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Detection and Classification of Vehicles Using Selected Methods of Image Processing

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ABSTRACT

Methods of vehicles detection and classification using image processing are becoming increasingly popular, especially due to their non-invasiveness in the road surface and relatively lower installation and maintenance costs. These methods are commonly used in traffic flow monitoring systems and detection of vehicles with specific parameters. Importantly, the use of video analytics methods is still characterized by sensitivity to external disturbances such as variable weather conditions. The work discusses selected data processing mechanisms that have been applied within the functioning vehicle recognition subsystem. As part of the analysis, the effectiveness of the applied solutions and sensitivity to the occurring weather conditions were assessed.

KEYWORDS: image processing, vehicle detection, vehicle classification

1. Introduction

Vehicle classification is an important issue related to traffic monitoring systems. Detection of vehicles and assignment to the appropriate class is currently carried out using a variety of measurement systems. Starting from loop classifiers, through radar and 3D scanners, ending with image processing methods. Vehicle classification is also possible through the use of various statistical methods, including discriminant analysis [1] and neural networks [2]. Importantly, due to the continuous development of image processing methods and the availability of libraries for machine learning, video methods are becoming more and more attractive. These methods do not require the use of specialized measuring devices and are finding application in case when there is no possibility of interference in the road surface.

The first stage of image processing is the vehicle detection process. For this purpose, various mechanisms of vehicle detection are used, including motion detection [9], color transform models [11] or vehicle license plate detection [6]. A common solution is also the use of Haar-like feature in order to create a represented set of features of a given object [10]. An example of such solution may be the detection of a license plate using the Haar cascade and thus the detection of a vehicle.

In process of classifying vehicles based of video images different approaches are used. An example is the use of bayesian networks [3], support-vector machine learning [4] or neural networks [5]. The last of these techniques, which is characterised by high efficiency of operation, has been used as part of this work.

2. Vehicle detection

In order to detect vehicles, the Haar cascade was used. In this case, the detection of objects is based on the method proposed in work [8]. It is a type of machine learning based on software training using a very large set of images divided into positive images (containing license plates) and negative images (not containing license plates). On collected positive images, the cascading software examines specific image features that occur on all tested samples. The following features are detected: edge, line and four-rectangle features (Fig. 1). Each feature is a single numerical value resulting from the difference of selected classifiers and the analysed part of the reference image [12].

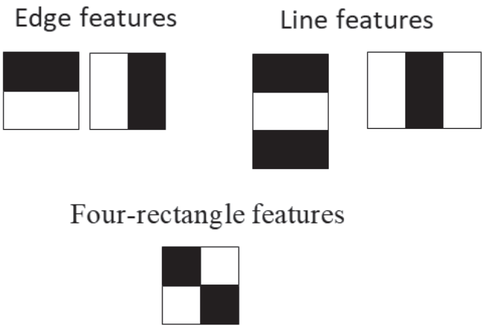

Fig. 1. The example of images for class car (own study based on [12]

In cascade different sizes and locations of the classifiers to search for a list of features are used. For example, a 24x24 pixel image can provide over 160,000 features to imporve classification. During learning, the acquired features on individual images are tested throughout the training set to eliminate non-essential features. Then the features are grouped into the next stages of classification. The classification takes place in a cascade. If at the beginning the image will not have the relevant feature it will be rejected and will not be qualified as a registration plate. This approach allows a significant reduction in computing power. Thanks to this, it is possible to detect vehicles in real time, where each frame of the recorded image can be subjected to detection of the license plate by the Haar cascade. For testing the Haar cascade used the open source project presented in [13]. The cascade was learned for European registration plates.

Table 1. The effectiveness of the vehicle detection [own study]

Camera	Number of vehicles	False Positive	Accuracy
Cam1 - day conditions	667	1%	97,6%
Cam2 - day conditions	313	3%	96,4%
Cam1 - night conditions	75	0%	94,5%
Cam2 - night conditions	88	7%	85,1%

Table 1 shows the effect of vehicle detection with the use of the Harr cascade. The assessment of effectiveness was carried out in day and night conditions for two observation points (cameras). Each camera registered two-lane traffic with the same direction of movement. The obtained results confirmed the high efficiency of the presented method.

3. Vehicle classification

Another part of the work is development of a vehicle classification method using image processing techniques. In this case a convolutional neural network was used. As a training set and validation data used the images of vehicles assigned by expert to proper vehicle class. The data was divided into 5 classes: car, commercial vans, lorry and buses, articulated lorry and motorbikes. The example of images is presented respectively at Fig. 2 to 6.

Fig. 2. The example of images for class car [own study]

Fig. 3. The example of images for class commercial vans [own study]

Fig. 4. The example of images for class lorry and buses [own study]

Fig. 5. The example of images for class articulated lorry [own study]

Fig. 6. The example of images for class motorbikes [own study]

All data was gathered from the several weigh in motion systems (WIM) which register basic parameters of vehicle such as axle load, length, speed etc. What is important as show in the Fig. 2-6 collected images were recorded with different observation angles and different backgrounds.

The network was built based on the Tensorflow and Keras software [14]. The Tensorflow software is a low-level library that enables high performance numerical computations including the use of neural networks and the Keras software is a high-level application programming interface to use deep learning models. The architecture of network is presented at Fig. 7.

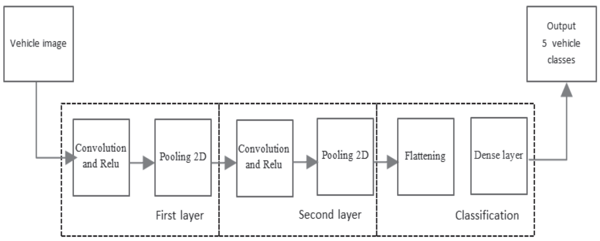

Fig. 7. The architecture of convolutional neural network [own study]

In work a stack of layers with use of sequential model was used. The model consist of 2 basic layers and densely-connected layer with 128 units (Fig. 7). As a the activation function the rectified linear unit was set and the output layer is using sigmoid activation. In order to compile network the *AdamOptimizer* and *categorical_crossentropy* loss function was used.

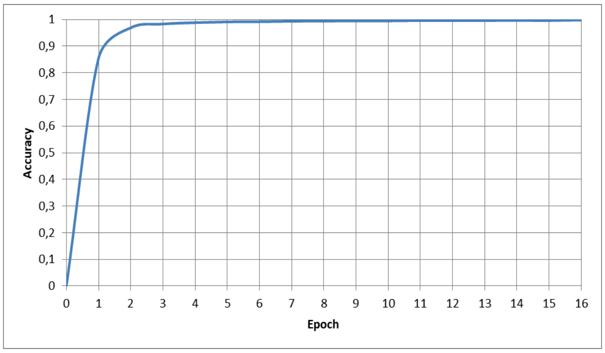

Fig. 8. The accuracy for particular epochs [own study]

To fit the model used the function *fit_generator* with total number of steps at level 8000. The number of epochs was determined based on the distribution of network accuracy (Fig. 8). A value of 10 was assumed for which 99,4% accuracy was achieved.

The training dataset contained almost 20 thousand of vehicle images. The number of images for classes car, articulated lorry and van was about 5 thousand per each class. The lowest number of data was for the motorbike class (Table 2).

Table 2. The effectiveness of the classification – training set [own study]

The class specified by an expert	The effectiveness of classification	The class specified by CNN method				
		Car	Articulated lorry	Lorry and bus	Motorbike	Van
Car	98%	5259	39	3	7	72
Articulated lorry	95%	7	4948	216	0	13
Lorry and bus	76%	21	691	2626	1	123
Motorbike	86%	17	13	3	510	50
Van	91%	215	124	101	1	4678

Using presented neural network method the overall accuracy for the training dataset was about 91%. The highest effectiveness obtained between the car and the lowest for lorry and buses. As show in Table 2 there are many errors in distinguishing between the class lorry/buses and articulated lorry.

The next part of the work was the assessment of testing set effectiveness. In first stage the testing set include image registered in favourable weather conditions. The example of images is show at Fig. 9.

Fig. 9. The example of images for favourable weather conditions [own study]

In Table 3 presented number of images per each class and the effectiveness of the classification. The high accuracy was obtained for the class car (98%) and van (94%) and lowest for articulated lorry in case of which there were several errors of classification into the lorry and buss category. The accuracy for the motorbike class was 100%, however in the testing set, due to the winter period, registered only two records.

Table 3. The effectiveness of the classification – testing set 1 [own study]

The class specified by an expert	The effectiveness of classification	The class specified by CNN method				
		Car	Articulated lorry	Lorry and bus	Motorbike	Van
Car	98%	147	0	0	0	3
Articulated lorry	87%	0	95	14	0	0
Lorry and bus	92%	0	11	152	0	2
Motorbike	100%	0	0	0	2	0
Van	94%	8	0	0	0	122

The second stage of testing was checking the accuracy for winter conditions. The example images of data set is presented at Fig. 10.

Fig. 10. The example of images for winter weather conditions [own study]

In case of winter condition the number of vehicle records per each category, despite motorbikes, was about 120-150 (Table 4). In this testing set there weren't any motorbikes registered. The highest accuracy was obtained for the cars (99%) and the lowest for commercial vans (68%). The classification of lorries was at level 85% and articulated lorries 94%.

Table 4. The effectiveness of the classification – testing set 2 [own study]

The class specified by an expert	The effectiveness of classification	The class specified by CNN method				
		Car	Articulated lorry	Lorry and bus	Motorbike	Van
Car	99%	138	0	0	0	1
Articulated lorry	94%	0	139	9	0	0
Lorry and bus	85%	1	19	134	0	3
Motorbike	-	-	-	-	-	-
Van	68%	34	0	4	0	82

Summarizing the tests of the vehicle classifier in different weather states, the authors did not noticed significant sensitivity for winter conditions for car, articulated lorry and lorries. Only for the van class there has been a noticeable decrease in the classification levels. It is worth noting that confirmation of submitted conclusions requires performing test on increased research sample and in more diversified weather conditions.

4. Conclusion

The analyses presented in the paper showed a high usefulness of the presented methods of vehicle detection and classification. However, these works have been made separately. This separation basically resulted from the necessity of obtaining a large set of data for the neural network learning process - nearly 20,000 records were used in the work. The next stage of work will be a combination of both presented mechanisms into one common system and the evaluation of its effectiveness in real traffic conditions. As part of future work, authors are planning to increase the number of layers in the neural network in order to improve accuracy of model. Also testing different combinations of learning sets will be performed. In addition, the use of a graphics processor is considered to increase the efficiency of the neural network learning process.

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