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Adaptive Multi-National License Plate Extraction

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Abstract. *The paper represents the automatic plate localization component of a multi-national Car License Plate Recognition (CLPR) system. The approach includes stages of preprocessing, edge detection, filtering, detection of plate's position, slope evaluation, character segmentation and recognition. Single frame gray-level images are used as the only source of information. In the experiments Israeli and Bulgarian license plate images obtained at different daytime and weather conditions were used. The results have shown that the approach is robust to illumination, plate slope and scale and is insensitive to plate's country peculiarities.*

Keywords: *image processing, segmentation, license plate recognition.*

1. Introduction

While the first industrial automatic systems of Car License Plate Recognition (CLPR) started emerging in 80-ies [17,5], an outburst of commercial systems occurred in 90-ies. Nevertheless that hundreds 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 variations;
- being robust to broken strokes, printing defects, noise, etc.;
- being robust to camera-car mutual position;
- giving a real-time response [2,10,14].

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

- License Plate Localization (LPL);
- License Plate Optical Character Recognition (LPOCR), including plate clip segmentation into characters.

In practice, LPOCR serves also as a verifier [6], 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 in an attempt to find better candidates. On its turn, LPL might be used to refine clipping at LPOCR stage, whenever required.

It would be tempting to base a CLPR system on one of the commercial "off-the-shelf" OCR packages, which are available today at very affordable price. Unfortunately, due to the complex image contents such OCR packages do not manage to segment the plate strip properly in very many cases. The explanation is straightforward: commercial OCRs are designed to address primarily a printed page and/or well-structured form processing and recognition. License plate imagery is characterized with multi-modal intensity distribution, low resolution of the characters, and significant, often unpredictable, noise factors.

Many authors have simplistically viewed the LPL problem as a dichotomy problem between the light background and the dark characters [3,16] resolved via global binarization thresholding. This approach would only work in a constrained environment and uniform illumination. S r i d h a r et al.[20] used global binarization combined with gray scale morphology aimed at cleaning the image.

Another popular approach, which seems to become dominating since 2nd half of 90-ies, is based on edge detection, gradient and other variants of intensity derivatives [9,10,11]. These techniques are sensitive to noise and illumination variation, therefore they need to be supported or complemented by other methods.

The LPL task of the only research that recognized importance of incorporating a multi-national support into CLPR systems [11] was largely facilitated by using an infrared sensor to trigger image capture. The latter causes the LP distance from the camera and LP position within the frame to be quite stable. In addition to that the infrared camera was used.

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. The system is robust to illumination, plate slope and scale and is insensitive to plate's country peculiarities.

The paper is organized in the following way: Section 2 overview the whole system design; Section 3 describes preprocessing procedures; Section 4 considers the image segmentation which ends up with issuing plate candidate clips, the feasibility of which is verified by a series of tests described in Section 5. In Section 6 some experimental results are presented. Directions for the further improvement of the localization accuracy are outlined in Section 7.

2. License plate localization: an overview

The LPL stage goal is to clip the plate as tight as possible while preserving the information, necessary for the further recognition, intact. The goal is achieved via applying a series of processing steps, as with every step we try to eliminate as much irrelevant information as possible and focus on what would help detecting the license plate. Computation efficiency is also taken into account. As noted in Section 1, an important part of the LPL functioning is its collaboration with the LPOCR, which is a part of the verification module, see Section 5. The LPL flow-chart is presented in Fig. 1.

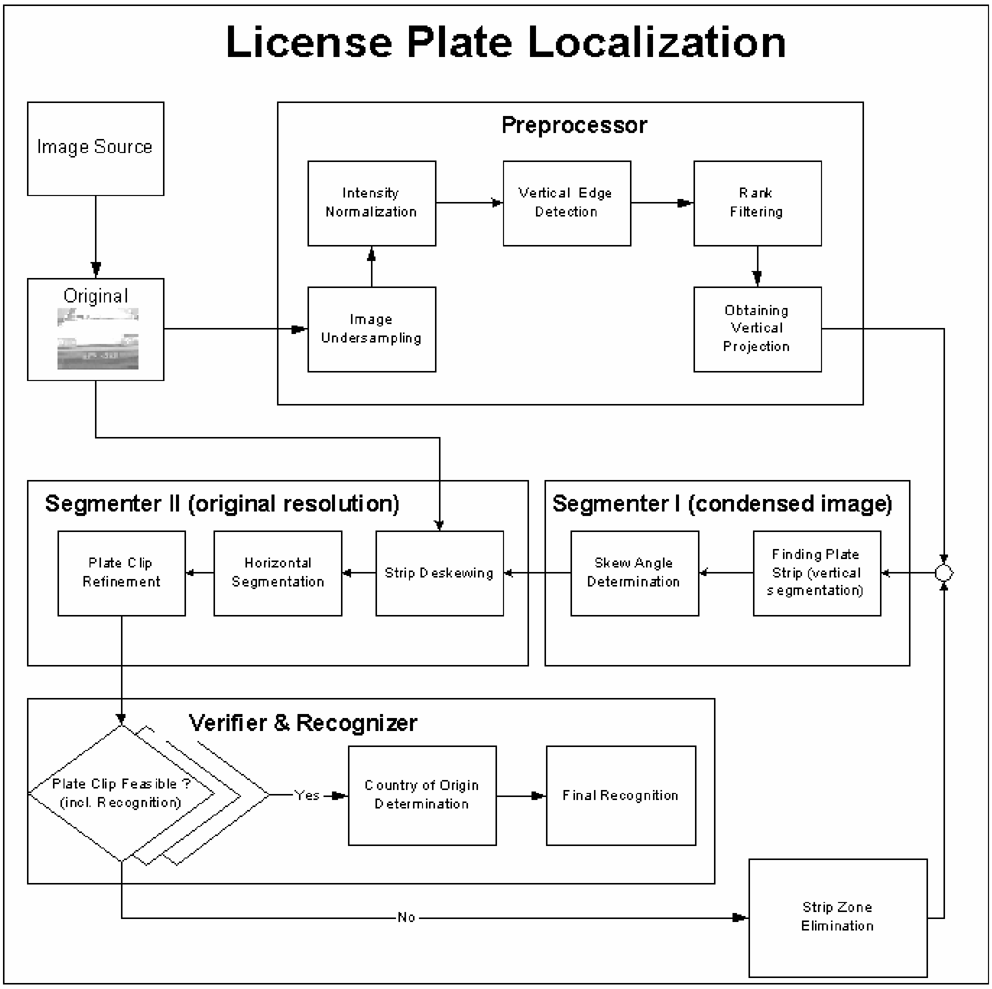


Fig. 1. LPL of a CLPR system

3. Preprocessing

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 in which they are applied.

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 the 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.

One of the important requirements to the LPL technique is the ability to work at varying illumination both indoor and outdoor. Due to various reasons the plate zone might not be the brightest or the most contrast place in the image. To diminish the impact of that, the image undergoes a pixel-wise intensity normalization transform, which substitutes the original intensity with its logarithm.

3.1. Vertical edge detection

One of the basic assumptions of CLPR systems is that the plates are oriented mostly horizontally. Another assumption, based on numerous observations, is that the plate zone is characterized with relatively high density of sharp contrast alterations between the characters and plate's background; see e.g. [10,6]. Many abrupt intensity changes in a car image might exist outside the plate zone but it is less likely to have there as many as 10-15 such sharp intensity changes that are quite close to each other. Having these two assumptions in mind, we apply Roberts' edge operator to the log-intensity image in order to emphasize the vertical edges. As a result, the vertical edges are stressed while the rest of the image looks quite flat see Fig. 2b. It could be anticipated that major impact will be produced in the license plate area.

3.2. Rank filtering

As seen in Fig. 2b, there is a clearly visible cluster of high density of bright edges in the plate zone. To materialize this observation potential, another intermediate step is needed. Namely, a horizontally oriented rank-filter of $M \times N$-element size (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. (The intensities are sorted in an ascending order where 0 corresponds to the black level). This step leads to the creation of a bright-elongated spot of ellipsoidal shape in plate's zone; while the low intensity pixels prevail on the rest of the image, see Fig. 2c.

3.3. Vertical projection acquisition

The preprocessor ends up with obtaining a vertical projection $P(y)$, as shown in Fig. 2d. This projection is smoothed by 5-element uniform weight filter to decrease the random noise influence.

4. Plate segmentation

4.1. Prime clipping of the plate

The forthcoming segmentation works in phases. The first stage consists in finding a vertically bounded horizontal strip loosely locked on the plate. To compute its vertical bounds we first find y-coordinate for which has maximum value, i.e.

$$y_{max} = \text{ArgMax}\,[P(y)]. \tag{1}$$

Then, the bound y_{top} is found as a first y coordinate when moving from y_{max} up for which the following condition is satisfied:

$$y_{top} = \text{Arg}\,[P(y) \leq 0.2P(y_{max})];\ \text{where}\ y = y_{max}, y_{max} - 1, \ldots, 0. \tag{2}$$

Note, that $y_{top} < y_{bottom}$ for raster images stored in computer memory. is evaluated similarly by moving downwards, i.e. increasing in (2). The weight coefficient 0.2 was empirically chosen so that the most of the projection volume remains within the zone between y_{top} and y_{bottom}, so the “over-cut” situations are prevented.

4.2. Plate skew evaluation and deskewing

After the evaluation of plate’s vertical bounds according to equations (1) and (2), the such bounded strip is clipped from the image, see Fig. 3a. Due to the vehicle tilt, vehicle position and orientation with respect to the camera, etc, a plate zone might appear skewed in the image, sometimes heavily. The skew is a disturbing factor for

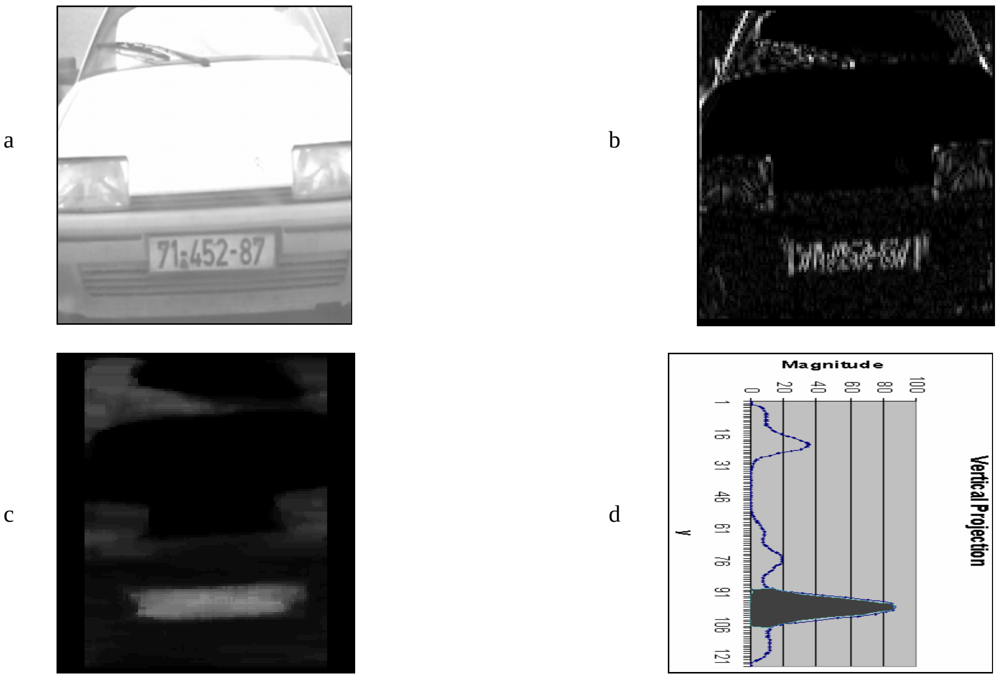


Fig. 2. Original image of 467?500 pixels condensed to a size of 117?125 pixels (a); stressed vertical edge image (b); rank-filtered image (c); vertical projection with the plate strip shown in dark gray (d)

reliable CLPR functioning as it may prevent LPL from accurately finding and clipping the plate zone. Thus, the skew elimination processing is incorporated.

A technique used for detecting the skew is similar to the one applied in [21], in which Hough transform (HT) served as a tool for acquiring angular projections of a printed black-and-white document. Dealing with gray-level imagery in this work we have used the Radon transform (RT) instead of the HT. In an attempt to measure the skew, the following equation, inspired by [21], was found applicable to the Radon space in this work context:

$$\theta_{\text{plate}} = \mathrm{ArgMax}\left[\sigma\{R(\rho)_\theta\}\right], \tag{3}$$

where $\theta \in \left[-\theta_{\text{start}}, \theta_{\text{end}}\right]$, ($\theta_{\text{start}} = \theta_{\text{end}} = 10°$ was chosen for this research), σ is a standard deviation, $R(\rho)_\theta$ is the angular projection under θ.

Sometimes, the clipped as described in Section 4.1 strips are too narrow due to the reduced resolution and there might not be enough "evidences" to that the RT or HT will reliably determine the skew, therefore we cut the plate strip from the original image for the sake of RT/HT, see Fig. 3a. The efficiency is less critical because the analyzed strip is relatively narrow.

Still, one should have in mind that the RT is more computationally expensive than HT. The method combining RT applicability to gray-level imagery and its accuracy with the relative efficiency of the HT can be found in [18, 22]. In this work, we have modified the RT in the HT style; attempting to save computation time and making it more robust for the plate skew measurement. Namely, the RT was applied to those edge pixels the intensity of which exceeded a certain threshold.

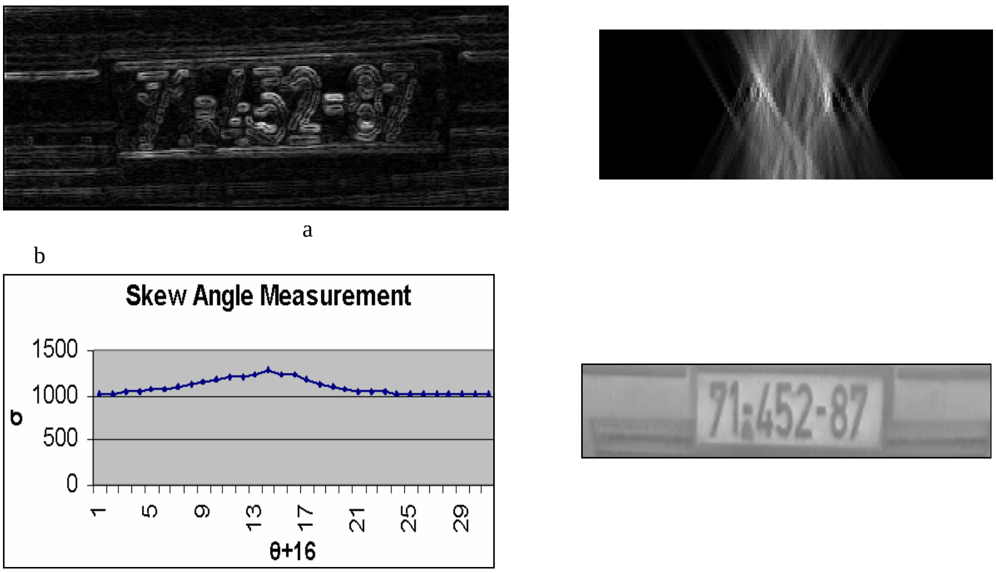


Fig. 3. Skew detection and deskewing: extended image strip with horizontal edges emphasized (a); Radon transform space of (a), θ is a vertical axis (b); dependency of σ versus θ (is shown in positive range of angles) (c); deskewed image strip of original resolution (skew of –3° was detected, i.e. θ = 13° on the graph) (d)

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 $-\theta_{plate}$. Piece-wise linear interpolation is used to compute the deskewed image intensity, see Fig. 3d. We have not investigated "nearest neighbor" interpolation scheme, which is simpler and faster. Deskewing is applied only if θ_{plate} is not equal to zero, otherwise the strip is clipped from the original image "as is" according to y_{top}, y_{bottom}. One may decide not to deskew the slightly skewed images of say $|\theta_{plate}|<\theta_{thresh}$, where θ_{thresh} is a threshold angle, which could be set to, say, 1°.

4.3. Horizontal segmentation

The original image, clipped and deskewed as shown in Fig. 3d, is processed by horizontal edge detection operator, see Fig. 4a. We would desire to get a bright spot on the edge image, which later would allow projecting it and reliable decision making upon the projection behavior. It is again possible to use rank filter as it was done at the stage of vertical segmentation. This time, however, we encounter the image of the original size, and rank filter would be a costly solution, even if it were applied to a narrow vertically bounded strip. Much simpler and cheaper solution is to use a series of morphological erosions [6] with primarily horizontally oriented structured elements. A result of such processing is shown in Fig. 4a.

The horizontal segmentation is accomplished in two phases. First, the horizontal projection $P(x)$ is obtained and convolved with a filter of a length equal to the roughly estimated plate length. The maximum of convolution x_{max} is then obtained similarly to y_{max} in (2) and used as a starting point for searching the right and left plate boundaries. This search is in fact the second phase of the horizontal segmentation and is based on the localization of significantly wide gaps while moving from the convolution maximum x-coordinate outwards, see Fig. 4b. Gaps on the edge image will correspond to valleys in the projection, so we need detecting two such gaps x_{left} and x_{right} being situated from the left and right of the plate zone, respectively; x_{max} is obviously expected to belong to the plate zone. The adaptive search of x_{left} and x_{right} is described below more formally.

To be less dependent on the local noise we require a certain minimum width for these gaps, say, l_{gap}. Let $P_{total} = \sum_{x=0}^{N-1} P(x)$ be the total horizontal projection volume. Let define a gap "power" $P(x)_{gap}$ for a given x coordinate as the cumulative intensity of hypothesized gap's projection of l_{gap} width, i.e. $P(x)_{gap} = \sum_{j=x-l_{gap}/2}^{x+l_{gap}/2-1} P(j)$. Let define also $P(x)_{rest\_right} = \sum_{j=x+1}^{N-1} P(j)$, which expresses the cumulative "power" of the projection lying from the right-hand side of a given x-coordinate. We introduce then two adaptive thresholds $T_1 = w_1 P_{total}$ and $T_2 = w_2 P_{total}$ depending on the projection volume. The horizontal coordinate of the strip x_{left} should satisfy the following conditions:

$$x_{left} = \mathrm{Arg}[P(x)_{gap} < T_1 \text{ and } P(x)_{rest\_right} < T_2], \quad (4)$$

where $x = x_{max} - 1, x_{max} - 2, \ldots, 0$. As in the vertical projection case, here the current gap candidate coordinate x moves from x_{max} to the left, i.e. towards $x = 0$ seeking the a

b

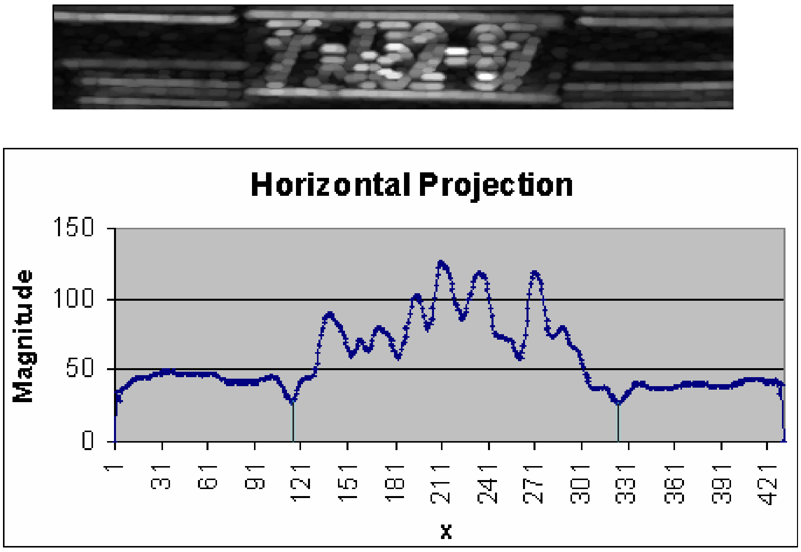


Fig. 4. Horizontal segmentation and plate zone refinement: edge image after erosion operations (a); horizontal projection of (a) with left and right boundaries designated (b).

first for which (4) conditions are satisfied. The gap power coefficient w_1 was set to 0.005 in this research; while the "rest right" power coefficient $w_2 = 0.5$. The idea behind (4) is to find an *x*-coordinate with low enough gap power, and ensure that there is enough power from the right in order not to invade the plate area. Similarly, the right plate boundary x_{right}, as $P(x)_{rest\_left}$ is used instead. Here is the place to use heuristics determined by the application constraints such as plate size, aspect ratio, etc.

5. 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 small subset of CLPR tasks, when the system works indoors in such static environment as, say, a parking lot. In the latter case the system might "learn" the background during the setup, and the plate localization goal becomes facilitated to a large degree. Otherwise, the system must be ready to face any random combinations of pixel intensities in the background. As to the foreground, i.e. the plate, it might not be present in many of the frames at all, which must be clearly and reliably indicated by the system.

Working outdoors in a non-predictable environment, a system often encounters situations when the actual plate is present but is not necessarily the leading candidate. The verification stage aims at checking a given plate candidate feasibility.

Implementation-wise, there are several context-dependent conditions that should be satisfied in order to approve a plate candidate:

- Geometrical constraints, such as width, height, aspect ratio
- Gray-level distribution considerations (the plate background is expected to be lighter than the characters [1])

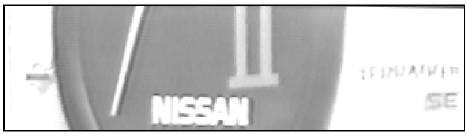
If a plate candidate passes all these tests, it is presented to the LPOCR for ultimate approval. Noisy patterns which pass occasionally the previous tests are filtered out at this stage, see e.g. [12]. An example of verified and approved plate candidate is presented in Fig. 6g. LPOCR detailed description lies beyond this paper scope.

5.1. Gray-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, see e.g. Fig. 5a.

Our approach is based on image intensity statistics analysis. The statistics are derived from the intensity histogram. Firstly, we try to separate the image into the dark and light modes by finding a global binarization threshold. Otsu algorithm [15] is applied for that purpose. If the binarization threshold is correctly determined, we expect that a feasible plate candidate will have a larger number of light pixels, i.e. of intensities, above than the threshold, than those laying below. Secondly, this condition is verified by comparing the binarization threshold with the intensity median. The plate candidate is plausible when the intensity median of the plate zone is significantly lighter than the threshold. The plate candidate from Fig. 6f passes geometric consistency tests, but it is rejected on the gray-level consistency test, because its median is much darker than the threshold.

a



b

Fig. 5. A source image (a); wrong plate candidate with dominating dark intensity levels, rejected by the gray-level consistency test (b)

5.2. Verification test failure

As shown in LPL workflow see Fig. 1, when one of the tests fails, the current plate candidate strip is eliminated from the vertical edge image and the system goes back to the segmentation stage to look iteratively for the next plate candidate. A system setup parameter sets the maximum number of iterations allowed.

Instead of blackening the failed plate candidate zone on the vertical edge image, we rather set to zero the corresponding bins on its projection, which is much faster

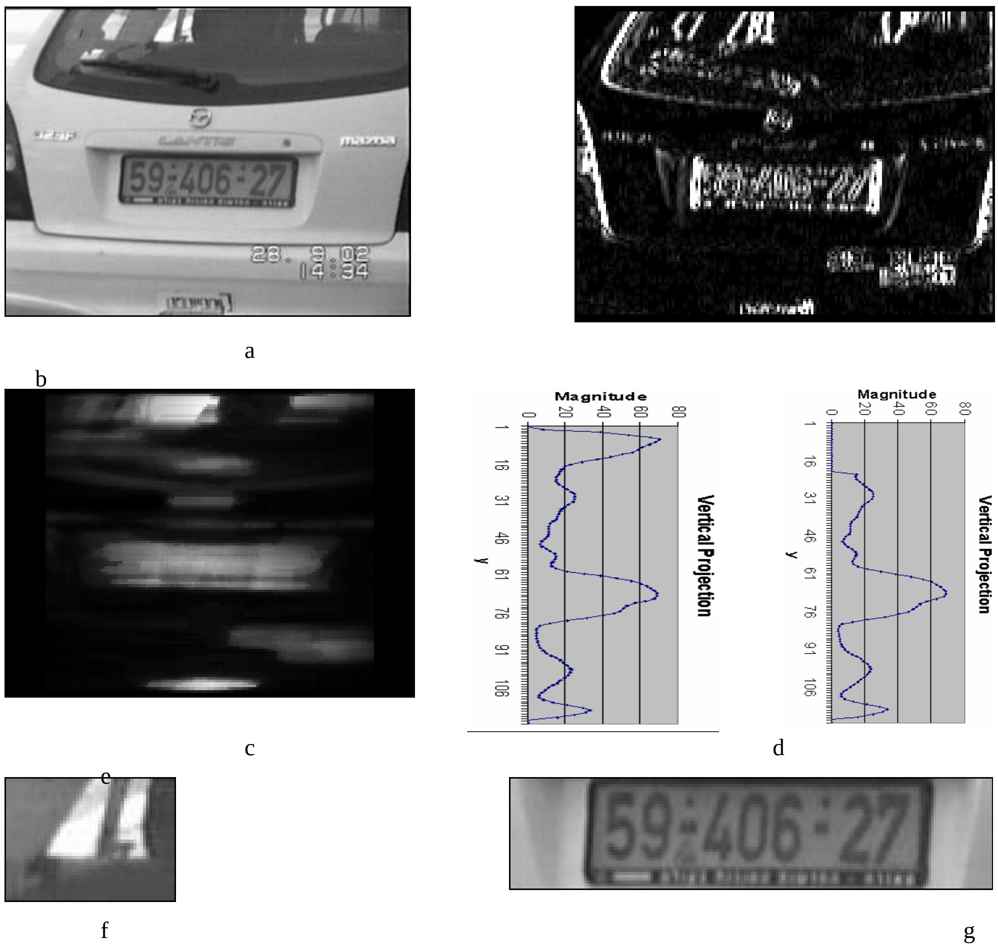


Fig. 6. Illustration of the iterative LPL scheme: image from [2] of original size of 320?240 undersampled to 160?120 (a); its vertical edge image (b); image after the preprocessing (c); vertical projection of (c) (d); same after zeroing the strip of the rejected plate candidate from (f) (e); proper license plate found at the second iteration (g)

and handier. The next iteration works with the manipulated projection and finds next maximum as shown in Fig. 6e and Fig. 6g.

The method of manipulating projection bins in the case of plate candidate rejection has a certain disadvantage compared to tackling the vertical edge image [10]. By zeroing projection bins, we, in fact, eliminate the whole strip between the left and right image boundaries, which is good enough for the vast majority of cases.

6. Experimental results

Extensive testing has been conducted with more than 120 Israeli and Bulgarian vehicles. Images have been captured from various distances and viewing angles. Image size has varied from 64K to 1M pixels. JPEG image compression was tried along with a raw uncompressed gray level imagery. Intensity depth was in the range between 32

(4 bits) and 256 (8 bits) gray levels. 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 background. The system was found quite robust to all above-mentioned factors. 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 at the verification stage. It is important to stress that there have been zero false positive errors, which explains the relatively high share of rejected plates due to the conservative tests while approving plate "candidates". Proprietary OCR was necessarily activated among the other verifier tests and some of the plates were mistakenly rejected due to OCR's imperfections.

7. Discussion and conclusion

The basic elements of a CLPR system including plate location, character separation and recognition are presented in this paper. The goal of the research is to investigate the possibility to create a comprehensive system for multi-national vehicle identification based on the license plate recognition. In that case no additional hardware, such as e.g. transmitters, mounted on a vehicle, and responders will be required.

Although, commercial OCR packages cannot serve as a "magic wand" for a CLPR system (see Section 1), they could be very useful after the segmentation and proper character separation. Then, a relatively high read rate could be expected. It is difficult to estimate how high the read rate would be for the plate characters. Good OCR programs are capable of reading scanned pages of a reasonable resolution and quality with up to 99% and even higher [13]. License plate imagery is equivalent to very low text scanning resolution, additionally hindered by a non-homogeneous background and lightning conditions. Still, at least on most readable by a human eye plates, we could expect read rate levels of 90% and higher. Such experiments are on going. 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;
- Satisfactory character recognition accuracy is reached.

The images were captured under different weather and season conditions, daytime, surrounding scenery, different distance between the camera and the vehicle, plates in normal position and tilted ones, presence of structured noise like screws, flags etc. In vast majority of cases 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 first detected candidate was rightly approved by the verifier for about 60% of the images. The conclusion is that in case of reasonably good images the above-described plate localization approach yields excellent results.

Further directions of the research lay in applying techniques known as “multi-expert” combination, or simply “voting” in a context of conventional OCR/ICR systems [7]. Use of an RGB camera with a priori knowledge about the plate background/ foreground colors available would allow higher precision of the plate segmentation. Finally, applying the algorithm to sequential frames of the video stream captured for a given plate, i.e. the multi-frame setup would yield an additional gain in accuracy [1].

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Адаптивно извличане на многонационални регистрационни номера на коли

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(Р е з ю м е)

Статията разглежда проблема за автоматичното локализиране на многонационални регистрационни номера в една система за разпознаване. Подходът включва етап на предварителна обработка, откриване на граници, филтрация, откриване на положението на регистрационния номер, оценка на наклона, сегментация на символите и разпознаване. Източник на информация са изображения с различни нива на сиво. В експеримента са използвани израелски и български регистрационни номера, получени при различни условия на осветление и различни климатични условия. Резултатите показаха, че подходът е устойчив към изменения в осветлението, наклона на табелката, изменения в мащаба на символите и е нечувствителен към характерните за страната особености.