Vehicle License Plate Recognition Based on Edge Detection

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Abstract — **A vehicle license plate recognition system is proposed. The focus is on a new method for detecting number plates. The method is based on the detection of contours and the use of geometric information about the contours. To detect the contours, a mathematical image model based on a two-dimensional discrete-valued Markov chain with two states was used. To reduce computational resources, we propose to carry out detection of number plates by the bit planes of the senior, most informative digits of the digital image. The proposed method allows to significantly reduce the computational cost of detecting the license plate and, accordingly, on the recognition of vehicle license plate symbols. Character recognition accuracy reaches 92%.**

I. Introduction

Automatic recognition systems of vehicle license plates (VLP) are used in monitoring, observing and traffic control systems. In most studies, the main stages of license plate recognition are [1]: image preprocessing, plate detection, license plate image segmentation into symbols and text character recognition. An important and basic step in recognizing vehicle number symbols is the detection and localization (detection) of areas that potentially contain license plates in the image. An error in detecting a license plate will lead to a failure of the algorithms in the subsequent steps and a decrease in the accuracy of character recognition. The procedure for detecting a plate is a difficult task due to the wide variety of the processed image characteristics: size, color, spatial orientation of the plate, scene complexity. Moreover, the quality of detection significantly depends on the image contrast, the presence of distortions caused by natural artifacts, glare, greases, etc. It should also be noted that the global increase in video data due to an increase in the number of vehicles and video monitoring cameras, creates significant problems for their analysis and real time processing. To solve this problem, should be either increase the power of the servers, or use algorithms that require small computing resources.

There are various approaches to localizing vehicle license plates [1-9]: edge detection filters (Prewitt, Sobel, Canny, Laplacian of Gaussian, Harris), color and texture features extraction, the Radon and Hough transforms, morphological operations, wavelet transforms, convolutional neural networks, genetic algorithms, etc. Table I presents a comparative analysis of the characteristics of some methods of localizing number plates.

TABLE I. CHARACTERISTICS OF LOCALIZATION ACCURACY AND PROCESSING TIME OF KNOWN METHODS

Method	Accuracy, %	Processing time, sec	System configuration
Morphological operations [3]	84.3	-	-
Statistical binarization and the Radon transform [4]	86.2	0.73	Intel Core 2 Duo T6600 with 2.2 GHz processor and 2 GB RAM
Convolutional neural networks [5]	87. 0	0.23	Intel Core i5 machine (2.4 GHz) with 8 GB RAM, GT-740M GPU
Sobel filter, morphological operations [6]	92.0	-	2.26 GHz CPU
SIFT feature [7]	96.0	0.26	Pentium 4 with 2.4 GHz CPU and 1 GB RAM
Color and texture features extraction [8]	96.4	3	AMD 1.75 GHz CPU and DDR400 512 MB
Convolutional neural networks, Gabor filter [9]	99.0	0.16	Intel Xeon (2.4 GHz) with Nvidia GeForce GTX 1080Ti GPU

Most of the proposed methods for localizing vehicle number plates on the image have a long processing time and / or low level of accuracy.

Therefore, despite the significant number of existing methods for detecting VNP, the task of ensuring high accuracy of localization of number plates while reducing computing resources is relevant.

The aim of this work is to develop a method for detecting license plates of vehicles in the image, providing high accuracy of recognition of text characters while reducing computational resources.

This paper is structured as follows. Section II details the method of detecting the contours of vehicle license plates based on the representation of the image in the form of a two-dimensional Markov chain. Section III contains a brief description of the procedures for the segmentation of images of license plate characters and recognition of text symbols are required for number plate recognition. Experimental results and their comparison with other algorithms are presented in Section IV. Section V contains conclusions.

II. METHOD FOR VEHICLE LICENSE PLATE DETECTION

Detection methods based on transformations [1], [3], [9-12] which use information about color and texture features [7], [9], and convolutional neural networks [8], [9] have high requirements for the computational power of hardware and potentially complicate their implementation and application in real time systems.

In contrast to these methods, methods based on contour analysis are more suitable for the problem of localizing the image of a number plate. Methods that use contour information to detecting number plates do not require training or the preparation of special templates and allow to finding vehicle license plates of different sizes and at different angles. Because contour points make up an insignificant part of all points in the images, working with them allows you to reduce the amount of processed information and improve a performance of recognition systems of license plates of vehicles.

The disadvantage of contouring methods is their low resistance to noise, changes in illumination, various image distortions due to weather conditions, etc. To improve quality of images obtained in difficult lighting conditions, are applied methods based on the merging of infrared and visual image data; based on the alignment of the histograms of the brightness of the digital image, etc. [1, 10, 11]. To remove noise and smoothing images, Gaussian, median, bilateral filters can be used [1, 2, 10-12].

The initial data for this work were RGB images of vehicles. Each color component of the RGB image is a digital halftone image (DHI), represented by bit binary numbers. It makes possible to present a digital data center with a set of bit binary images (BBI). To reduce computational resources, the allocation of circuits was carried out according to the BBI of one of the oldest, most informative bits of the DHI. It should be noted that in order to distinguish the number plate contours, it is necessary to take into account the DHI of all three components, since it is possible not to get the boundary of the number plate on the DHI of one component.

To transfer the RGB image to the DHI, we used formula (1), proposed by ITU-R Recommendation BT.601-7

$$I = 0.299R + 0.587G + 0.114B\,. \tag{1}$$

Taking into account the nature of the statistical relationship between the elements in the DHI, they can be approximated by multilevel discrete-valued Markov processes [13–15], and BBIs can be approximated by Markov processes with two equally probable discrete states $M_1^{(l)}$, $M_2^{(l)}$ ($l=\overline{1,g}$) and transition probability matrices ${}^1\Pi^{(l)} = \left\| {}^1\pi_{ij}^{(l)} \right\|_{2\times 2}$ (horizontal) and ${}^2\Pi^{(l)} = \left\| {}^2\pi_{ij}^{(l)} \right\|_{2\times 2}$ (vertical) ($l=\overline{1,g}$).

Fig. 1 shows the fragment of the two-dimensional l-th BBI of a Markov random field.

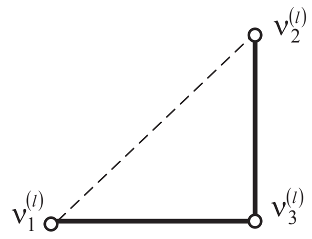

Fig. 1. The fragment of the two-dimensional BBI of a Markov random field

In accordance with the mathematical model proposed in [13], [14], the amount of information in a binary element $\nu_3^{(l)}$ relative to the elements located horizontally $\nu_1^{(l)}$ and vertically $\nu_2^{(l)}$ is defined as the difference between the element's own information $I\left(\nu_3^{(l)}\right)$ and the elements mutual information $I\left(\nu_1^{(l)},\nu_2^{(l)},\nu_3^{(l)}\right)$:

$$I\left(\nu_3^{(l)} \mid \nu_1^{(l)},\nu_2^{(l)}\right) = I\left(\nu_3^{(l)}\right) - I\left(\nu_1^{(l)},\nu_2^{(l)},\nu_3^{(l)}\right) =$$
$$= -\left[\log p\left(\nu_3^{(l)}\right) + \log \frac{p\left(\nu_3^{(l)},\nu_1^{(l)}\right) p\left(\nu_1^{(l)},\nu_2^{(l)}\right) p\left(\nu_2^{(l)},\nu_3^{(l)}\right)}{p\left(\nu_1^{(l)}\right) p\left(\nu_2^{(l)}\right) p\left(\nu_3^{(l)}\right) p\left(\nu_3^{(l)},\nu_2^{(l)},\nu_1^{(l)}\right)}\right] =$$
$$= -\log \frac{w\left(\nu_3^{(l)}\middle|\nu_1^{(l)}\right) w\left(\nu_3^{(l)}\middle|\nu_2^{(l)}\right)}{w\left(\nu_3^{(l)}\middle|\nu_2^{(l)},\nu_1^{(l)}\right)}, \tag{2}$$

where $p(\nu_i^{(l)})$, $i=\overline{1,3}$ is the a priori probability density of element values; $p(\nu_1^{(l)},\nu_2^{(l)},\nu_3^{(l)})$, $p(\nu_i^{(l)},\nu_j^{(l)})$, $i \neq j = \overline{1,3}$ are joint probability density values of the elements; $w\left(\nu_3^{(l)}\middle|\nu_1^{(l)}\right)$, $w\left(\nu_3^{(l)}\middle|\nu_2^{(l)}\right)$ are one-dimensional density of probabilities of transitions; $w\left(\nu_3^{(l)}\middle|\nu_1^{(l)},\nu_2^{(l)}\right)$ are probability density of transitions in two-dimensional Markov chain.

The probabilities of the transition from combinations of states of neighborhood elements $\nu_1^{(l)}$ and $\nu_2^{(l)}$ to the state of an element $\nu_3^{(l)}$ are numerically determined by the argument of expression (2) and form a transition matrix of the form:

$$\Pi = \begin{Vmatrix} \pi_{iii}^{(l)} & \pi_{iij}^{(l)} \\ \pi_{iji}^{(l)} & \pi_{ijj}^{(l)} \\ \pi_{jii}^{(l)} & \pi_{jij}^{(l)} \\ \pi_{jji}^{(l)} & \pi_{jjj}^{(l)} \end{Vmatrix}; \; i, j = \overline{1,2}; i \neq j,\; l = \overline{1,g}. \tag{3}$$

Elements of the matrix Π (3) are associated with the elements of the matrices ${}^{1}\Pi$ and ${}^{2}\Pi$ the relations:

$$\begin{aligned}
\pi_{iii}^{(l)} &= \pi(\nu_3^{(l)} = M_1^{(l)} \mid \nu_1^{(l)} = M_1^{(l)}; \nu_2^{(l)} = M_1^{(l)}) = \frac{{}^{1}\pi_{ii}^{(l)}\, {}^{2}\pi_{ii}^{(l)}}{{}^{3}\pi_{ii}^{(l)}}, \\
\pi_{iji}^{(l)} &= \pi(\nu_3^{(l)} = M_1^{(l)} \mid \nu_1^{(l)} = M_1^{(l)}; \nu_2^{(l)} = M_2^{(l)}) = \frac{{}^{1}\pi_{ii}^{(l)}\, {}^{2}\pi_{ij}^{(l)}}{{}^{3}\pi_{ij}^{(l)}}, \\
\pi_{jii}^{(l)} &= \pi(\nu_3^{(l)} = M_1^{(l)} \mid \nu_1^{(l)} = M_2^{(l)}; \nu_2^{(l)} = M_1^{(l)}) = \frac{{}^{1}\pi_{ij}^{(l)}\, {}^{2}\pi_{ii}^{(l)}}{{}^{3}\pi_{ij}^{(l)}}, \\
\pi_{jji}^{(l)} &= \pi(\nu_3^{(l)} = M_1^{(l)} \mid \nu_1^{(l)} = M_2^{(l)}; \nu_2^{(l)} = M_2^{(l)}) = \frac{{}^{1}\pi_{ij}^{(l)}\, {}^{2}\pi_{ij}^{(l)}}{{}^{3}\pi_{ii}^{(l)}},
\end{aligned} \tag{4}$$

where ${}^{r}\pi_{ij}^{(l)}$ $(i, j = \overline{1,2};\; r = \overline{1,3};\; l = \overline{1,g})$ are the elements of transition matrices in one-dimensional Markov chains with two states - ${}^{1}\Pi$, ${}^{2}\Pi$ and matrices – ${}^{3}\Pi = {}^{1}\Pi \times {}^{2}\Pi$.

To detect the contours, the calculated amount of information is compared with a threshold:

$$\begin{aligned} H = \Big[& I(\nu_3^{(l)} = M_1^{(l)} \mid \nu_1^{(l)} = M_1^{(l)}, \nu_2^{(l)} = M_1^{(l)}) + \\ + & I(\nu_3^{(l)} = M_1^{(l)} \mid \nu_1^{(l)} = M_1^{(l)}, \nu_2^{(l)} = M_2^{(l)}) \Big] \Big/ 2 \end{aligned}. \tag{5}$$

Getting the contour image, it was assumed that the probabilities of transitions between image elements are a priori known. It is typical for images obtained under the same conditions.

The result of this procedure is a combination of closed contours of different contrast areas. The contours have a thickness of one pixel, which facilitates the task at the stage of recognition of the symbols of the VLP. The proposed method for selecting the object contours requires less computational resources than the well-known methods (Sobel, Laplacian of Gaussian, Canny, etc.). Comparison operations with two neighboring elements are required. It should also be noted that the proposed algorithm gives a significantly lower percentage of false contours than, for example, the Canny method. It gives a significant gain in processing speed at the stage of contour search.

To solve the problem of localization of the license plate is searched contours that match certain criteria, namely: compliance with the sizes width and height, as well as their ratio and the presence of contours of the characters within the intended contour of the license plate.

The result of the detection algorithm is the selection of the intended areas corresponding to the number plate of the VLP, the rectangular frame.

The VLP localization algorithm is shown in Fig. 2.

III. Segmentation and recognition algorithms

After the license plates were localized, an image containing only the number was generated and normalized. This procedure is to size and orient the image number obtained in the previous step to the desired view [1].

The next step is to analyze the background color of the number plate to determine the type of number. In Russia according to GOST R 50577-2018, there are several types of state license plates, which differ in background color. The background color must be known to perform the further character recognition procedure, as with a different type of license plate (different background), a different sequence of characters on the number plate is used. In this paper, we consider only images of license plates on a white background.

To segment an image of a license plate into images of individual symbols, the method of histogram analysis [1] is used, which ensures high accuracy of symbol separation with small computational resources. The method is based on calculating the brightness in all columns of a binary image of a number plate and determining the columns in which the average intensity differs significantly from the threshold value.

For character recognition, the method of correlation analysis is used when comparing with a template, the advantages of which are ease of implementation, high reliability in the absence of interference, high accuracy of recognition of characters with defects and high speed with a small alphabet. In accordance with the recognition algorithm, the image of each symbol is scaled to a size corresponding to the size of the patterns used, and then the correlation coefficients are calculated based on the comparison of the received symbol image with all the patterns. The symbol image that has the highest correlation coefficient value is associated with a text character that is added to the license plate string if the correlation coefficient is exceeded by 0.5. In the case when the largest coefficient does not exceed the value 0.5, an asterisk "*" is added to the line of recognized symbols of the processed license plate and the symbol is unrecognized.

To recognize license plates from other countries, consider the color of the license plates, the sequence of the location of letter and digital signs, and increase the base of patterns of the symbols used on the license plates.

IV. Experimental results

The simulation of the developed algorithm was performed on a set of 436 test RGB images of different resolutions in the MATLAB environment. A comparison of the detection algorithm based on the two-dimensional Markov chain and the known contour methods (Prewitt, Sobel and Canny) was carried out. To implement the known methods, standard functions of the MATLAB environment were used. The detection of the contours by the developed algorithm for all images was carried out according to the highest level of DHI.

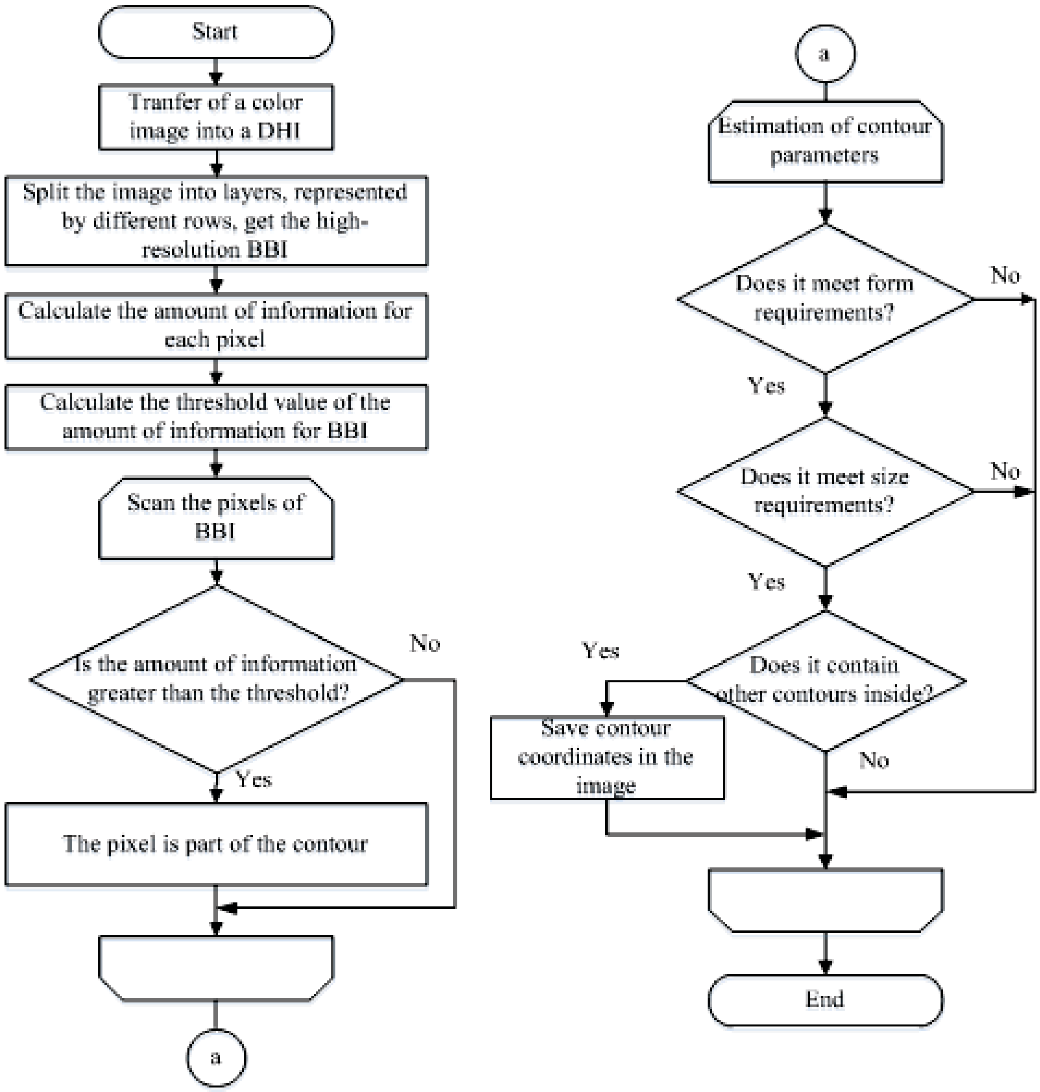

Fig. 2. The algorithm for the VNP localization in the image

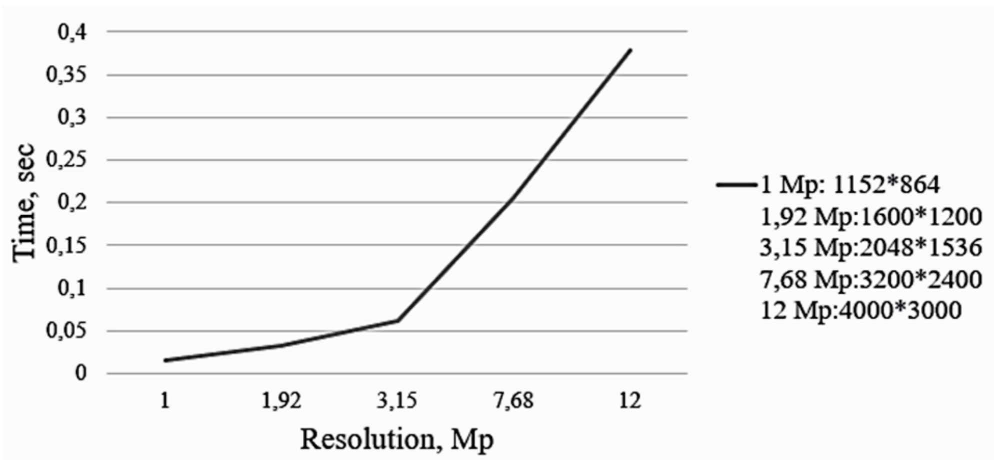

Fig. 3. Dependence of the time of VLP detection and character recognition on the resolution of the test image

Table II presents the results of the algorithm comparison for accuracy and time of detection of the number plate contours. Time estimates are for 3 megapixel images. The time estimates included the time taken to select and search for contours that match certain conditions.

The study was conducted in the operating system Windows 7 on the processor Intel Core i5-3570K, 3.4 GHz, 8 GB of RAM.

TABLE II. RESULTS OF THE ALGORITHM COMPARISON FOR ACCURACY AND TIME OF DETECTION OF NUMBER PLATE CONTOURS

Method	Number plate is fully detected, %	Number plate is partially detected, %	Number plate is not detected,%	Number plate detection time, s
Prewitt	84.64	10.32	5.04	0.186
Sobel	89.91	6.23	3.86	0.186
Canny	94.03	4.83	1.14	0.51
Two-dimensional Markov chains	91.47	4.12	4.41	0.046

From the results in Table II, it can be seen that the proposed method is better in terms of the accuracy of detecting boundaries than the Sobel and Prewitt methods and is 3% worse than the Canny method. The methods of Prewitt and Sobel in most cases do not allow to accurately determine the number plate in the image due to the presence of gaps in the circuit or due to false contours. A large number of undetected number plates by the proposed method is associated with the low contrast of a number of images and the inability to detect the number plate in the high-resolution BBI. To solve this problem, you should either increase the contrast of the image, or select contours according to the BBI of another category. The detection algorithm allows to detect a number plate for a beveled angle of up to 15 degrees.

The obtained estimates of the detection time of the contours indicate the advantages of the developed method in comparison with the known methods of boundary detection up to 11 times.

The total detection time of the license plate and character recognition depends significantly on the original image, namely, its resolution, background, number of cars, etc. Fig. 3 shows the dependence of the total processing time by the proposed algorithms for plate detection, segmentation and recognition on the resolution of the test image. For tested images ranging in size from 1 to 12 megapixels, the time spent on detection and recognition of characters is, respectively, from 0.015 to 0.38 seconds.

Most modern automatic license plate recognition systems widely use cameras with a resolution of more than 3 megapixels. Fig. 4 presents a graphical diagram of the shares of time spent by each processing procedure in the total time character recognition for an image of 3 megapixels (2048×1536).

The chart shows that the highest time costs are for the first two procedures: the contouring procedure and the localization procedure. The above results once again confirm that reducing the detection time will significantly reduce the overall VLP detection time.

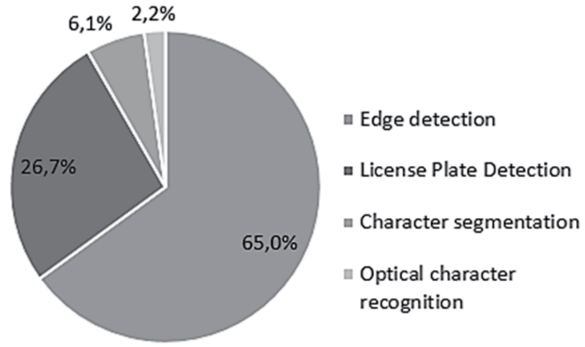

Fig. 4. Time spent by each procedure in the total processing time of the test image

To evaluate the quality of the VLP recognition system, following indicators we used: probability of correct license plate recognition, probability of mis-recognition, probability of missing a license plate, probability of conditional recognition. The estimates of the quality indicators of the proposed system for the selected image database are listed below:

- probability of correct recognition -91.96%;
- probability of conditional recognition is 92.23%;
- probability of mis-recognition - 5.12%;
- probability of missing a number is 8.44%.

Fig. 5 shows an example of the localization and recognition of the license plate characters: a) the original image; b) binary image of the 8th (most significant) bit of the DHI used to select the contours; c) the result of localization of a plate according to the contour image; d) the result of localization of a plate in the RGB image and character recognition; e) the result of a program. The example shows successful to distinguish VLP at two cars as well as the results of recognition of license plate characters by the developed method.

IV. CONCLUSION

The article presents a method of recognizing vehicle license plates based on a contour detector. To detect the VLP, we used geometric information about the contours and mathematical image model based on a two-dimensional discrete-valued Markov chain with two states.

The developed method can significantly reduce a computational cost of detecting and, accordingly, recognizing vehicle license plate characters. For a 3-megapixel image, VLP detection and character recognition time was 0.065 s. The presented recognition system can be operable when a license plate image deviates up to 15 degrees from the horizon.

Character recognition accuracy reaches 92%.

a)

b)

c)

d)

e)

Fig. 5. VLP detection and character recognition example

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