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SYSTEM OF LICENSE PLATE RECOGNITION CONSIDERING LARGE CAMERA SHOOTING ANGLES

The system of automatic license plate recognition (ALPR) is a combination of software and hardware technologies implementing ALPR algorithms. It seems to be easy to achieve the goal but recognition of license plate requires many difficult solutions to some non-trivial tasks. If the license plate is oriented horizontally, uniformly lighted, has a clean surface, clearly distinguishable characters, then it'll be not too difficult to recognize such a license plate. However, the reality is much worse. The lighting of each part of the plate isn't equal; the picture from the camera is noisy. Besides, the license plate can have a big angle relative to the camera and be dirty. These obstacles make it difficult to recognize the license plate characters and determine their location on the image. For instance, the accuracy of recognition is much worse on large camera angles. To solve these problems, the developers of automatic license plate recognition systems use a different approach to processing and analysis of images. The work shows an automatic license plate recognition system, which increases the recognition accuracy at large camera angles. The system is based on the technology of recognition of images with the use of highly accurate convolutional neural networks. The proposed system improves stages of normalization and segmentation of an image of the license plate, taking on large camera angles. The goal of improvements is to increase of accuracy of recognition. On the stage of normalization, before histogram equalization, the affine transformation of the image is performed. For the process of segmentation and recognition, Mask R-CNN is used. As the main segment-search algorithm, selective search is chosen. The combined loss function is used to fasten the process of training and classification of the network. The additional module to the convolutional neural network is added for solving the interclass segmentation. The input for this module is generated feature tensor. The output is segmented data for semantic processing. The developed system was compared to well-known systems (SeeAuto.USA and Nomeroff.Net). The invented system got better results on large camera shooting angles.

Keywords: license plate recognition system; machine learning; convolution neural networks; Mask R-CNN; image analysis.

Introduction

Automated license plate recognition systems (ALPR) have many areas of application today. It can be automatic accident detectors, which can call the police and ambulances. It also can be automatic sending of fines, which are already used on Ukrainian roads, payment systems in paid parking lots, and so on. Any of these automated systems can effectively function only with the automated license plate recognition ability.

ALPR systems are not only present a huge practical interest [1], but also theoretical. Because of this example, it is possible to check and analyze many different combinations of various algorithms. In the simplest case, such a system should consist of two modules: an image-processing module and a module for extracting the relevant information (car plate information).

Of course, this is just a primitive overview of the topic. If such a system should be used on real roads, many factors should be taken into account (lighting level, angle, image quality, etc.) [2, 3].

Today exists a big amount of different ALPR systems that can be divided into two groups – hardware and software systems.

Hardware ALPR systems it's systems that process data directly by a built-in environment (usually it's a camera that contains built-in software). The software method of processing the data means a process of transferring data to another device (usually its server), for necessary processing operations.

The main characteristics of such systems are the proportion of correctly recognized numbers; the angles of the license plate relative to the camera; the recognition distance and the speed of the vehicle.

Existing ALPR systems have a high quality of recognition only in strictly defined conditions of their application in terms of lighting, angles, and distances for the cameras used, the size of the license plate in the image, and so on. These restrictions are imposed on both types of used automatic license plate recognition systems: both hardware [4] and software [5]. Requirements for camera position in automatic license plate

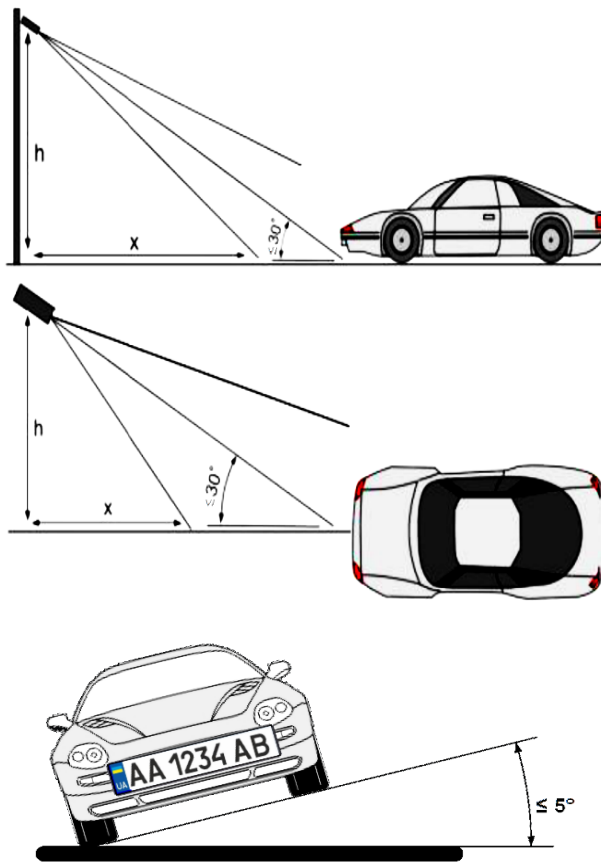recognition system and restrictions [6, 7] on their use are shown in Fig. 1.

Fig. 1. Requirements for camera position
(installation angle for vertical mounting – up to 30°,
installation angle for horizontal mounting – up to 30°,
roll angle – no more than +-5°)

Such restrictions complicate the use of modern ALPR systems in real situations on public roads, especially in the presence of multi-lane traffic, large camera shooting angles, bad visibility of license plates, and in difficult weather conditions [8, 9].

Increasing of efficiency of ALPR systems in real situations on public roads is possible only through the integrated use of technologies for optical character recognition and artificial intelligence [10, 11].

Implementing applications like this will not be possible without the use of artificial intelligence systems [12, 13].

There are many applications of the neural network of various structures to detect objects in noisy images: multilayer fully connected perceptron neural networks [14], convolutional neural networks [15], capsular neural networks [16, 17], etc.

The main idea of the paper is the use of convolutional neural network Mask R-CNN in ALPR systems. The architecture of this neural network, its features, and its advantages are analyzed in the work.

The following tasks can be distinguished in the work:
– analysis of existing algorithms of similar systems;
– analysis of the principles of construction and operation of a particular model with Mask R-CNN;
– research of model with Mask R-CNN and analytical comparison of the proposed system with analogues.

Analysis of the license plate recognition system

Before proceeding to the analysis of ALPR algorithms should briefly formulate features of the researched system – it should function effectively in conditions of public roads of Ukraine with the large camera shooting angles.

The model of ALPR systems must recognize car plates and first of all, it's important to be familiar with the basic structure of car numbers in Ukraine.

The types and structure of license plates are strictly defined. Each plate in Ukraine has the appropriate size and structure. All these characteristics can be found in DSTU 4278: 2019.

The most common is type 1 (Fig. 2). It has strictly defined characteristics: height – 112 mm; length – 520 mm; the number of characters – 8 (4 digits and 4 letters).

Fig. 2. License plate type first

All the processes of the ALPR system can be divided into four main stages (Fig. 3): image preprocessing, selection of the license plate on the image, segmentation of the license plate into individual characters, recognition of segmented characters. The most appropriate algorithms are used at each of these stages.
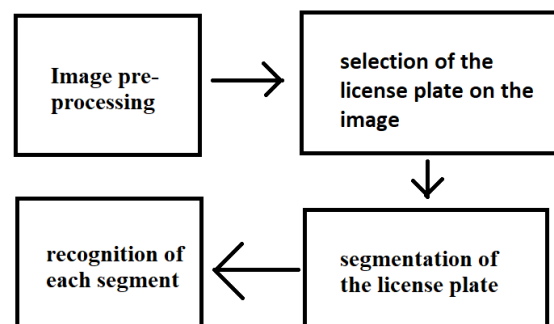

Fig. 3. Block diagram of the model of recognition of license plates

The algorithms for image pre-processing include the following: media filtering algorithm; equalization of histograms [18, 19].

The media filtering algorithm consists of selecting an image mask (for example, 3x3 pixel square), arranging the brightness values of these pixels, and determining the median value that will be applied to that mask.

If our mask is square 3x3 then the median value is 5th and if 5´5 then 13th.

The image histogram is a discrete function of the following type:

$$f(i) = \frac{n_i}{n}, \qquad (1)$$

where n_i – amount of pixels of picture that has i brightness level; n – amount of all pixels of picture.

Function f (i) normalized $0 \le f(x) \le 1$. Brightness values are plotted on the abscissa axis: $0 \le i \le 255$, on the y-axis – the values $0 \le f(x) \le 1$. The equalization method evenly increases the range between the brightness values present in the image, thereby increasing its contrast, thus the difference in the brightness of the half-tones will be greater. According to the formula, the histogram is transformed so that it takes the maximum-minimum brightness range

.

$$S_k = g(x_k) = \sum_{i=0}^{k} f(x_i) = \sum \frac{n_i}{n}, \qquad (2)$$

where S_k – the final brightness of the pixel, $f(x_i)$ – the value of the histogram at the x_i point, k – range.

S_k value lie in range $0 \le S_k \le 1$. If we want to use $0 \le S_k \le 255$ range, we should multiply S_k by 255.

Among the methods of the license number selection in the image, we can highlight the formula of affine transformations:

$$x' = \frac{a \cdot x + b \cdot y + c}{g \cdot x + h \cdot y + 1}, \qquad (3)$$

$$y' = \frac{d \cdot x + e \cdot y + f}{g \cdot x + h \cdot y + 1}. \qquad (4)$$

If you use these transformations, you can convert any quadrilateral to a rectangle. Fig. 4 shows a distorted image of the rectangle ABCD, which is obtained from the camera. This image was taken at a wide-angle camera. The coordinates of the point k are distorted in the image. In Fig. 4, b shows the result of the affine transformation (3) – (4). There is no distortion in the ob-

tained rectangle ABCD. The real coordinates of the point k(2,3) are obtained.

Image segmentation is the operation of dividing the input image into zones of interest for future research. In the system of recognition of license plates, the segmentation process is the process of selecting each number or letter on the plate. There are various methods of finding special areas in the image, one of which is segmentation based on neural networks. This method (based on neural network Mask R-CNN) is used in the model.
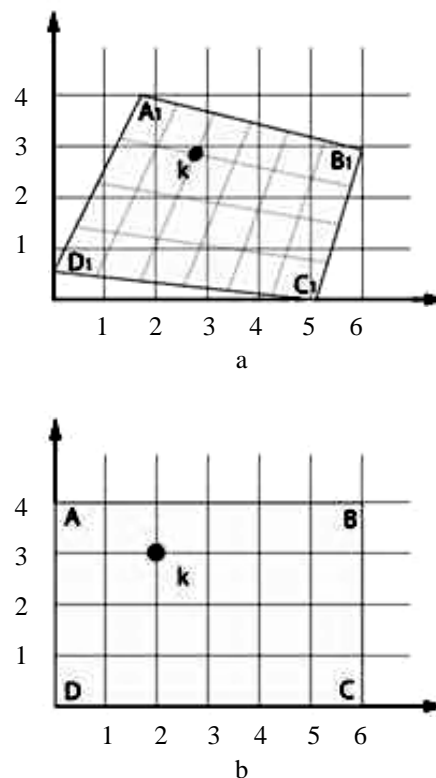

Fig. 4. Transform an arbitrary quadrilateral area into a rectangular

The last stage is the recognition of each character on the license plate. This issue uses a large number of different algorithms, but the main ones that find practical application are two: the method of reference vectors [20] and the method of neural networks. The method of reference vectors consists in transferring data into a larger space and searching for a separating hyperplane. A visual example of the algorithm of reference vectors is shown in Fig. 5.

In Fig. 5 blue dots belong to one class and green dots belong to another class. In this figure, you can see the disadvantage of this method. The decision depends on the training data because all three hyperplanes of this example satisfy us.
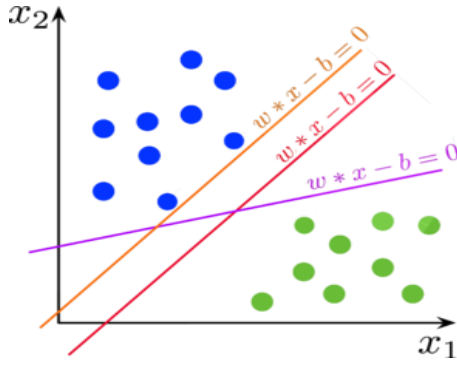
Fig. 5. Visualization of the method
of reference vectors

Fig. 7. General scheme of work Mask R-CNN

Because the method of reference vectors has this disadvantage, our model uses the neural network technologies.

Neural network Mask R-CNN

The main part of the whole project is the architecture of the neural network Mask R-CNN [21, 22]. This architecture is derived from previous neural networks (Fast R-CNN & Faster R-CNN) [23]. The Mask R-CNN architecture is based on the instance segmentation problem means that the model not only finds objects of one class in the image but also can select all segments of the corresponding class in this image.

The model first selects specific regions, and then uses the Convolution Neural Network (CNN) for each of the selected regions. The general scheme of operation of the convolutional neural network is shown in Fig. 6, and the general scheme of work Mask R-CNN is shown in Fig. 7.

It should be noted that there are many different CNN architectures: VGG, ResNet, DenseNet and so on. However, the nuclear CNN of Mask R-CNN is the architecture of CaffeNet (AlexNet).

Selective Search is used as the main search algorithm for segments that are later fed to the convolutional network [24].
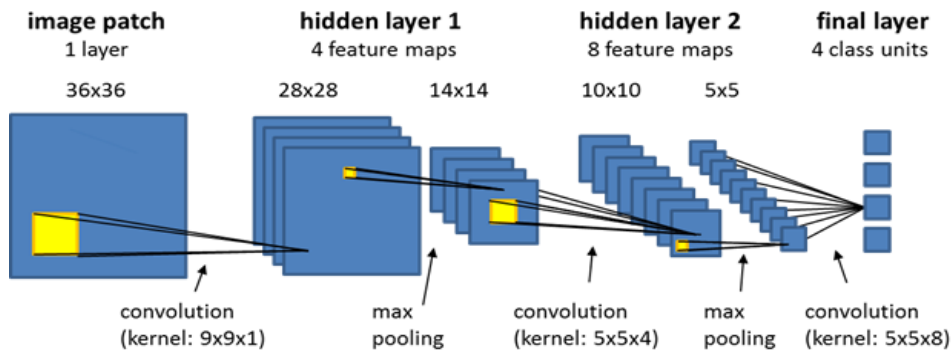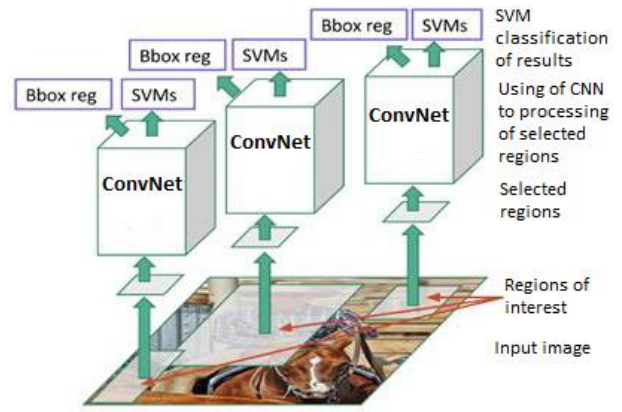
The authors of this neural network faced one significant problem. Memory greedy learning process of the neural network. By the way, this process needs a big amount of processing. Because even for simple cases, each fragment had to be stored in memory for each sub-net separately. The combined loss-function was used for simultaneous training of softmax-classifiers and bbox regressor [24]:

$$L(p, t^u, v) = L_{cis}(p, u) + \lambda[u \geq 1] L_{loc}(t^u, v), \quad (5)$$

$$L_{cis}(p, u) = -\log p_u, \quad (6)$$

$$L_{box}(t^u, v) = \sum_{i \in \{x,y,w,h\}} L_1^{smooth}(t_i^u - v_i), \quad (7)$$

where u – class of the object that actually present in the region;

$L_{cis}(p, u)$ – log los s for u-class;

$v = (v_x, v_y, v_w, v_h)$ – real dimensions of the frame for more accurate capture of the object;

$t^u(t_x^u, t_y^u, t_w^u, t_h^u)$ – obtained frame measurements;

L_{loc} – loss-function between real and obtained frame measurements;

Fig. 6. General scheme of operation of the convolutional neural network

λ – the initial coefficient, which serves to balance both loss functions (it should be noted that in the initial version of the model it was equal to one);

$$L_1^{smooth}(x) = \begin{cases} 0.5x^2, & |x| < 1, \\ |x| - 0.5, & |x| \geq 1. \end{cases} \qquad (8)$$

This approach helps solve the object detection problem (for the Fast R-CNN model), but not instance segmentation. An additional segment of such an object is used to distinguish the pixels of one object from another. In fact, it solves the problem of instance segmentation from the obtained feature tensor (Fig. 8).

For the approach described earlier, the general loss function is also used, which has the following form:

$$L = L_{cis} + L_{loc} + L_{mask}. \qquad (9)$$

Implementation

As a programming environment, we used PyCharm IDE and Python 3.7 as a programming language because as they are most common in the machine learning segment and free for an academic license.

It is also impossible to imagine the implementation of a machine-learning model from scratch, which is why a large number of third-party libraries were used.

NumPy is the most common library for working with tensors (multidimensional arrays). It allows in a short amount of time to make a large number of complex calculations with the entire tensor (the dimension of which can reach 14x14x512 in the simplest models). The general purpose of the library is to work with arrays and represent high-level mathematical functions.

OpenCV is a library of open-source computer vision and machine learning. It includes more than 2,500 algorithms, which have both classical and modern algorithms for computer vision and machine learning.

SkiPy is an open library of high-quality scientific tools. SciPy contains modules for optimization, integration, special functions; signal processing, image processing, genetic algorithms, solving common differential equations, and other problems that are solved in science and engineering.

TensorFlow is probably the most common library for machine learning and deep learning. It was developed by Google and includes a set of various fundamental functionalities for working with neural networks.

PyTorch is an open machine-learning library based on the Torch library, used for applications such as computer vision and natural language processing. It is developed mainly by the artificial intelligence research team of Facebook. It is free and open-source software released under the Modified BSD license.

Keras. Most of all modern neural networks use this library for analysis and development in this direction. Keras itself is an add-on to libraries that provide functionality for working with neural networks (such as TensorFlow).

When comparing this network with a similar one, the following result was derived (Fig. 9).

An assessment of the license plates recognition system is carried out on a test sample, which consisted of 1040 cars photos with Ukrainian license plates, 130 images for viewing angles 0, 10, 20, 30, 40, 50, 60, 70 degrees.
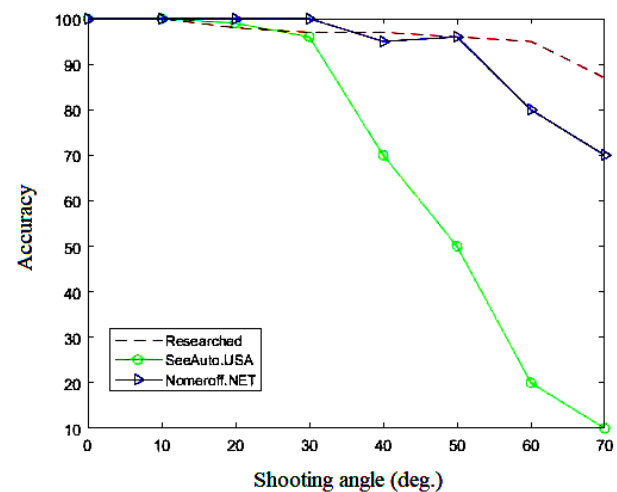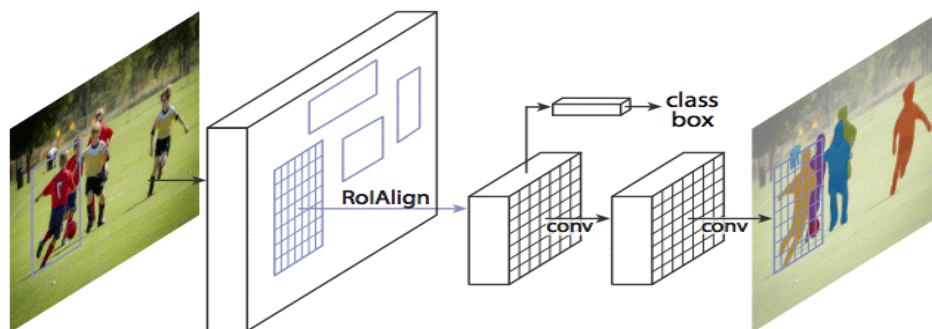

Fig. 9. Comparison of the network with analogues

Fig. 8. Solving the problem of instance segmentation using Mask R-CNN

For assessment, the quality of the model was used classification accuracy indicator [25]. Accuracy is the most common criteria for determination of efficiency of classification and it's defined as the ratio between correctly classified samples (all license plate symbols) to total number of samples (recognizable license plates):

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}, \qquad (10)$$

where TP – true positive; FN – false negative; FP – false positive; TN – true negative.

The accuracy was calculated for every possible shooting angle.

The resulting quality classification of license plates for the investigated system was over 0.95 for shooting angles less than 60 degrees.

Because of the comparison, it can be concluded that SeeAuto.USA [26] has worse indicators (number of correct recognitions) than a developed system at large viewing angles. Starting at a viewing angle of 50 degrees, the system shows good results (Accuracy = 0,96) as SeeAuto.USA (Accuracy = 0,5).

It should be noted that the project was based on the network Nomeroff.Net, in which the artificial neural network Yolov5 was used as a detector [27, 28]. The developed system with Mask R-CNN as a detector has better recognition results for shooting angles more than 50 degrees.

Conclusions

The work aimed to analyze the theoretical and practical problems associated with the creation of systems for the automatic recognition of license plates. The paper firstly shows information about Ukrainian license plates. Then the work divides the problem of classifying the number into several subsystems. For each subsystem, a description of algorithms and methods for solving each problem is presented.

Another task was to study and illuminate one of the most effective systems in this area – the neural network Mask R-CNN, which was created to effectively perform the task of instance segmentation.

The final part of the work presents the results of a comparative study of the system with some of the known software applications. Based on the conclusions of this comparative study, it is possible to get a clear idea of the possibilities of such a system in real situations on public roads.

The resulting accuracy of license plates classification for the researched system was more than 0.95 for viewing angles less than 60 degrees, similarly compared with known analogs, and significantly better than known analogs – for viewing angles over 50 degrees.

According to the results of the research, this license plate recognition system works optimally under different operating conditions. Moreover, this system shows excellent results compared to other similar systems (even at large angles and with different levels of illumination).

As a result, an effective system for license plates recognizing, the principles of its construction and operation were researched.

The purpose of further research is to check the efficiency of the proposed model on datasets with license plates of other countries and other real ALPR.

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СИСТЕМА АВТОМАТИЧНОГО РОЗПІЗНАВАННЯ АВТОМОБІЛЬНИХ НОМЕРІВ ПРИ ВЕЛИКИХ КУТАХ ЗЙОМКИ КАМЕР

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Система автоматичного розпізнавання автомобільних номерів – апаратно-програмний комплекс, який реалізує відповідні алгоритми розпізнавання. Незважаючи на зовнішню простоту завдання, розпізнавання номерів передбачає вирішення низки нетривіальних питань. Якщо автомобільний номер розташований строго горизонтально, освітлений рівномірно, має чисту поверхню, чітко помітні символи, то розпізнати такий номер не важко. Але практично такі умови зустрічаються дуже рідко. Найчастіше освітлення нерівномірне, на зображенні з камери є різні шуми. Крім того, номер може бути розташований під суттєвим кутом до камери та покритий плямами бруду. Це ускладнює розпізнавання символів номерного знаку та визначення місцезнаходження номера на зображенні. Зокрема, точність розпізнавання істотно знижується при великих кутах зйомки камер. Для вирішення перелічених проблем розробниками систем автоматичного розпізнавання номерів застосовуються різноманітні методи обробки та аналізу зображень. У статті запропоновано систему автоматичного розпізнавання автомобільних номерів, яка збільшує точність розпізнавання при великих кутах зйомки камер. Запропонована система базується на технології розпізнавання зображень з використанням згорткових нейронних мереж. У запропонованій системі вдосконалено етапи нормалізації та сегментації зображення номерного знаку автомобіля. Мета удосконалення – підвищення точності розпізнавання автомобільних номерів, отриманих при великих кутах зйомки камер. На етапі нормалізації перед еквалізацією проводиться афінне перетворення зображення. Для сегментації та розпізнавання номерного знаку використовується нейронна мережа Mask R-CNN. Як основний алгоритм пошуку сегментів обрано алгоритм Selective Search. Для прискорення навчання мережі запропоновано використовувати об'єднану loss-функцію. Введено додатковий модуль згорткової нейронної мережі для вирішення задачі внутрішньокласової сегментації. На вхід даного модуля надходить сформований тензор ознак. На виході модуля отримаємо сегментовану інформація для семантичної обробки. Проведено порівняльне дослідження запропонованого підходу з відомими реалізаціями систем автоматичного розпізнавання автономерів SeeAuto.USA та Nomeroff.Net. Запропонована система при великих кутах зйомки камери показала кращі результати.

Ключові слова: система розпізнавання автономерів; машинне навчання; згорткові нейронні мережі; Mask R-CNN; аналіз зображення.

СИСТЕМА АВТОМАТИЧЕСКОГО РАСПОЗНАВАНИЯ АВТОМОБИЛЬНЫХ НОМЕРОВ ПРИ БОЛЬШИХ УГЛАХ СЪЕМКИ КАМЕР

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Система автоматического распознавания автомобильных номеров – это аппаратно-программный комплекс, который реализует алгоритмы распознавания. Несмотря на внешнюю простоту задачи, распознавание номеров предполагает решения ряда нетривиальных вопросов. Если автомобильный номер расположен строго горизонтально, освещён равномерно, имеет чистую поверхность, чётко различимые символы, то распознать такой номер не составит труда. Но на практике такие условия редко встречаются. Чаще всего освещение неравномерно, на изображении с камеры имеются различные шумы. Кроме того, номер может быть расположен под существенным углом к камере и покрыт пятнами грязи. Это затрудняет распознавание символов номерного знака и определение местонахождения номера на изображении. В частности, точность распознавания существенно падает при больших углах съемки камер. Для решения перечисленных проблем разработчиками систем автоматического распознавания номеров применяются разнообразные методы обработки и анализа изображений. В статье предложена система автоматического распознавания автомобильных номеров, которая увеличивает точность распознавания при больших углах съемки камер. Предложенная система базируется на технологии распознавания изображений с использованием сверточных нейронных сетей. В предложенной системе усовершенствованы этапы нормализации и сегментации изображения номерного знака автомобиля. Цель усовершенствования – повысить точность распознавания автомобильных

номеров, полученных при больших углах съемки камер. На этапе нормализации перед эквализацией проводится аффинное преобразование изображения. Для сегментации и распознавания номерного знака используется нейронная сеть Mask R-CNN. В качестве основного алгоритма поиска сегментов выбран алгоритм Selective Search. Для ускорения обучения сети и проведения классификации предложено использовать объединенную loss-функцию. Введен дополнительный модуль сверточной нейронной сети для решения задачи внутриклассовой сегментации. На вход данного модуля поступает сформированный тензор признаков. На выходе модуля – сегментированная информация для семантической обработки. Проведено сравнительное исследование предложенного подхода с известными реализациями систем автоматического распознавания автономеров SeeAuto.USA и Nomeroff.Net. Предлагаемая система при больших углах съемки камеры показала лучшие результаты.

Ключевые слова: система распознавания автономеров; машинное обучение; сверточные нейронные сети; Mask R-CNN; анализ изображения.

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