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RECOGNITION OF LICENSE PLATES SYMBOLS OF DIFFERENT FORMATS

Urgency of the research. *Typically the recognition process includes the following steps: license plate detection, license plate normalization, segmentation of the license plate image into separate symbols and symbols recognition. The effectiveness of license plate recognition depends on each of the indicated recognition stages, but for recognition of the license plates of different formats the key stages are segmentation and recognition stages. Therefore the development of the recognition method of the license plates symbols of different formats is an actual task.*

Target setting. *Different formats of car numbers have different fonts and different arrangement of characters, which complicates the process of recognizing car numbers.*

Actual scientific researches and issues analysis. *General trends that have been identified by the analysis of publications indicate that for character recognition of car numbers used convolutional neural network, fully connected neural networks, correlation analysis, binarization images and histograms of brightness.*

Uninvestigated parts of general matters defining. *All analyzed methods are well suited for recognition of the symbols of well-visible license plates. This makes difficult to apply such methods in real conditions as the license plates can be dirty or poorly visible.*

The research objective. *The purpose of the article is to describe the method of recognizing car numbers of different formats, which has a high percentage of correct recognition and can be used to recognize car numbers on the video stream from cameras located above the tracks.*

The statement of basic materials. *For recognition of the symbols of license plates it is suggested to use the brightness histogram of the binarized image, for symbols recognition - a specially created neural network with the ability of recognition the alternative parts of the original image of the license plate and for removing the incorrectly recognized symbols - the list of license plates formats.*

Conclusions. *The proposed method successfully copes with the task of license plate recognition with confidence 95-99 %. But as the test results show the method has several drawbacks. First, this method does not easily recognize the "trash" in the image and often confuses it with the symbol 'I'. Second, on the dirty license plates or on false detection this method repeatedly uses alternative recognition which leads to a significant load on the processor.*

Keywords: *recognition; convolutional neural network; license plate.*
Fig.: 6. Bibl.: 21.

Introduction. Modern systems of license plate recognition are mainly oriented to the recognition of plates of a specific country[1], although there are products that are able to recognize the license plates of many countries simultaneously[2-6]. However, both the first and second systems are closed and have a high cost, and there are no open methods that can recognize license plates with great certainty. Therefore, recognition of license plates is an actual task at the moment.

Typically, the recognition process includes the following steps: license plate detection, license plate normalization, segmentation of the license plate image into separate symbols and symbols recognition. Detection of the license plate can be made with the help of the Haar detector[7] and normalization by different methods[8-10]. The effectiveness of license plate recognition depends on each of the indicated recognition stages, but for recognition of the license plates of different formats the key stages are segmentation and recognition stages, because different formats of license plates have different fonts and different arrangement of symbols on the plate which makes difficult recognition of license plate. Therefore, the development of the recognition method of the license plate symbols of different formats is an actual task.

Analysis of recent research and publications. At the moment there are many articles describing the recognition of license plates of one or many formats.

In [11] detection of a license plate and its recognition is performed using convolutional neural networks without a separate segmentation step. Also, possible simplifications of the created neural networks for use on mobile platforms are indicated. However, the processing time of the recognition algorithm still remains too large for use it on desktop or mobile processors.

In [12] the method of detection and recognition of license plates of Egypt is described. Detection is carried out by means of selection of corners, expansion operation, special filling, erosion, blurring and filtration. Segmentation is performed by image binarization, erosion operation and horizontal projection of brightness. Recognition is performed using correlation analysis. During the research it was found that such method of detecting a license plates

works well under the some special conditions and is completely inappropriate for others. Segmentation of this method obviously will not work in case of dirty plates, and as a result the license plate can not be correctly recognized.

In [13] the method of recognition of license plates by means of artificial neural networks is described. Detection is carried out by means of selection of contours. Segmentation is performed using vertical projection of luminosity and recognition by using an artificial neural network on a binary image with preliminary refinement of binarized symbol images. This method works well for high-quality photos, but it is not suitable for recognizing license plates from a real video stream in conditions of poor visibility or in case of dirty plates.

In [14] the detection of license plates is performed using contour highlighting and SVM [15]. Segmentation is performed by finding of contours and searching of closed regions of these contours. Recognition is performed by convolutional neural network. This method of recognition also can not work on dirty license plates, since a "glued" pair of symbols can not be correctly recognized by a neural network. As for the neural network itself, in comparison with the network used in this method, it has too complicated construction, a lot of parameters and, consequently, a low speed.

All the above mentioned methods were tested on photos of cars where the license plate has a much higher resolution and has no contamination, as a result of which these recognition methods can not have a high percentage of correctly recognized license plates on a real video stream.

The goal of an article Describtion of the recognition method of the license plates symbols of different formats, which has high recognition rate and can be used in practice for recogntion of the license plates from video streams received from cameras located above the tracks.

Segmentation of the license plate images of different formats. This stage can be divided into several sub-stages:

- binarization of the license plate image;
- specification of the boundaries of license plate symbols;
- determination of the position of individual symbols.

Binarization of the license plate image. Binarization[16] of the image greatly simplifies further processing, since after binarization the image consists only of "white" and "black" pixels. There are various methods of binarization of images[17-19].

Researches show that in the case of the same license plate formats the best variant of binarization is binarization over the area of symbols[18]. But such binarization is not able to correctly determine the binarization threshold since the symbols occupies from 24 % (Figure 1 (a)) to 44 % (Figure 1 (b)) of license plate of different formats.
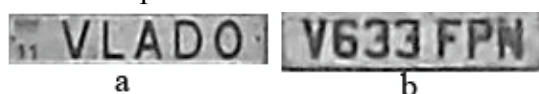

Fig. 1. License plates whose symbols occupy different areas

A "hard" binarization, which assumes setting the binarization threshold as an unchanged number from 0 to 255 (with the same brightness range) gives a result that does not allow us to determine the boundaries of symbols on a set of license plates, since the results of binarization in this way depend on the illumination of the license plate, which in real conditions can not be the same. Methods of adaptive binarization[19] are intended for binarization of images in which the brightness is distributed unevenly. In real conditions the recognition of license plates rarely occurs in conditions of uneven illumination. In addition, adaptive binarization methods create noises that have influence on next stage of recognition.

Therefore, it was decided to use Otsu's method[17] of binarization, which calculates the binarization threshold depending on the illumination of the image. But, since the normalization method has limited accuracy, it is proposed to use in the method the additional inner rectangle with the following parameters to determine the binarization threshold:

$$xS = 0.1*wP,$$
$$yS = 0.2*hP,$$
$$wd = wP*0.8,$$
$$hg = hP*0.8,$$

(1)

where xS, yS – initial position of the rectangle along the X-axis and along the Y-axis respectively; wP, hP – width and height of the normalized image respectively; wd, hg – width and height of the inner rectangle respectively.

The results of binarization by this method are shown in Fig. 2.

a   b

Fig. 2. Source and binarized images of license plates

Specification of the boundaries of license plate symbols. As a rule the methods of normalization defines exact boundaries of plate but not boundaries of symbols that is necessary for further recognition stages.

Determination of the upper bound of symbols it is proposed to perform into two steps. The first step is to sort out one by one horizontal line of image from 0 to height/3 value on Y-axis, where "height" is a height of the normalized image. In each of these lines it is necessary to find the longest continuous stretch of white pixels. The line with the maximum value of the coordinate on Y-axis, which would contain a portion of white pixels with width exceeding the 0.4 of the original image width, should be stored for the second stage. The second step is to sort out the lines from value that was obtained in the first step to a value of height/3 on Y-axis, where "height" is a height of the normalized image, and look for solid black line. The first line that would have white pixels is considered as symbol boundary. Definition of the lower bound of symbols is offered to be carried out on a similar algorithm.

For determination of the left boundary of symbols it is offered to look over vertical lines from value 0 to width/4 on X-axis, where "width" is a width of the normalized image. For each line it is necessary to check the count of white pixels. The first line which will meet a condition: the count of white pixels more than 0.98 heights of the image or less than 0.02 heights of the image – will be considered as left border of symbols. Definition of the right border is offered to be carried out on a similar algorithm.

For determination of the position of individual symbols it is needed to determine:

1) the count of white pixels for each column ($cw(i)$) of the binarized and normalized license plate image. A graphical representation of the result of this operation is shown in Figure 3: the count of white pixels per column corresponds to the length of the vertical white line in each column, which starts from the top of image;

2) the maximum (*mxCount*) and minimum (*mnCount*) count of white pixels per column on a binarized image;

3) the average value (*avg*) of the white pixels count per column on a binarized image (one value for all image);

4) the minimum (*mn*) and maximum (*mx*) values that will be used to find the left and right border of symbol according to the following formulas:

$$mn = round(avg*0.3) + mnCount,$$
$$mx = round(avg*0.7) + mxCount$$

(2)

where *round(x)* – rounding operation.

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Fig. 3. Binary image of the license plate and the count
of white pixels (on Y-axis) by the columns

Then borders of the symbol are determined in such way:

1) the left border (i position on X-axis) of the symbol is achieved when the following three conditions are true:

$$cw(i-1) <= mn, cw(i) > mn, cw(i+k) > mx ; \qquad (3)$$

2) the right border (j position on X-axis) of the symbol is achieved when the left border is found and following three conditions are true:

$$cw(j-1) > mx, cw(j) <= mx, cw(j+k) <= mn , \qquad (4)$$

given that $0 < i < mx$, $0 < j < mx$, $0 < k < i+k <= mx$, $0 < k < j+k <= mx$, for each symbol $j > i$.

For all founded symbols *S(i)* the following condition is verified:

- if the width *S(i)> MAX_WIDTH*, then a new binarization of the part of the image where the symbol *S(i)* is located with a threshold of 7 units smaller than the previous one is performed and a first stage begin again.

- if the width *S(i) <= MAX_WIDTH*, then the result is stored.

Here, *MAX_WIDTH* – maximum possible character width that was determined experimentally (30 pixels).

Character recognition. To recognize individual symbols a convolutional neural network, which is described in [20], was created and trained.

The algorithm for character recognition using the specified neural network consists of the following steps:

1) preparing the image for recognition;

2) application of a neural network to separate parts of the image;

3) analysis of the results;

4) select the most likely format of the recognized license plate.

Preparing the image for recognition involves the histogram equalization of the gray image of the license plate in order to classify the images by neural network without taking into account the contrast and brightness parameters of the image.

The stage of neural network application to individual parts of the image assumes the following sub-steps.

1) the symbol is cut out with the founded coordinates along the X-axis from the binary image. If the width of the symbol is less than 15 pixels, then a 15-pixel section is cut from the image (pixels are added to the right and left). This is done for correctly recognition of the I symbols, which is a simple vertical line. If cut only 3-5 pixels, which occupies this symbol, then the neural network often confuses garbage with this symbol;

2) normalization of the symbols image occurs by cutting off white vertical lines to the left and right and white horizontal lines from the top and bottom on the binarized image. After this the obtained coordinates are used to cut out the symbol from the original equalized gray image of license plate;

3) a gray symbol image is transmitted to the neural network. Since the neural network receives images of 24x24 pixels on the input the image is zoomed without distortion of proportion and inserted in the center of the image of 24x24 pixels, which before it is filled with brightness of 200 units (the neural network on such images was trained). The result of recognition is stored for further analysis;

4) if the neural network recognize not the symbol I with a confidence of less than 0.3 (for reliability from -1 to +1), then the following test is performed. If the height of the symbol is less than 0.7 of the height of the original image of the normalized license plate, an attempt is made to recognize the symbol without taking into account the sub-step of normalization (second sub-step). If on the contrary – an attempt is made to find white horizontal lines in symbol on a binarized cut image in order to eliminate possible trash for those symbols whose size is less than the height of the license plate (for example, such symbols exist on Russian license plates). In both cases, the result is selected with greater reliability and is stored for further analysis.

The analysis stage is based on the Heuristic over Segmentation method [21]. In general, this method is applicable to the case of symbols recognition when symbols boundaries can not be determined reliably as for handwriting character recognition. Regarding the license plate recognition, the above segmentation method sometimes splits the symbols H and M into two parts when they come into contact with another symbol, which can not be separated from them by the projection of brightness. An example of such pair symbols is shown in Figure 4.

EAA 9150 MK

Fig. 4. License plate on which it is impossible to separate pair symbols

The essence of analyze stage is to compare the recognition reliability of the part of image with a certain predetermined value taking into account the symbol that has been recognized. Then, if it is necessary, an alternative recognition to another part of image that spans more than one segmented symbol is applied. Also, an alternative recognition to the some equals parts of image that consist of more than one segmented symbol can be used. In result a graph of alternative recognitions is constructed and the most reliable recognition path is selected from it.

In this method it is proposed to do the following. If the reliability of the recognized symbol is less than a certain value (in our case 0.3) or if the recognized symbol is 'I' (the neural network learned to recognize the halves of the letters H and the left half of M as the symbol 'I'), then it is necessary to combine the current symbol with the next one. Next, it is necessary to check the width of the cut out section. If it is larger than some value (in our case 19 pixels), then it is necessary to divide the section into two identical parts and each of the received sections is sent to the neural network. If both results have high reliability (> 0.5), then it is considered that the symbols have been recognized correctly and the analysis process is applied to the next character. Otherwise, the obtained results are stored for further choice between alternatives. Also in such case other alternatives are recognized: if the width of the cut-out section is less than the maximum symbol width (30 pixels), then the character is sent to the neural network recognition (naturally, it zooms in and is inserted into the 24x24 pixel image). If the obtained results are highly reliable, then it is considered that the character was recognized correctly and an algorithm goes to the next unused section. Otherwise, an attempt is made to combine the current section with the third and so on, until the section width exceeds the critical value (50 pixels). When merging third and other sections the recognition steps of dividing into two parts and recognizing the whole symbol with the storing or choosing recognition results (depends on reliability) are repeated. In the end, if a symbol with high reliability has not been received, the symbol with the highest reliability or a pair of symbols, each of which has a reliability greater than 0, and one of which has the greatest reliability, is selected.

An example of recognition with results and reliability as well as alternative recognition is shown in Figure 5.
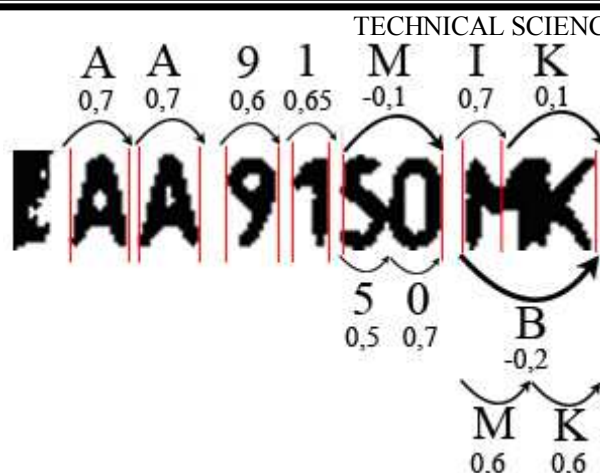
Fig. 5. An example of license plate recognition with alternative variants

After all the symbols, the reliability of which is less than 0, are removed.

The step of choosing the most suitable format includes comparison the recognized sequence of characters with predefined patterns of license plates. For example, the most common Ukrainian license plates formats has two such patterns: UC-DDDD-CC and DDD-DD-CC, where U – the symbols A-C, I; D – digits; C – symbols A-C, E, H, M, I, K, O, P, T, X and the digit 0 (the analogue of the symbol O). For Lithuanian license plates has the following pattern: LLL-DDD, where L is the characters A-Z and the digit 0. The choice of this or that license plate pattern is based on the probability of the characters and the distance between them: it is necessary to select the pattern in which characters that are not suitable for this format have the recognition reliability is no more than 0.5 (the exception of the symbol 'I') and the distance between blocks of individual characters is greater than between the neighboring characters in block (for example, distance between block LLL and DDD in Lithuanian pattern is greater than between symbols in blocks). In case when several patterns fall into the recognized characters at once it is necessary to choose one in which any of the not suitable for pattern symbols has less reliability than any symbol that can be eliminated in another format. For example, let the identified symbols 'LLC12345PO' with confidence 0.3, 0.3, 0.3, 0.3, 0.4, 0.4, 0.4, 0.4, 0.7, 0.3. In this case, some symbols were not recognized correctly, and in fact the indicated sequence of characters falls under both the format of Ukrainian and Lithuanian license plates. If the Lithuanian pattern is chosen, it turns out that the symbol 'P', having reliability above 0.5, is discarded. If the Ukrainian pattern is selected the 'LLC' symbols having a reliability of less than 0.3 are discarded. Since the symbol 'P' has more reliability then the Ukrainian pattern in this case is much more reliable than the Lithuanian one, and this if do not take into account the distance between the symbols, which may not correspond to the Lithuanian pattern. In the case when at least one symbol (with the exception of 'I') which must be eliminated by pattern has a reliability greater than 0.5, then it must be assumed that the license plate does not fall into any format.

The results of correctly and incorrectly recognized license plates using this method are shown in Figure 6. The total percentage of correctly recognized license plates strongly depends on the degree of license plate visibility and weather conditions. This method was tested with a real video stream camera, which is located above the highway, and which has good license plate visibility (Figure 6). The width of the license plates was from 120 to 150 pixels. The correct recognition percentage was 95-99 %.

With motion detection and processing of every 5 frames this method could process 10 recognition channels on an Intel I5-7500 processor.

Fig. 6. Correctly (a) and incorrectly (b) recognized license plates

Conclusions. This method successfully copes with the task of license plate recognition with confidence 95-99 %. But as the test results show the method has several drawbacks. First, this method does not easily recognize the "garbage" in the image and often confuses it with the symbol 'I'. Second, on the dirty license plates or on false detection this method repeatedly uses alternative recognition which leads to a significant load on the processor.

Further work on license plates symbols recognition can be directed towards improving the quality and speed of recognition. In particular it is planned to test the method of symbols recognition in which the convolutional layers of the neural network process the whole normalized license plate image and the full connected layer must apply to specific output areas of the last convolutional layer. This should improve the quality of recognition and for poorly visible license plate increase the recognition speed by reducing the time for alternative symbols recognition.

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РОЗПІЗНАВАННЯ СИМВОЛІВ АВТОМОБІЛЬНИХ НОМЕРІВ РІЗНИХ ФОРМАТІВ

Актуальність теми дослідження*. Зазвичай процес розпізнавання автомобільних номерів включає такі етапи: детектування номера, його нормалізація, сегментація зображення номера на окремі символи та розпізнавання символів. Ефективність розпізнавання автомобільних номерів залежить від кожного етапу, але для розпізнавання автомобільних номерів різних форматів ключовими етапами є сегментація та розпізнавання символів. Тому розробка методу розпізнавання символів автомобільних номерів різних форматів є актуальним завданням.*

Постановка проблеми*. Різні формати автомобільних номерів мають різні шрифти та різне розташування символів, що утруднює процес розпізнавання автомобільних номерів.*

Аналіз останніх досліджень та публікацій*. Загальні тенденції, що були виявлені в результаті аналізу публікацій, вказують на те, що для розпізнавання символів автомобільних номерів використовуються згорткові нейронні мережі, повнозв'язані нейронні мережі, кореляційний аналіз, бінаризацію зображень та побудову гістограм яскравостей.*

Виділення недосліджених частин загальної проблеми*. Усі проаналізовані методи підходять для розпізнавання символів на добре видимих автомобільних номерах. Оскільки в реальних умовах автомобільні номери можуть бути брудними або погано видимими, то використання зазначених методів є недоцільним.*

Постановка завдання*. Метою статті є опис методу розпізнавання автомобільних номерів різних форматів, який має високий відсоток правильного розпізнавання та може бути використаний для розпізнавання автомобільних номерів на відеопотоках з камер, розташованих над трасами.*

Виклад основного матеріалу*. Для розпізнавання символів автомобільних номерів пропонується використовувати гістограму яскравості бінаризованого зображення, для розпізнавання символів – спеціально створену нейронну мережу з можливістю розпізнавання альтернативних частин вихідного зображення автомобільного номера і для відсіву неправильно розпізнаних символів – список форматів автомобільних номерів.*

Висновки відповідно до статті*. Запропонований метод успішно справляється з завданням розпізнавання автомобільних номерів з достовірністю 95–99 %. Але, як показують результати тестування, цей метод має кілька недоліків. По-перше, цей метод погано розпізнає «сміття» на зображенні і часто плутає його з символом «I». По-друге, на брудних номерах або при помилковій детекції номера цей метод багаторазово використовує альтернативне розпізнавання, що призводить до значного навантаження на процесор.*

Ключові слова*: розпізнавання; згорткова нейронна мережа; автомобільний номер.*

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РАСПОЗНАВАНИЕ СИМВОЛОВ АВТОМОБИЛЬНЫХ НОМЕРОВ РАЗЛИЧНЫХ ФОРМАТОВ

Актуальность темы исследования. *Обычно процесс распознавания автомобильных номеров включает следующие этапы: детектирование номера, его нормализация, сегментация изображения номера на отдельные символы и распознавание символов. Эффективность распознавания автомобильных номеров зависит от каждого этапа, но для распознавания автомобильных номеров различных форматов ключевыми этапами является сегментация и распознавание символов. Поэтому разработка метода распознавания символов автомобильных номеров различных форматов является актуальной задачей.*

Постановка проблемы. *Различные форматы автомобильных номеров имеют различные шрифты и различное расположение символов, что затрудняет процесс распознавания автомобильных номеров.*

Анализ последних исследований и публикаций. *Общие тенденции, которые были выявлены в результате анализа публикаций, указывают на то, что для распознавания символов автомобильных номеров используются сверточные нейронные сети, полносвязные нейронные сети, корреляционный анализ, бинаризация изображений и построение гистограмм яркостей.*

Выделение неисследованных частей общей проблемы. *Все проанализированы методы подходят для распознавания символов на хорошо видимых автомобильных номерах. Поскольку в реальных условиях автомобильные номера могут быть грязными или плохо просматриваются, то использование указанных методов является нецелесообразным.*

Постановка задачи. *Целью статьи является описание метода распознавания автомобильных номеров различных форматов, который имеет высокий процент правильного распознавания и может быть использован для распознавания автомобильных номеров на видеопотоке с камер, расположенных над трассами.*

Изложение основного материала. *Для распознавания символов автомобильных номеров предлагается использовать гистограмму яркости бинаризованного изображения, для распознавания символов – специально созданную нейронную сеть с возможностью распознавания альтернативных частей исходного изображения автомобильного номера и для отсева неправильно распознанных символов – список форматов автомобильных номеров.*

Выводы в соответствии со статьей. *Предложенный метод успешно справляется с задачей распознавания автомобильных номеров с достоверностью 95–99 %. Но, как показывают результаты тестирования, этот метод имеет несколько недостатков. Во-первых, этот метод плохо распознает «мусор» на изображении и часто путает его с символом «1». Во-вторых, на грязных номерах или при ложной детекции номера этот метод многократно использует альтернативное распознавание, что приводит к значительной нагрузке на процессор.*

Ключевые слова: *распознавание; сверточная нейронная сеть; автомобильный номер.*
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