Adaptive License Plate Image Extraction

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Abstract: *The paper represents the automatic plate localization component of a Car License Plate Recognition system. The approach concerns stages of preprocessing, edge detection, filtering, detection of the plate's position, slope evaluation, and character segmentation and recognition. Single frame gray-level images are used as the only source of information. In the experiments Israeli and Bulgarian license plates were used, camera obtained at different daytime and whether conditions. The results derived have shown that the approach is robust to illumination, plate slope, scale, and is insensitive to plate's country peculiarities. These results could be also usable for other applications in the input-output transport systems, where automatic recognition of registration plates, shields, signs, etc., is often necessary.*

Key words: *Car license plates, Image processing, Segmentation and Recognition, Input-output transport information systems*

1. INTRODUCTION

While the first industrial automatic systems of Car License Plate Recognition (CLPR) started emerging in 80s, cf. Sgurev, Gluhchev et al [1], an outburst of commercial systems occurred in 90s, cf. also [2, 3]. Nevertheless that a lot of CLPR systems are available in the market worldwide, the research and development still continues and new sophisticated solutions to plate localization, character segmentation and recognition appear. This is due to the growing demand for the automatic vehicle identification required for traffic control, border control, access-control, calculation of parking time and payment, search for stolen cars or unpaid fees, and the requirement for reliable identification at different lighting conditions, presence of random or structured noise in the plate, and nationality specific features, concerning plate's size and type of characters.

A system for automatic CLPR consists of a camera (color or gray level), frame grabber, computer and specially designed software for image processing and analysis. A system should be ready to work with alternative image acquisition equipment, as well as with previously or remotely captured and stored images. It should be capable of:

- working indoor and outdoor
- working in a wide range of illumination conditions
- being invariant to size, scale and stroke thickness
- being robust to broken strokes, printing defects, noise, etc.
- being robust to camera-car relative movement
- giving a real-time response,

as shown by Cohen et al [4], Kim et al [5], and Nelson [6].

A CLPR system can be conceptually considered as containing two separate processing stages:

- License Plate Localization (LPL)
- License Plate Character Recognition (LPCR).

In practice, cf. Hsieh et al [7], LPCR serves also as a verifier, providing an indication that the clipped image fragment, referred to below as a "plate candidate" at the LPL stage is the actual plate, otherwise LPL iterates attempting to find better candidates.

The most popular approach, which seems to become dominating since 2^d half of 90s, is based on edge detection, gradient and other variants of intensity derivatives, e.g. Kim [5], Jilin [8], and Lee [9]. These techniques are sensitive to noise and illumination variation, therefore they need to be supported or complemented by other methods.

This paper represents the LPL component of a CLPR system, which works with single frame gray-level images, obtained at different daytime and weather conditions, as an input. It is organized in the following way: Section 2 describes preprocessing procedures; Section 3 considers the image segmentation the effect of which is verified as described in Section 4. Section 5 presents some experimental results. Discussion and conclusion are included in Section 6.

2. PREPROCESSING FOR PLATE CANDIDATE IDENTIFICATION

The preprocessing has to improve the image and facilitate its analysis. Below, a series of preprocessing steps, involved in our research, is described in the order they are applied. Most of them can be considered heuristic modifications of well-known image processing techniques, e.g., cf. Sonka et al [10], and the paper accents generally on their joint application to the aims of LPL. Also, for reasons of readability, many experimental constants hereinafter are given as they are, i.e without any attempt for parametrization.

The original image might be quite large (up to 1M pixels and even larger), as the image size might vary depending on the image acquisition equipment in use, and require much processing work. Because of trade-off between the size and processing time, we first undersample the image to about 120 columns using simple and fast pixel decimation while preserving the original aspect ratio.

2.1. Vertical Edge Detection

There are two basic assumptions about the CLPR systems:

- plates are oriented horizontally and
- plates, which zone is characterized with relatively high density of sharp contrast alterations between the characters and plate's background, cf. Lee et al [9], and Huang and Suen [11].

Having these two assumptions in mind, we apply Roberts' edge operator to the log-intensity image in order to emphasize vertical edges (Fig.1b).

2.2. Rank Filtering

As shown in Fig.1b, there is a clearly visible cluster of high density of bright edges in the plate zone. To detect it, a horizontally oriented rank-filter of $M*N$ size (the horizontal size M is much larger than N) is applied to the whole image. Each image pixel is replaced with 80%-percentile of pixel intensity in the area covered by the filter mask. This step leads to the creation of a bright spot of ellipsoidal shape in the plate's zone (Fig.1c).

3. PLATE CANDIDATE SEGMENTATION

3.1. Vertical Projection Acquisition

The preprocessing step ends up with obtaining a vertical projection, as shown in Fig.1d. To decrease the random noise the projection is smoothed by a 5-element uniform filter, cf. e.g. [10].

3.2. Prime Clipping of the Plate

The forthcoming segmentation works in phases. The first stage consists in finding a horizontal strip loosely locked on the plate. To compute its vertical bounds, we find the y-coordinate for which the vertical projection $P_V(y)$, cf. Fig.1d, has a maximal value, i.e.

$$y_{plate} = Arg(\max_{0<y<Y}\{P_V(y)\}) \qquad (1)$$

Then the both bounds y_{top} and y_{bottom} of the plate image are found as:

$$\begin{aligned} y_{top} &= \underset{0<y<y_{plate}}{MaxArg}[P_V(y) = 0.2P_V(y_{plate})] \\ y_{bottom} &= \underset{y_{plate}<y<Y}{MinArg}[P_V(y) = 0.2P_V(y_{plate})] \end{aligned}, \qquad (2)$$

where Y is the image height (in pixels), and 0.2 is an experimental expert constant for the concrete case Y=125, cf. Fig.1d.

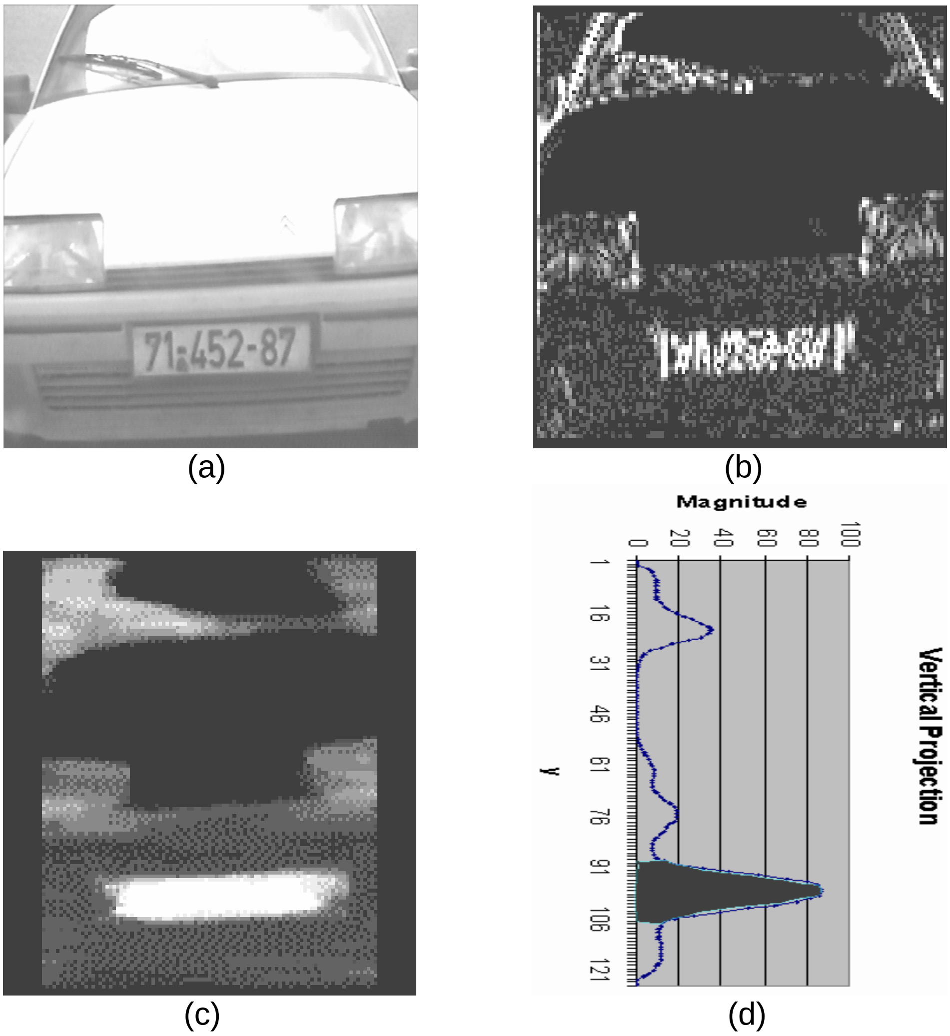


Fig.1. (a) Condensed original image; (b) vertical edges therein;
(c) the rank-filtered image; (d) the vertical projection $P_V(y)$.

3.3. **Plate Skew Evaluation**

After evaluation of the plate's vertical bounds according to (1) and (2), the strip is clipped from the image (cf. Fig.2a).

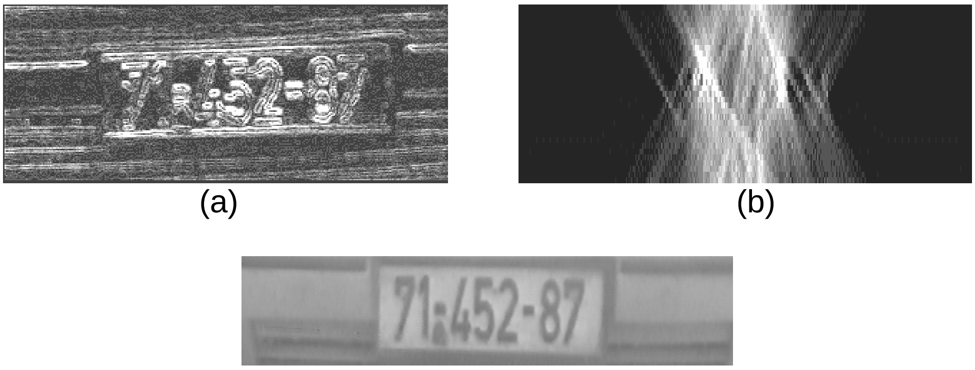
Due to the vehicle's position and orientation with respect to the camera, a plate zone might appear skewed. The skew may prevent LPL from accurately finding and clipping the plate zone, therefore the skew, if present, must be eliminated. The applied technique is similar to the one described by Srihari and Govindraju [12], where Hough transform (HT) is used for acquiring angular projections. Dealing with gray-level imagery in this work we have used Radon transform (RT) instead of HT. The following equation was found to be applicable to the radon space:

$$\theta_{plate} = Arg(\max_{\theta}\{\sigma[R(\rho)_\theta]\}) \quad , \tag{3}$$

where $\theta \in [-\theta_{start}, \theta_{end}]$, ($\theta_{start} = \theta_{end} = 8°$ was chosen for this research) and σ is a standard deviation, applied on $R(\rho)_\theta$, the initial image angular projection of the RT space $R(\rho,\theta)$ under θ, (cf. Fig.2b).

To save computation time and making the RT more robust for the plate skew measurement, we have modified it in the HT style, in accordance with Shapiro [13] and

Dimov [14]. Besides, the RT was applied to those edge pixels only, the intensity of which exceeded a certain threshold.



(a) (b)

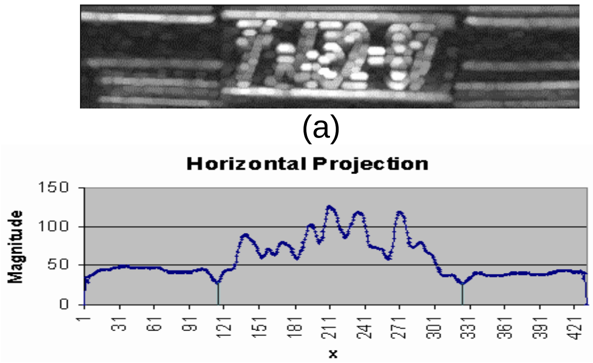
(c)

Fig.2. Skew detection and deskewing:
(a) extended image strip; (b) its Radon transform space $R(\rho,\theta)$, θ on vertical;
(c) deskewed image strip (skew of $\theta = -3°$ was detected)

Having θ_{plate} evaluated according to (3) and y_{top} , y_{bottom} determined from (2), the strip is cut from the original image and deskewed by rotating it by angle $\theta = -\theta_{plate}$ (cf. Fig.2c).

3.4. **Horizontal Segmentation**

The clipped and deskewed image is processed by horizontal edge detection operator. It is again possible to use rank filter but this will be a costly solution because this time the processed image is of original size. Following Huang and Suen [11], we use of a series of morphological erosions with primarily horizontally oriented structured elements would be much simpler and cheaper solution. The obtained result is shown in Fig.3a.



(a)

(b)

Fig.3. Horizontal segmentation and plate zone refinement:
(a) edge image after erosion;
(b) the horizontal projection $P(x)$ with left and right boundaries designated.

For the horizontal segmentation we evaluate first the horizontal projection $P(x)$, cf. Fig.3b, as a convolution with a filter of a length equal to the roughly estimated plate length. The position x_{plate} of the convolution maximum is obtained by analogy to y_{plate} , cf. (2). Then x_{plate} is used as a starting point for searching x_{left} and x_{right}, the horizontal plate boundaries. The search is based on the localization of significant gaps while moving from the x_{plate} position to the right for x_{left} , and to the left for x_{right} . More precisely:

$$x_{left} = \underset{0<x<x_{plate}}{MaxArg}[P_\Delta(x) < 0.005 \ \& \ P_L(x) < 0.5]$$
$$x_{right} = \underset{x_{plate}<x<X}{MinArg}[P_\Delta(x) < 0.005 \ \& \ P_R(x) < 0.5] \quad , \qquad (4)$$

where $P_\Delta(x) = \frac{1}{P_{total}} \sum_{j=x-\Delta}^{x+\Delta} P(j)$, $P_L(x) = \frac{1}{P_{total}} \sum_{j=1}^{x-1} P(j)$, $P_R(x) = \frac{1}{P_{total}} \sum_{x+1}^{X-1} P(j)$, $P_{total} = \sum_{j=0}^{X-1} P(j)$, *X* is the image width (in pixels), *Δ* defines the averaging interval (2*Δ*+1) for $P_\Delta(x)$, and 0.005 and 0.5 are experimental expert constants for the concrete case *X*=425, *Δ*=2, cf. Fig.3b.

The idea behind (4) is to find a *x*-coordinate with low enough magnitude, and not to "cut" while *x* is still within the plate area. Here is the place to use heuristics determined by the application constraints such as plate size, aspect ratio, etc.

4. PLATE CANDIDATE VERIFICATION

Ideally, a CLPR system should not impose any restrictions on image content. The background is entirely beyond developer's control and any prediction or assumption about the background behavior might lead to the localization failure. The exception is a smallest subset of CLPR tasks, when the system works indoors in such static environment as, say, a parking lot. Working outdoors in a non-predictable environment, a system often encounters situations when the actual plate is either not presented at all, or is present but is not necessarily the leading candidate. The verification stage aims at checking a given plate candidate feasibility. For this the following context-dependent conditions are tested: geometrical constraints, such as width, height, aspect ratio, and gray-level distribution considerations (the plate background is expected to be lighter than the characters). If the plate candidate passes all these tests, it is presented to the LPCR.

4.1. Cray-level Distribution Consistency Considerations

The edge-based approach, adopted in this work, does not differentiate between the intensity transition sign. Therefore, there is a need to distinguish between the regular and the reverse intensity situation, when characters are lighter than the background (Fig.4a).

(a)

(b)

Fig.4. A regular and a reverse intensity situation:
(a) a source image; (b) wrong plate candidate with dominating dark levels.

Our approach is based on image intensity analysis. First we try to separate the image into dark and light parts. The algorithm of Otsu [16] is applied for that purpose. In case of a feasible plate candidate there will be larger number of light pixels (intensities above the threshold), than those lying below. This condition is verified by comparing the threshold with the intensity median. The plate candidate is plausible when the intensity median of the plate zone is higher than the threshold.

When the test fails the current plate candidate strip is eliminated and the system goes back to the segmentation stage to look iteratively for the next plate candidate.

5. EXPERIMENTAL RESULTS

Extensive testing has been conducted with more than 150 Israeli and Bulgarian vehicles. Images have been captured from various distances and viewing angles. Image size has varied from 64K to 1M pixels. JPEG and PNG image compression was tried along with a raw uncompressed gray level imagery. Different daylight conditions were examined, from bright sunlight illumination to foggy winter half-darkness. Very frequently the plate zone has been in a shadow and the contrast of characters has been poor with regard to the plate's background. Situations of mixed illumination, where certain portions of the plate were shadowed, while the others were brightly illuminated, caused problems and sometimes led to rejection of the whole plate.

The true license plate zone was correctly located and approved on more than 90% of the images. The rest of the cases were rejected by one of the consistency tests. It is important to stress that there have been zero false positive errors, which explain the relatively high share of rejected plates due to the conservative tests while approving plate "candidates".

6. DISCUSSION AND CONCLUSION

The basic elements of a CLPR (Car License Plate Recognition) system are presented in this paper, generally accenting on the problems of LPL (License Plate Localization) instead of the LPCR (License Plate Character Recognition) therein. This reflects the LPL specifics of CLPR application, where the problems of LPCR are usually considered priori resolved by usage of conventional OCR (Optical Character Recognition) software.

The goal of the research is to investigate the possibility to create a comprehensive system for multinational vehicle identification based on the license plate recognition. In that case no additional hardware such as transmitters mounted on the vehicle or additional sensors are required. The preliminary results obtained on real data are quite satisfactory. They could be summarized as follows:

- Reliable verification of the plate candidate generated at the phase of localization is achieved
- Accurate plate segmentation under varying illumination and various image distortions is obtained.

In vast majority of classes the plate was contained into one of the detected prospective horizontal strips (plate candidates). Only few images of extremely poor quality (poor contrast and missing part of the plate) attempted more than three prospective strips. The conclusion is that in case of reasonably good images the above-described plate localization approach yields excellent results.

License plate imagery is equivalent to very low text scanning resolution and non-homogeneous background and lighting conditions in addition. Use of an RGB camera would allow higher precision of the plate's position detection and segmentation.

It should be mentioned finally that these results could be obviously extended to other applications in the input-output transport systems, where automatic recognition of registration plates, shields, signs, etc., is necessary, for instance, for the multi-modal transportation necessities, i.e. not only for cars, but for ships, trains, palettes, etc.

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