Majority voting approach and fuzzy logic rules in license plate recognition process

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***Abstract*— This article discusses common approaches to the development of ANPR systems. The main idea of the article is the parallel use of several different classifiers for OCR and fusion of obtained data for improving the recognition accuracy.**

***Index Terms*— ANPR, OCR, classification, feature extraction.**

I. Introduction

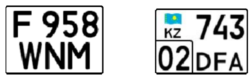
Intelligent systems of traffic control are in-demand systems because of the fact that a number of vehicles, highways increases with the country's economic development. They are most widespread in solving problems such as security of different objects (information security), the development of traffic management systems, tracking certain vehicles for government agencies (stolen cars, cars identification with suspicious persons, drunk driving, etc.), monitoring and control on the road. Development of such systems has a long history since the 80s to the present day [1]. The development of automatic number plate recognition (ANPR) technologies, their improvement is primarily due to the fact that these applications are in demand in the market, and also because of their use in different spheres (the parking fees, collection of fines), different sets of characters for license plates, enhancement or invention of new methods and algorithms for ANPR [2].

Analysis of existing ANPR systems shows that they are based on traditional methods and algorithms for image analysis and processing. Most of them work insufficiently on poor quality images, do not work on complex (diverse) scenes, since it is difficult to locate the region of interest, as well as functioning only under strictly defined conditions (lighting, camera angle, brightness, etc.). One of the motives for developing this work is the replacement of the government standard 1993 with the government standard 2012 which significantly changed the requirements to ANPR systems. The license plate of 2012 has the following considerable differences from the old license plate of 1993:

– a flag and code abbreviation “kz”;
– a line separating the province number of the main part of the license plate;
– reduced font size of characters and spacing between characters.

a) b)

Fig. 1. One-line license plate a) - government standard in 1993, b) - government standard in 2012.



a) b)

Fig. 2. Two-line license plate a) - government standard in 1993, b) - government standard in 2012.

Various studies on the ANPR identify the following general steps: the detection of the region containing the license plate; segmentation of license plate; feature extraction of each character and their further classification [3]. Some researchers refer segmentation, feature extraction and classification into one task of optical character recognition (OCR) [4].

We define following key steps of ANPR:

1) preprocessing of the original image into a form that does not depend on the conditions of image registration (lighting, uneven brightness distribution of light sources, blur, noise, etc.);
2) localization on the resulting image candidates potentially containing license plate and conduction of heuristic analysis on found candidates for exclusion of false areas using the formal representation of geometric characteristics;
3) normalization and segmentation of license plate;
4) recognition of segmented single character (character analysis based on the feature extraction that is independent on the scale, font, geometric distortions and gaps, finding the features vector; character classification);
5) validation of the OCR results based on number syntax check.

Steps above determine the general scenario of ANPR systems without considering the characteristics of particular algorithms used at appropriate stages. The use of specific algorithms and approaches for solving individual tasks of scenario may require some adjustments in the composition and sequence of steps. However, analysis of the ANPR problem suggests that this structure of recognition scenario is the most common and almost invariant to the selected algorithms.

In this paper we review the fourth step - the process of recognition of segmented single character. So, we work with already segmented and normalized images. In our case, we consider the approach for developing a robust system. The main idea of this article is improving the system stability using the approach of parallel implementation of several different methods of character recognition and building a majority voting system in which the result of the work is based on voting or selecting the most probable option.

II. Related work

Due to the demand for commercial ANPR software many applications were created that often have the same type of structure consisting of localization, segmentation and recognition algorithms. In [2, 5, 6] researchers consider the recognition process as a sequence of the following parts: license plate detection followed by license plate character recognition. Yang, Hu, Yu, An, Xiong [7] present a system which includes the image acquisition, license plate location, character segmentation and character recognition as well as in work of Hsu, Chen, Chung [8].

The essential step before classification is the process of feature extraction. Zheng, He, Samali, Yang introduce the work where the characters on a license plate image are extracted by a method based on an improved blob detection algorithm for removal of unwanted areas [9]. The paper of Chang et al. describes the process of feature extraction where segmented characters are standardized [10]. Nejati, Pourghassem, Majidi extract features using the method based on directional projections and Kirsch edge detector [11]. Martinsky in his work describes two different types of feature extraction: statistical image processing (region based edge detection) and skeletonization and structural analysis [5]. The general methods for OCR are the following: an artificial neural network-based OCR [12], Chang, Ryoo, Lim use in their work artificial vision to solve a task of classification [13]. Chang et al. [10] and Wu et al. [14] use the classifiers of support vector machine (SVM) to train and then recognize characters. One of the most common methods of OCR is neural networks, particularly multilayer perceptrons. Nejati, Pourghassem, Majidi use mixture of experts which apply the multilayer perceptrons to classify the extracted characters [11]. Martinsky views following neural networks: McCulloch-Pitts binary threshold neuron, percepton, feed-forward neural network [5]. The use of several classifiers is shown in the work of Chen, Chang, Liu [15].

III. General approach to feature extraction and classification in proposed system

A. System overview

The image, obtained from the camera, has different characteristics - metrics that affect the quality of the recognition process. We distinguish the following metrics:

– image distortions;
– size and dimension of localized license plate;
– angle of license plate capture;
– contrast of the original image.

There exist following types of distortion: blurring, mosaic pattern, ringing, false edges, various kinds of noise on images, the distortion produced by the camera optics, such as spherical aberration. Noise and blurring have the greatest impact on the quality of the recognition process. Other types of distortion can be omitted as they may appear on individual frames and we can select from the video stream the frame without given above distortions, except distortions such as the spherical aberration that can be corrected by the image capture step.

The next metric is the size and dimension of localized license plate. Due to the fact that the Closed Circuit Television (CCTV) cameras have rather narrow range of image resolution, many license plate recognition algorithms give unsatisfactory results at small sizes of the localized license plate.

The angle of license plate capture plays an important role since by the deviation of more than 20 degrees the characters on the license plate go through strong geometric distortion and are difficult to normalize. Only some recognition algorithms work equally well for the license plates with different angles of capture. The main part of the OCR methods require normalized plate.

Under conditions of lack of light or of specific characteristics of the camera the original image contrast may be low which also affects the quality of character recognition.

Taking the metrics given above into consideration we need to use for the OCR the methods or a combination of such methods that would be resistant to these kinds of distortions and provide a high percentage of the character recognition.

The key element of classification step is the requirement to take into account the wide variations of the character images from one class. This is due to the variability of the input data and to the results of previous steps, which can make their specific distortions in the input data for OCR.The essential step before classification is feature extraction which is a process of transformation of segmented and preprocessed images into a form of descriptors, which are suitable as an input for classifiers.

Since we have accurate information about what template of license plate and how the characters are arranged on it, we can apply various classifiers depending on what kind of template is used and on what the position of this character on template is. The color of background can be used to determine the type of license plate template, it will allow us to determine whether the license plate belongs to an individual, legal body, diplomatic mission, non-resident or the state entity according to the government standard 2012. The height and width of license plate can be used to determine if the license plate is one-lined or two-lined.

The idea of parallel classifiers is that we supply the same vector X (obtained in the step of the pixel bitmap conversion into a predetermined features vector) to the input of different classifiers. Second option is when the bitmap is converted in a given features vector using several various methods, and the resulting vectors X_i are supplied to corresponding classifiers C_i (Figure 3). The advantage of this option is that we can choose the most effective pair of bitmap conversion function and classifier.

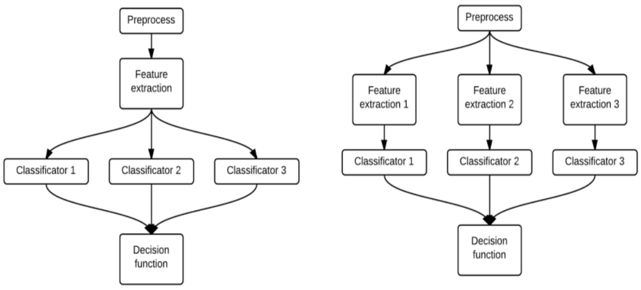


Fig. 3. The model of parallel implementation of the classifiers.

On next step we need to determine the optimal number of required classifiers. It should be based on considerations of the system performance balance and accuracy of character recognition. Also the number of classifiers may be dynamically-sized and may depend on the following factors:

- the overall system performance and compute capacity of hardware;
- the external conditions of the system operating, such as lighting, atmospheric precipitations;
- camera quality and its features.

It’s important that under the certainty of the classifier it should not be considered the accuracy of the classification method trained on a particular dataset, but the accuracy of the combination of the bitmap conversion function and classifier. This is significant, since the features vector conversion function can bring in its errors to the operation of the entire system.

Having several different classifiers executed parallel, we come to the step of the obtaining the final result of OCR. There are several different scenarios:

- if the half+1 classifiers retrieve same character, then we can state that this character entered as input;
- in case when less than half of classifiers returned the same character, we apply Bayesian theorem to calculate the probability that the character was recognized properly. If the probability is within the required accuracy, we believe that the character was recognized correctly, otherwise, next option is to select;
- if all classifiers retrieve different characters, then we choose the character that was obtained from the classifier with least error (all errors of classifiers are weighted previously).

Some classifiers (RVM) can return the probability that this character was recognized correctly. Such data can be used in the case of classifiers step-wise execution. It means the classifiers are implemeted step-wise until the given accuracy of recognition, or until the time limit for the recognition of one character, since the system should operate in the soft real-time.

We suggest to use a majority voting system [4] based on fuzzy logic. Methods of fuzzy logic, the theory of fuzzy sets and relations are now widely used in modeling the control and recognition systems, that is, where it is necessary to assess the situation and make a decision in terms of inaccurate information or if having fuzzy objectives and constraints [16,17,18]. Fuzzy logic allows to formalize quantitative fuzzy concepts operated by an expert at describing their perceptions of the real system, their wishes, recommendations, management purposes.

For solving the problem of recognition it is important which method to use, so it is first necessary to determine the dependence of given metric on a number of factors. In this regard, we consider the problem of choosing a recognition method in fuzzy reasoning information environment, and to implement it use the method of fuzzy inference.

The production model of selection scenario of recognition method allows on value of four fuzzy variables: DISTORTION with term-set {"yes", "no"}, RESOLUTION with term-set {"low", "medium", "high"}, ANGLE with term-set {"0-7", "8-14", "15-20"}, CONTRAST with term-set {"0-0,35", "0,36-0,7", "0, 71-1 "}, evaluate the output linguistic variable METHOD OF RECOGNITION on the term-set {"Method1","Method2","Metod3"}. Fuzzy selection scheme of recognition method is presented on Figure 4.

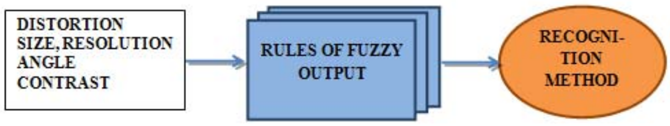


Fig. 4. Fuzzy selection scheme of recognition method.

The rules of production model help to implement a majority voting system for choosing the appropriate recognition method.

We plan to build an "error map" of classifier using statistical methods, so we can determine how often and with what characters classifier fails. For example, the classifier can often confuse the character "O" and "0". So we can correct the work of parallel classifiers and improve the accuracy of the majority voting system.

B. Implementation details

The work on the project is in progress and so far there was made a training dataset and implemented all preprocessing steps: detection, localization, normalization and segmentation. Dataset for OCR counts 2054 plates of standard 2012 and 1530 plates of standard 1993. There is also a database of model license plates containing all possible numbers for the standards 2012 and 1993 in a one- and two-line form. The total amount of characters for training and testing the proposed system reaches over 8000 images.

For the experiment the programming language Python and following libraries were used :

- computer vision libraries opencv and scikit-image;
- math library numpy;
- machine learning library scikit-learn.

In the course of research two feature extractions were implemented. In the first case the image was divided into 6 regions, after that we define edge type in each region using the method described in [5].

In the second case the structural analysis was used [6]. The first step is skeletonization in which we obtain one pixel wide skeleton of a character. In the following the features are searched for the obtained skeleton. In this case we have two types of features:

- terminal points appear as end lines of character skeletons;
- T- and X-joints are joints where three or more lines of the skeleton merge in one point.

As distinct from the method in [6] our algorithm has been simplified, e.g. Molder, Boscoianu, Stanciu, Vizitiu place the non-median feature symbols in a separate class and the feature vector is formed for them different. The number of different types of points and their position and order can form a feature vector that is used for further classification (Fig. 5) [6]. But this method of obtaining the feature vector does not allow distinguishing characters such as "0", "O" and "D" or "8" and "B" in the right degree, because these characters have same features in given feature vector (Fig. 6).

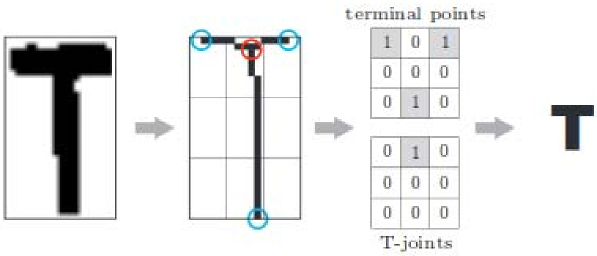


Fig. 5. Skeleton feature example.

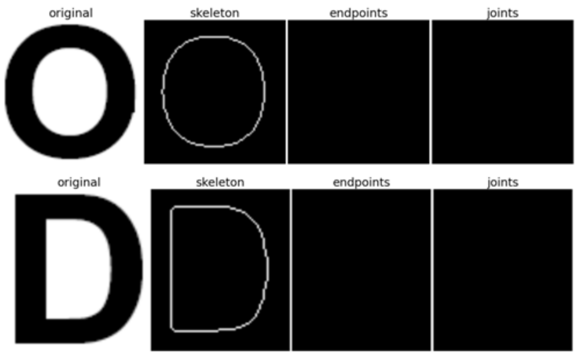


Fig. 6. Similarity of characters in a given feature vector.

So now one of the criteria of the feature vector selection is occurrence of black pixels in the central zone of character. In the case if there are no black pixels in the center of the image then we choose the feature vector based on edge type.

In conditions of low contrast of the original image the method based on edge type showed the best results that is due to the appearance of distortions during the process of character skeletonization, i.e. there may be abnormal endpoints and joints for the given character.

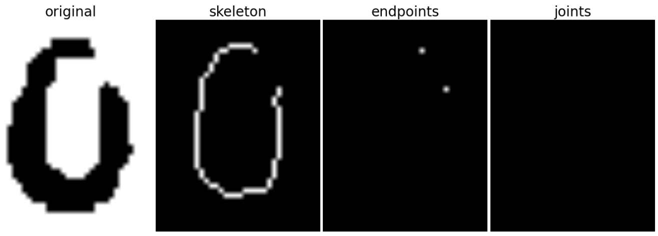


Fig. 7. Structural distortion of the character.

The structural analysis method is sensitive to the distortions of the image, the following image (Fig. 7) does not allow a character recognition with the method of the structural analysis, because there are endpoints, that are unusual for this character. At the same time the method based on edge type can cope with slight distortions of this kind.

The feature vector based on edge type functions well if the characters have undergone slight rotation otherwise the performance of the feature vector lowers.

During the experiments the following classification methods were tested: C-Support Vector Classification and Linear Support Vector Classification of machine learning library scikit-learn. For the C-Support Vector Classification method the following kernel types were tested: 'Linear', 'Poly', 'RBF' and 'Sigmoid'. The core 'Linear' showed the best result, the core 'RBF' has the second result. The kernels 'Poly' and 'Sigmoid' showed unsatisfactory results with recognition accuracy of less than 50%.

Also the experiments using the probability estimation method of Wu were performed [19]. This method can improve the performance of the majority voting system, as the choice of end result is considered based on the feature vector that has the higher probability of accurate recognition for the given recognized character. It should also be noted that using this approach of Wu is expensive and we should conduct additional studies of efficiency of its use.

The application of the majority voting approach eliminates the errors caused by the failure to distinguish some of the characters in a given feature vector due to similarity (identity) of characters in this feature vector, and also allows to level up disadvantages of each feature vector.

For the reason considered above we plan to continue working on the majority voting approach for the receiving more accurate recognition result. There will also be applied set of rules that will make corrections in the result of the system depending on the metrics described above.

IV. CONCLUSION

Using the principle of the majority voting system and the set of rules depending on metrics of original image can improve the accuracy of ANPR systems without applying higher-quality cameras. This remains pertinent in the Republic of Kazakhstan as in many cases the implementation of ANPR systems is performed based on the existing network of video surveillance cameras on the roads. In this situation updating the cameras is impractical and often impossible due to the lack of funds for the installation of more advanced cameras. These methods also allow predicting the errors and inaccuracies in the process of ANPR, which is an important factor for improving the quality of software and algorithms used. Automatic testing of each module and the entire system allows creating an explicit service-level agreement (SLA), which is an important factor for the main client - the legal bodies of the Republic of Kazakhstan.

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