

INVESTIGATION OF THE METHODS OF AUTOMATIC NUMBER PLATE RECOGNITION

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The principles of automatic symbol recognition on the number plates at the low resolution of the source image have been investigated in this work. Various methods of image enhancement, symbol segmentation on the number plates as well as classification and symbol definition for the data of low resolution camera, have been analysed here.

Keywords: localization, optical symbol recognition, segmentation, detection, image enhancement methods, computer vision, vehicles

Introduction

Many technical and information industries, related to the information acquisition, processing, storage and transmission, are increasingly oriented to the development of the systems, in which the information has the mode of the image [1]. Image processing automation task remains relevant to the present day, as it is widely used in the information systems, where fast and on-line data processing within 24 hours, without human intervention is often required. The outstanding examples of such industries are security companies that provide services of monitoring, automatic tracing, violation recording, etc. It is also worth noting that the optical symbol recognition on the images is very important in the workflow automation systems, where the control process is often based on machine-readable documents [1]. Text recognition is also widely used for the scanned books and documents converting in electronic form, which makes possible text editing, word or phrase search, recordkeeping in a compact view, as well as data analysis for its further processing (for example, translation) [2].

Currently, there is no perfect text and symbol recognition method according to their images. Accurate printed text recognition can only be achieved in the relation to correct images, which, for example, were obtained by scanning of a paper document [2, 3].

There was a task to research and develop algorithms for the automatic number plate recognition. This includes analysis of image enhancement procedures by using filters [3], segmentation on the number plate [4], as well as the recognition of the determined symbols [2, 5, 6, 7].

1. Image Pre-Processing

The algorithms of the original image processing with the view of quality improvement are analysed [2, 3, 8]:

- Contrast improvement by the means of power-mode conversion.
- Sharpening spatial filters.

Variety of approaches to image enhancement is divided into two categories: processing methods in the spatial domain (spatial methods) and processing methods in the frequency domain (frequency methods) [2, 3]. The term of spatial domain relates to the image plane as such, this category combines approaches, based on direct image pixels manipulation. In turn, the processing methods in the frequency domain are based on the signal modification, generated by the application of Fourier transform to the image. This work considers only the spatial methods.

Contrast enhancement by the means of power-mode conversions

In order to use binarization and simplify segmentation and identification process in future, it's necessary to free the image from background. Therefore, you need to fade out the background, at the same time keeping marked symbols on the number plate.

It's possible to use contrast enhancement algorithms for such problem. Contrast enhancement may cause exposure in the areas of high brightness, which verge on dark parts.

For the purpose of such contrast enhancement mechanism, power-mode conversions were used. These conversions are of the form

$$s = c \cdot r^\gamma, \tag{1}$$

where c and γ are positive constants. Sometimes, the previously mentioned equation is written as

$$s = c \cdot (r + \varepsilon)^\gamma, \tag{2}$$

in order to introduce bias, and exclude zero value at the output. In this work the realization based on the formula (1), is going to be considered.

It is evident on the basis of equation (1) that when $c = 1$ and $\gamma = 1$, our original image will not be subjected to any changes. Therefore, let us take these values as critical points, and we will change the value of only one parameter, in turn, leaving the second parameter equal to one.

To estimate the intensity levels of pixels, the brightness histogram is being used.

Brightness histogram – is a graphical display of quantitative characteristic of pixel intensity (brightness) probability distribution.

The coefficient γ is showing the power, so it will exponentially change the value of pixel brightness.

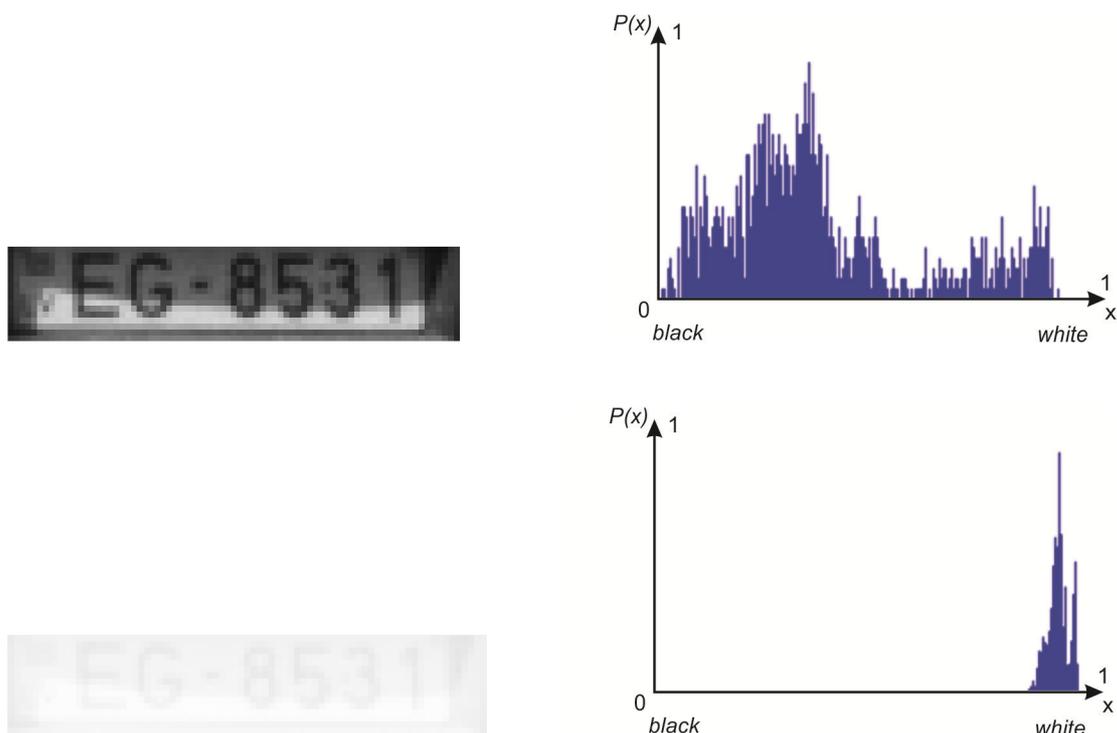


Figure 1. The original image and the use of contrast filter with the parameters $c = 1$ and $\gamma = 0.04$

On the basis of Figure 1 we can conclude: the less the value γ is, the brighter the picture is. The brightness histogram shows that all pixel intensities took their positions in the bright region, and they have a small range of values. Let's see then how much does the image change, when the coefficient γ is larger than one. Let's take the value of $\gamma = 10$.

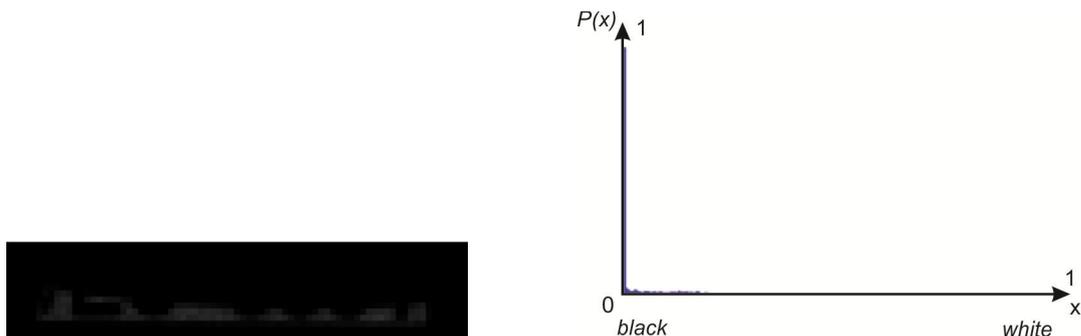


Figure 2. The use of contrast filter with the parameters $c = 1$ and $\gamma = 10$

As it is clear, our initial image became almost black. The further increase in the coefficient γ will be useless; in this case the entire image will be painted over with black pixels.

While analysing the equation (1), it is clear that if the value is $c < 1$, then by dividing the initial pixel brightness r , we will receive small s values, which should result in darkening of the image. Therefore, if $c > 1$, the output image will be brighter than the original at the entry, as the entire pixel intensity values will increase. As the maximum pixel brightness value equals to 1, we can only apply condition $c < 1$ to the coefficient, as the multiplication of 1 by the larger number will result in the image breakdown, and at the output there will be no image at all.

By virtue of the fact that transitions from black to white can be achieved by using only one coefficient γ , it will be modified in this work, and the coefficient c in all experiments will be equal to 1.

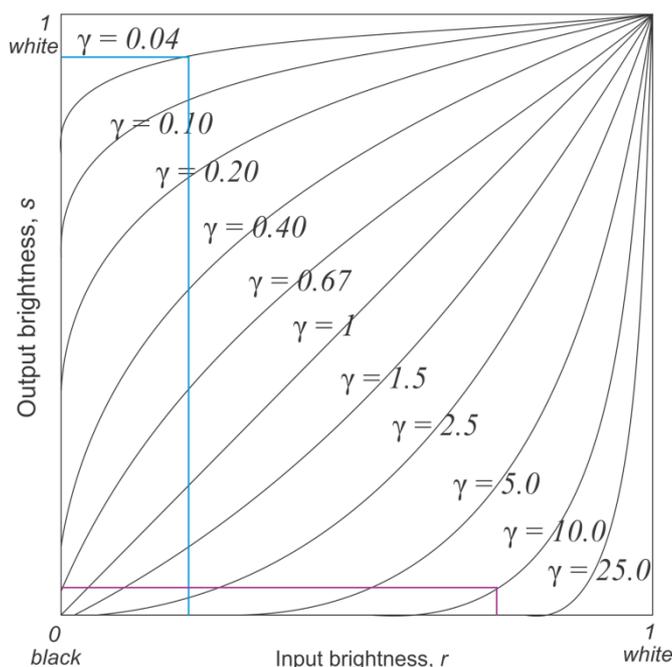


Figure 3. Graph of equation $s = c \cdot r^\gamma$, for different γ values (the constant $c = 1$) [2]

Figure 3 shows that the obtained values for $\gamma > 1$ are exactly the opposite of those, obtained when $\gamma < 1$. The figure also shows the cases that have been described above.

It was observed that before the sharpness improvement procedure it's necessary to fade out the background on the number plate (to make it lighter). But if to increase the contrast, the symbols on the number plate will also become lighter along with the background lighting. If the very bright image is being applied to the input of the algorithm to improve sharpness, it cannot distinguish symbols as fine details, as they will simply merge with the background. So, it was proposed to keep the image of the number plate to a neutral grey colour, where the background and symbols would have nearly the same

brightness. Symbols in this case will still have to stay darker in the image, and possible exposures will not be dangerous, as the maximum value in the brightness histogram will fall on the area of midpoint $[0, 1]$ of intensities. It worth noting that we are not interested in the extreme point, which falls exactly on the midpoint of intensities, the peak should gravitate to the light colour by approximately 30% from the middle of the whole scale. This ensures the greater background lighting.

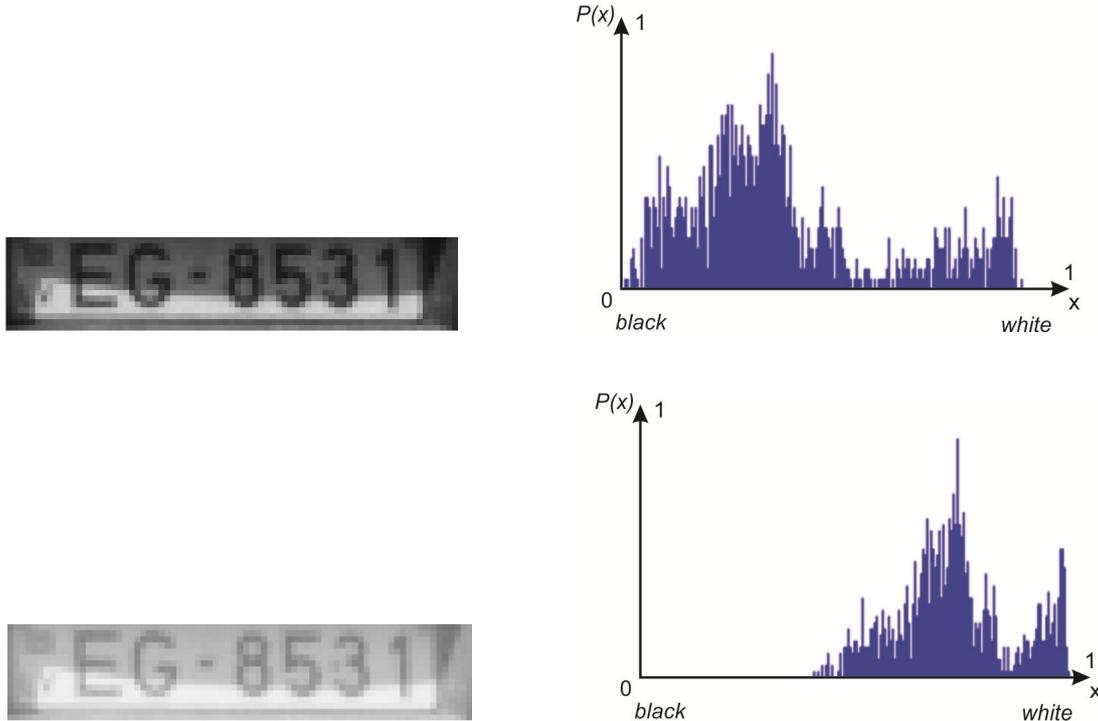


Figure 4. The original image and the result of the use of contrast filter manual adjustment with parameters $c = 1$ and $\gamma = 0.4$

After the contrast enhancement the light image was obtained, on which are still clearly visible symbols of the number plate. Then, the image after such processing is being applied to the input of the sharpening method.

Sharpening spatial filters

The sharpening is the enhancement of fine details or their quality improvement. In this work the sharpening filter, based on the second derivative, was implemented [2, 3, 6].

The first derivative of univariate function $f(x)$ is defined as the difference of values of neighbouring elements:

$$\frac{df}{dx} = f(x + 1) - f(x). \quad (3)$$

The analogous method is used for determination of the second-order derivative. This is the difference of values of neighbouring elements of the first derivative:

$$\frac{d^2f}{dx^2} = f(x + 1) + f(x - 1) - 2 \cdot f(x). \quad (4)$$

If to mark out a row in the image, and to calculate the first-order and second-order derivatives, then by comparing their responses, the following can be noted [2, 3]:

1. The first-order derivative usually results in thicker contours.
2. The second-order derivative provides a response of a greater value to the fine details – both at isolated points and the fine lines.

3. Response value of the first-order derivative with a gradual increase in brightness is generally higher at the beginning of the increase than the value of the second-order derivative. Therefore, there is a thickening of the contours.
4. On the contours with clear transition from brightness to another one, the second-order derivative provides a double response. That's why it intensifies the fine details in a greater degree.

Since we are working in two-dimensional space, the image processing should not be dependent on any moving direction in the present image. In the sharpening method implementation the concept of the mask is often being used. The mask is applied to the image, as a filter or sliding window, by modifying the central element of the selected area by means of its surrounding values of the brightness of the neighbouring pixels, as well as the coefficients of the mask itself. The very important is the fact that the mask should be *isotropic filter*, i.e., the result of the use of filter should not be dependent on the processing direction. Then, isotropic filters are stable to rotation; it means that by rotating the image and applying the filter we should obtain the same result as without rotation.

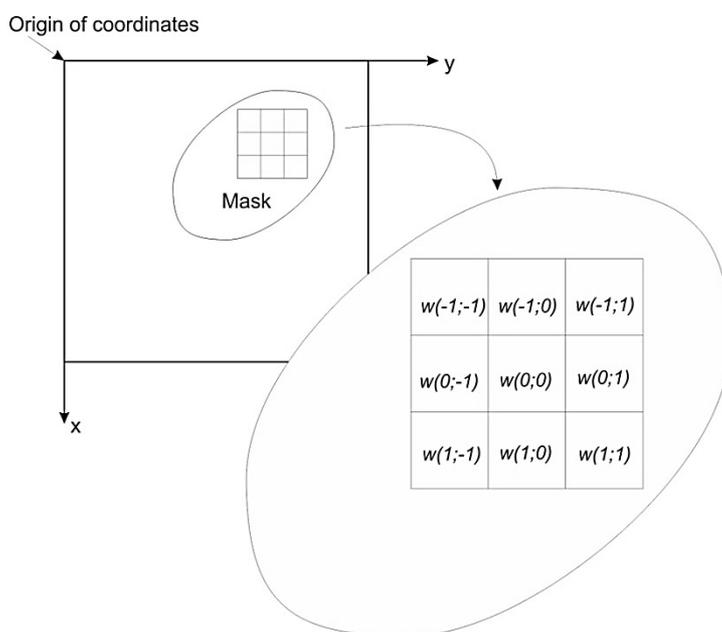


Figure 5. Filtering generation scheme [2]

As part of this work the *Laplace operator (Laplacian)* has been used [2], as it is an isotropic operator, and may be easily implemented. For the work with two-dimensional pixel array (a function of two variables $f(x, y)$), the Laplacian is defined as

$$\nabla^2 f = \frac{d^2 f}{dx^2} + \frac{d^2 f}{dy^2}. \quad (5)$$

In order to apply the equation (5) in the image processing, it should be led to the discrete form. Let's rewrite the formulas (3) and (4) for two variables, as we are working with the image

$$\frac{d^2 f}{dx^2} = f(x+1, y) + f(x-1, y) - 2f(x, y). \quad (6)$$

$$\frac{d^2 f}{dy^2} = f(x, y+1) + f(x, y-1) - 2f(x, y). \quad (7)$$

So, by substituting values $\frac{d^2 f}{dx^2}$ and $\frac{d^2 f}{dy^2}$ in the equation (5), we obtain the discrete formulation of the two-dimensional Laplacian.

$$\nabla^2 f = [f(x+1, y) + f(x-1, y) + f(x, y+1) + f(x, y-1)] - 4f(x, y). \quad (8)$$

Obtained equation (8) can be represented in the form of a mask, which is shown on Figure 6.

0	1	0
1	-4	1
0	1	0

Figure 6. Filter mask, used for the purposes of discrete Laplacian

Since the Laplacian is the second-order derivative, its application lays emphasis on the breakups of the brightness levels in the image and suppresses the areas with weak brightness changes.

To generalize the algorithm of the use of the Laplacian for the sharpness improvement, the following formula is being applied (9).

$$g(x, y) = \begin{cases} f(x, y) - \nabla^2 f(x, y), & \text{if } w(0, 0) < 0 \\ f(x, y) + \nabla^2 f(x, y), & \text{if } w(0, 0) \geq 0 \end{cases} \quad (9)$$

$w(0, 0)$ – the value of central mask coefficient.

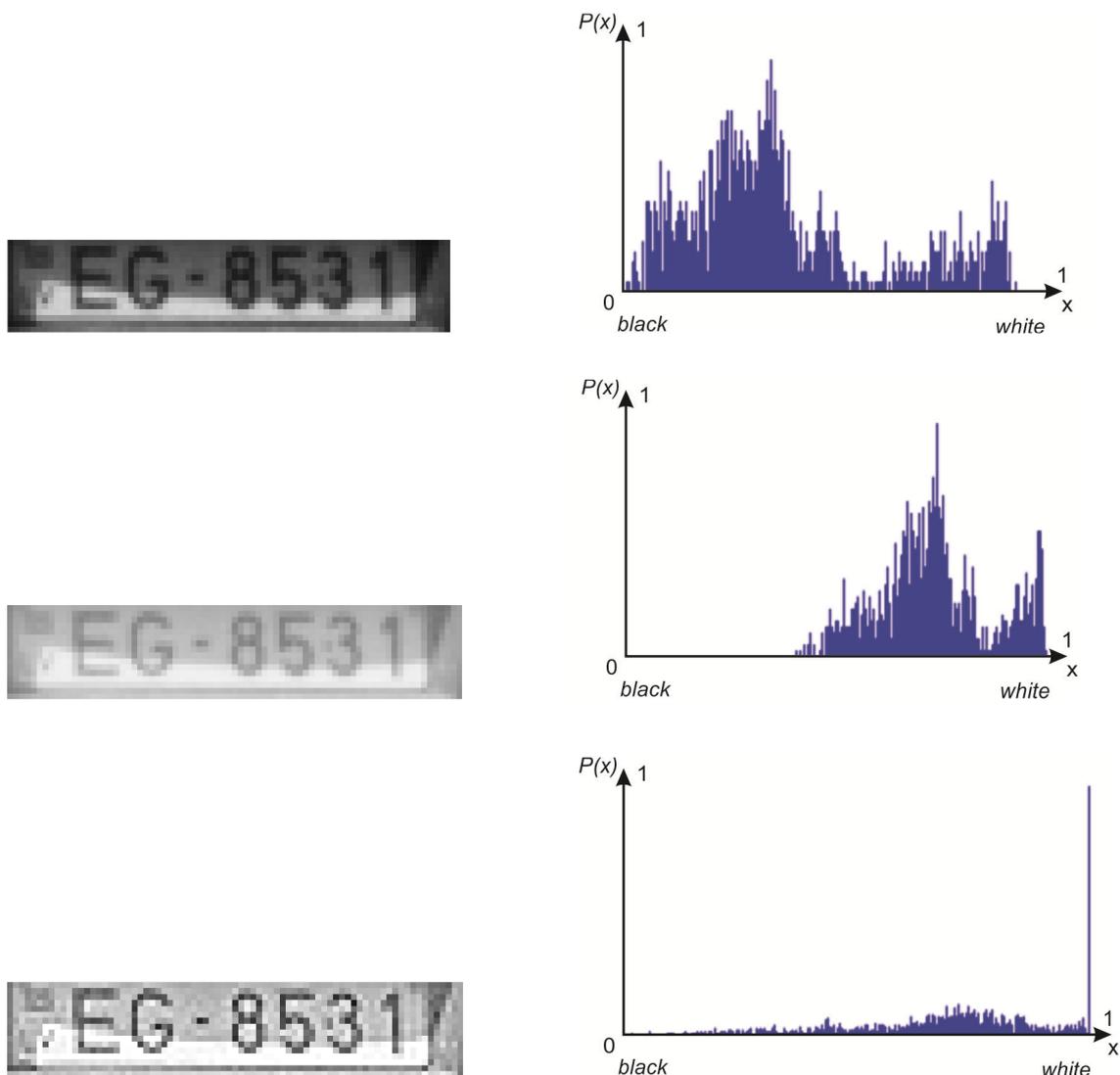


Figure 7. The result of the consecutive operation of the contrast increasing methods and sharpness improvement

In order to see in details the post-treatment changes of the number plate, as shown on Figure 8, the original number and the number after the sharpening procedure are zoomed in the graphics editor.



Figure 8. Sharpness algorithm output by the means of second-order derivative

2. Segmentation

The procedure of symbol segmentation on the number plate is carried out, and the problems, associated with this procedure are discussed. The implementations of existing methods are considered, their operation principles are described [2, 4]:

- Symbol segmentation on the basis of “profiles”.
- Algorithm of connected component selection.

Usually, segmentation algorithms are based on two basic properties of the brightness signal: *discontinuity* and *homogeneity*. In the approach, based on the discontinuity, the idea consists in the image decomposition on the basis of the signal abrupt changes, as the brightness differences in the image. In the second approach of homogeneity the image decomposition into domains is being used. The domains are homogeneous in the sense of preselected criteria [2, 3, 4].

Symbol segmentation on the basis of “profiles”

The most elementary method is to obtain brightness diagrams horizontally and vertically, in order to cut the number plate at the local extremum of the value [4, 8]. This approach is used in the symbol segmentation on the basis of “profile”. Reception of a clearer signal could be ensured by binarization, as the symbol pixels would gain a value of 0, and the background would contain only the value of 1. Then the symbol segmentation on the number plate becomes very simple. But as it turned out in the frame of this work, the binarization is not possible in the images of such resolution.



Figure 9. The application of binarization with global threshold of 0.6 to the original and enhanced images

Also, in the frame of this work the adaptive binarization [8] has been implemented, which theoretically should work better than the binarization with global threshold.



Figure 10. The application of an adaptive binarization to the original and enhanced images

The result of binarization with an adaptive threshold did not show better results, and in the context of the enhanced image even detected the noise in the image. Therefore, the binarization procedure for the image in such resolution has no sense. This binarization issue is very important, as some segmentation methods are working exclusively with binary images.



Figure 11. Matching of horizontal brightness diagram on the binary images

Algorithm of connected component selection

Algorithm of connected component selection is working exclusively with binary images, as its principle consists of filling with one (any) colour of a certain area, which is a complete unit, or, judging from the name of the algorithm itself – is connected.



Figure 12. Improved image, its binarization and application of algorithm of connected components

Before applying to the input, the image of the selected number plate should be zoomed. Implementation of algorithms of artificial image enlargement – is a hard work that requires individual consideration. Therefore, in the frame of this work the computer vision library OpenCV has been used, which allows scaling up the original image.

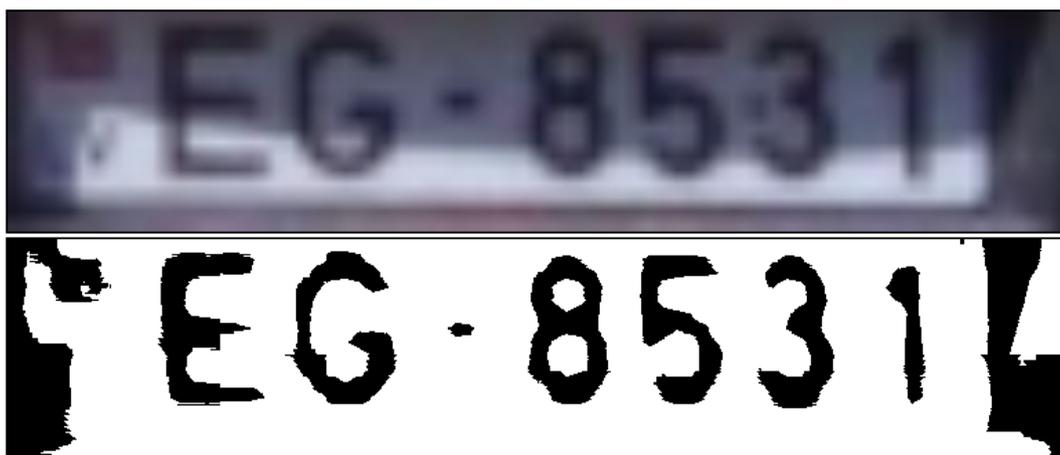


Figure 13. Original image, the image after the filter application and binarization procedure

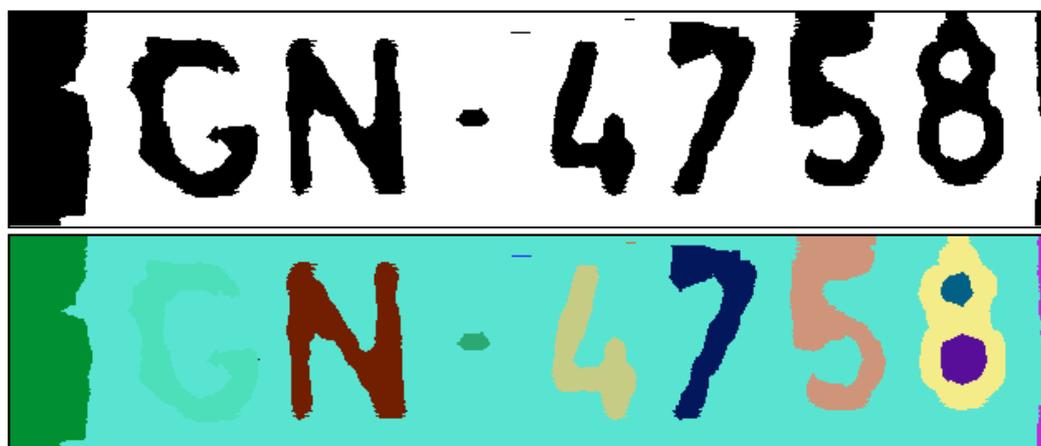


Figure 14. The result of the algorithm of connected components in the zoomed image

Segmentation of the difference of the brightness differential

In order to try the segmentation procedure in low image resolution, the author proposed his method, which is called “Segmentation of the difference of the brightness differential”. The first stage of the developed method is the obtainment of the brightness diagram horizontally.

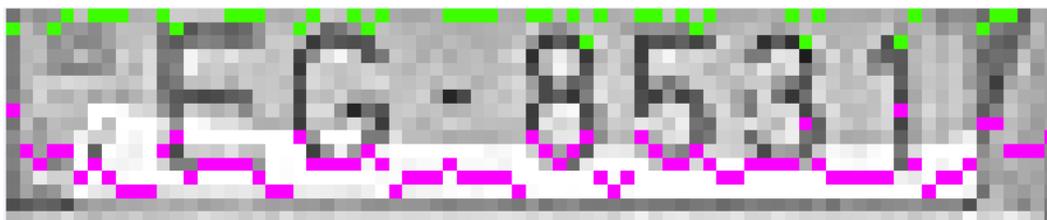


Figure 15. Calculation of the brightness (pink) diagram and its derivative (green)

Once we have obtained the brightness diagram, we calculate its derivative. As a result, the symbols on the number plate were placed in two signals. If to pay attention on the behaviour of the derivative signal, it's possible to note that in the area of the boundary of the symbol origin, the derivative signal of brightness decreases. In turn, the brightness diagram itself should have a small splash in this area, as there is dark symbol.

The whole algorithm is based on this simple observation.

- 1) The obtainment of the brightness diagram of the enhanced image.
- 2) The calculation of the derivative of the obtained brightness signal.
- 3) In each column of the image the difference between the derivative and its original signal is being calculated.
- 4) To sort the obtained difference – thus we will make a vector, whose division into two parts will show the location of the object and the background.
- 5) To divide the sorted vector into two equal halves.
- 6) Minimal differences – marked with “1”, maximum distance – with “0”.
- 7) With knowledge of positions (sequence) of minimal and maximal differences the binary code is being compiled.
- 8) Then, the decoding of the obtained code is being applied, by using the present parameters – minimum symbol width and the size of the interval between the symbols, which should not fall within the definition of interval.

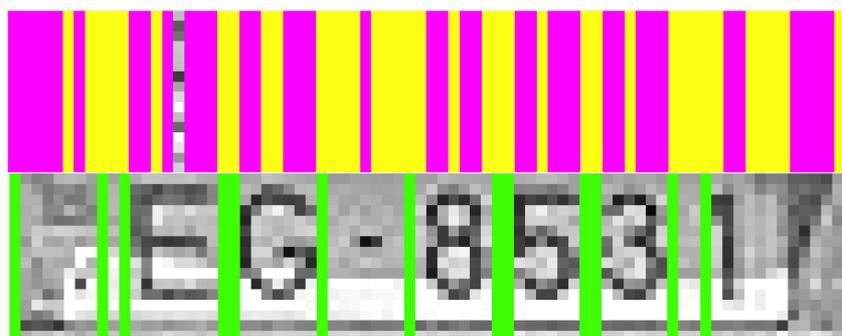


Figure 16. Algorithm output of the difference segmentation of the brightness differential

3. Symbol Recognition

The procedure of accented symbol recognition is being described [2, 5, 6, 7]:

- Symbol recognition on the basis of signal shape concordance.
- Symbol recognition by the means of mask method.

In the theory of object recognition there are two main categories of algorithms: methods, which are based on the *decision theory* and *structural methods*. The first category deals with the images described by the means of quantitative characteristics such as length, square, texture. The second category of methods is focused on the images, which are better described by qualitative characteristics, such as relational. In this work only the methods, which are based on decision theory, will be considered.

Symbol recognition on the basis of signal shape concordance

In the method of symbol recognition on the basis of signal shape concordance the main idea is to interpret the symbol as a signal along two axes – horizontal and vertical [2, 5]. The idea of this approach was adopted from the segmentation method by the means of “profiles”, when the interval locations between neighbouring symbols were determined in the similar way. But in the recognition issue we are interested in the signal shape of each symbol individually.

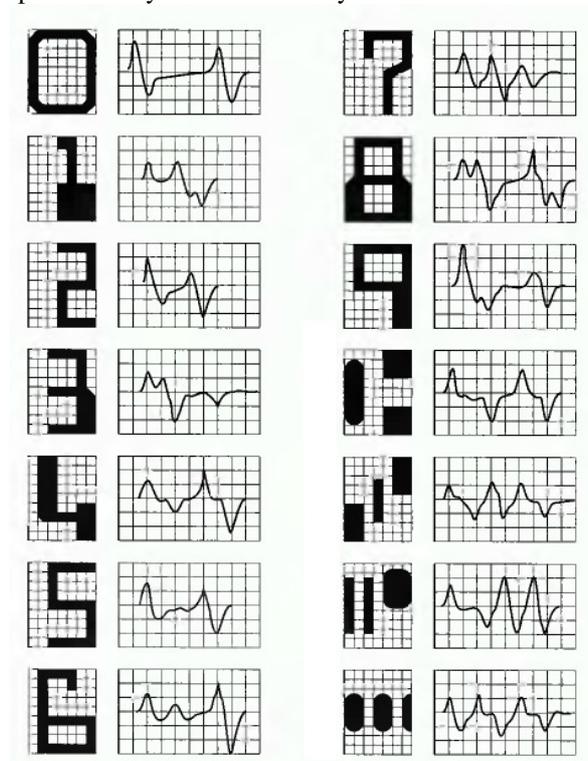


Figure 17. Symbol set of font E-13B and corresponding signal shapes

There is a reference signal presentation, which has been obtained from the symbol with correct shape and outlines [5]. Reference signals are obtained from the whole working alphabet, the recognition system operates with. When a signal is obtained from the scanned symbol of the number plate, it is sequentially corresponded with the entire reference alphabet of the signal, where the *least square method* is being applied for comparison, how similar is the current signal to the reference signal. A list of the sums of squared differences is made out, and the difference, which contains the minimum error (divergence), is being selected. The weak spot of the method is that it is designed for work only with one particular font, as well as when operated at the image, where the noises are presented, and one parameter – as the signal horizontally, is insufficient to determine the kind of a symbol. It’s also worth noting that the problem with the symbol height occurred, which disturbed the signal comparison.

Symbol recognition by the means of mask method

Once the segmented symbol has been obtained, the image of reference symbol is being matched pixel by pixel [2, 3].

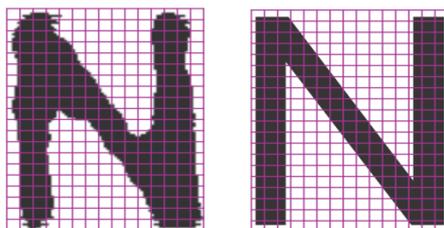


Figure 18. Segmented symbol and reference symbol

When the procedure of reference symbol matching has been completed, the calculation of difference between two symbols is taking place.

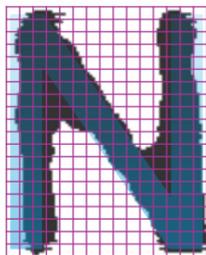


Figure 19. Reference mask matching

Once the difference of each pixel has been obtained, we summarize all differences and divide the sum by the total number of image pixels. Thus, we assess how similar are the data of the matched symbols.

Conclusions

In the first stage the image of the number plate was made smoothly concolorous in order to exclude the background, and to run off the details of the noise (e.g., shade) into a single plane with the background. Further, the modified image was transmitted to the input of the sharpness improvement algorithm. The second-order derivative intensified the transition contours from the background to the symbol, so it was possible to achieve background lighting and detection by the darker colour of the symbols. The procedure of the automatic coefficient adjustment, whose values are applied to the input of the implemented filters, is described.

In the course of analysis it was revealed that neither symbol segmentation method on the basis of “profiles” nor the method of connected component selection, could not successfully deal with the task in the images with low resolution. Hence, it follows that before applying to the input by the specified method, the image of the selected number plate is required to be zoomed.

The study identified the problem of symbol recognition, which consisted in the lack of intermediate action between the binary image and segmentation stage. Therefore, for the further improvement and change of the developed symbol recognition system for the number plates, it was proposed to implement the morphological image processing.

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„The article is written with the financial assistance of European Social Fund. Project Nr. 2011/0037/1DP/1.1.2.1.1/11/PIA/VIAA/007. The Support in Realisation of the Master Programme “Master of Natural Sciences in Computer Science” of the Transport and Telecommunication Institute”.