in C_n} \left((I_s - q_n)^T e \right)^2 = e^T \tilde{R}_n e \tag{7}$$

This is the largest eigenvalue of $\tilde{R}_n$. Once the unit vectors are obtained, the pixels belonging to the class C_n are assigned to C_{2n} or C_{2n+1} as follows

$$\begin{aligned} C_{2n} &= \left\{ s \in C_n : e_n^T I_s \le e_n^T q_n \right\} \\ C_{2n+1} &= \left\{ s \in C_n : e_n^T I_s > e_n^T q_n \right\} \end{aligned} \tag{8}$$

Splitting classes stops either when maximum vector number is reached or when the class variance is less than a predefined threshold.

Vector quantization explained above is applied only to the regions obtained by LPD system. Quantized image could be treated as n-ary image. Since we use two levels ($n = 2$), the resultant image is binary. Finally connected component analysis is applied to the quantized image to obtain the character segments.

4 Experimental Results

We have performed a series of experiments with real data where we demonstrate the robustness of our system and present the results in this section. The real data are provided by Multimedia Center at Istanbul Technical University. The image database contains vehicle (e.g., car, truck) images captured at daylight or night. We have made no assumption on the source of the plate (e.g., Turkey, Germany, Bulgarian, etc.), on the style, or on the format. We also performed experiments where there is more than one license plate in the image.

In our implementation, we first apply the Gabor filter at three different scales (9, 11, 15 pixels) and in four directions (0˚, 45˚, 90˚, 135˚) where large values indicate possible plate locations. We label each candidate plate region by using connected component analysis. Local vector quantization is applied over these regions. After local vector quantization, blob coloring process is applied to the quantized image to segment the characters and the segmented characters are labeled with different color.

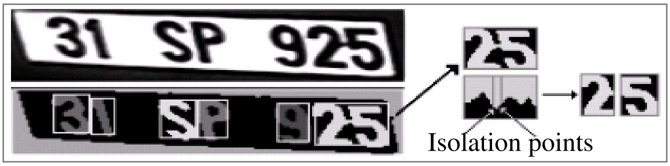


Fig. 4. Isolation of touching characters

We assume that each blob represents a single character and is not connected with any other object in the plate image. In practice, it is common to find digits connected to other digits that will appear as one big blob in the system. In the latter case, more complicated segmentation algorithms are needed to separate multiple characters into individual digits. Our expert system separates the connected character to individual characters by using vertical histogram of the blobs and other pre-defined rules. Fig.4. shows this segmentation process and the expert system gives the final decision. The expert system finally resolves any ambiguities associated with the segmented regions by using some local and geometrical rules as well as regular expressions of license plate character sequence.

The expert system compares the blob features with certain expected empirically calculated values. These features and rules are extracted based on experimental studies. Basic features of the blobs are;

- Blob area
- Number of blobs
- Blob height
- Blob width
- Blob position
- Distance between blobs

The expert system reduces the false alarm and output of the expert system is the bounding box for the license plates detected and their segmented characters.

Fig.5. shows four samples from the experimental results on 300 images of which 167 were taken day and the remaining were taken night conditions with various sizes, styles and forms of license plates. The resolution of these images ranged from 512×384 to 768×576 while the sizes of license plate regions in these images ranged from 173×37 to 211×47.

Fig. 5. Experimental results for five test images which include various sizes and forms of license plates.

Total computation time for a 512x384 pixels image was approximately 3.12 seconds on Intel® Pentium® 4, 1.4 GHz. The computation time depended on the image size and number of license plates in input image.

To evaluate the performance of LPD, detection metrics in [8] were used. In order to determine the performance of LPS, numbers of the correct characters were detected by the algorithm divided by the total number of actual characters in the test data set. Our license plate data set has 2198 characters. The actual number of characters was counted manually by visually inspecting all the test images. There are 2154 characters in the correctly detected licence plates. To evalute the performance of LPS we used only correctly detected license plates by the LPD. LPS and LPD performance results are shown in Table 1. These results indicate that the system is quite able to discriminate whether a given image contains a license plate and to produce a rough estimate of the plate.

Table 1. License plate detection and license plate character segmentation performance

	Rate	**Result**
LPD Performance	294/300	98 %
LPS Performance	2029/2154	94.2 %

5 Conclusions and Future Work

The results presented above have shown that our system is very effective in locating and segmenting the plate characters. However, the method is computationally expensive. For a 2D input image of size *NxN*, and a 2D Gabor filter of size *WxW*, the computational complexity of 2D Gabor filtering is in the order of W^2N^2, given that the image orientation is fixed at a specific angle. Future work will consider the way of alleviating the limitations of 2D Gabor filtering.

In conclusion, we presented a novel and robust approach for detecting and locating license plates in images and showed that it was capable of locating plate characters with high accuracy. As of our knowledge this is the first application of Gabor filters to license plate detection and license plate character segmentation problems. Our future work includes integration of this method with an optical character recognition system and analysis of the overall performance of the integrated system. We also seek cues for a fast implementation in order to apply the technique in real time.

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