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Method of vehicle classification using discriminant analysis

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ABSTRACT

Proper characteristics of the traffic flow is a particularly important issue in the process of optimizing the efficiency of transport networks as well as in the traffic control systems. One of the elementary parameters of traffic flows is the structure of vehicles, which evaluation, in case of the automatic systems, requires the implementation of proper algorithms and methods for vehicle classification. In the paper is presented a method of vehicles classification using the discriminant analysis. Furthermore authors developed a classifier, which aggregate data according to classification 8+1 in accordance with the TLS specifications and according with the classification presented in the specification COST 323. As input dataset to the classification method were used vehicle parameters recorded by the weight in motion systems.

KEYWORDS: road traffic, vehicle classification, discriminant analysis

1. Introduction

The issue of vehicle classification is still valid subject of research, which development is conducted for many years. The work can be distinguished by the two main research areas:

- searching algorithms to ensure the maximization of the efficiency of used so far methods of the classification,
- searching new methods for classification of vehicles in motion.

The division of classification methods can be carried out on the basis installation method, which leads to the award of methods:

- invasive (methods using inductive loop, pneumatic detectors, magnetic or piezoelectric sensors),
- non-invasive (method using radars, infrared sensors, recorders of sound levels, video cameras etc.).

Classification method can be also divided by the used qualifiers (axle configuration, the dimensions of the vehicle [1,2,3] and other features, such as the noise level [4] or the level of the induced substrate vibration [5]).

Comparison of classification capabilities for existing technologies, including the effectiveness of the classification obtained for the different methods presented in [6], which states inter alia that not all of the ways the classification is equally useful at low freedom of movement. Weigh-in motion (WIM) system uses similar qualifiers as the manual method, i.e. information is used at the same time by axle configuration and dimensions of vehicles. This allows to classify vehicles in 13 classes, which allows the classification according to the COST 323 and TLS standards with overall efficiency exceeding 90%.

However, taking into account the different solutions in measurement technology used within the WIM station, a large variety of methods of classification and the high demands of the market regarding the effectiveness of vehicle recognition, it is advisable to search for a universal method which will be based on the basic parameters of vehicles, measured on practically any WIM stations and on which the high measuring accuracy is required.

2. Method of vehicle classification using discriminant analysis

2.1. Characteristics of research material

The materials collected for the study were data recorded by the several WIM stations, with accuracy class B +(7) according to the

COST 323 specification. Schematic diagram of stations is presented in figure 1. Each station consists, among other equipment, of a set of inductive loops, wheel/axle load sensors and video detection cameras.

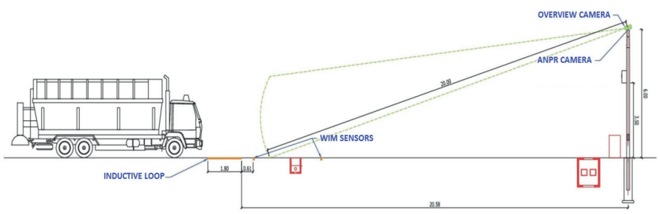

Fig. 1. Diagram of weigh-in motion station [own study]

In the study, from a recorded vehicle parameters, authors selected those features, which directly connected to the structure of the vehicle: number of axles, vehicle length, spacing between the first and second axis, the maximum and minimum wheelbase and the number of axles in the group. Additionally, in order to increase the diversification of the particular vehicles classes, parameter of the first axle load was selected. This value, as has been shown inter alia in [7], is a parameter of low volatility and can be used to calibrate the WIM systems.

The aim of the proposed method is to determine, on the basis of selected parameters the vehicle class according to the classification 8 + 1 (specification TLS) and COST 323. The description of both classifications is presented in table 1.

Table 1. The vehicle classes according to the 8+1 and the COST 323 specification [own study]

Description	Category (8+1)	Category (COST 323)
Other vehicles	6	8
Motorbike	10	8
Car	7	1
Van	11	1
Car with trailer	2	1
Lorry	3	2: Two axle rigid lorry 3: More than 2-axle rigid lorry
Lorry with trailer	8	6
Articulated lorry	9	4: Tractor with semi-trailer supported by single or tandem axles 5: Tractor with semi-trailer supported by single or tridem axles
Buses	5	7

According to the specifications given in table 1 classification 8+1 is much more demanding form of vehicle categorization. This classification requires, among other things, to distinguish motorcycles, passenger cars and commercial vehicles as separate groups. In the case of the COST 323 classification, determination of the vehicle class is primarily connected with the number of axles. Therefore, the authors decided that the method of classification presented in the article will be based on 8+1 standard (without the class "Other vehicles") while the designated category accruing to COST 323 will be derived from this method - determination on the basis of 8+1 classification and for lorry and lorry with trailer in an additional condition concerning the number of axes.

In the next part of the work the authors propose the use of the procedure based on discriminant analysis, which was among others presented in [8].

2.2. Discriminant analysis

The basis of the proposed vehicles classification method is discriminant analysis, which is statistical method for examining differences between groups of objects based on a set of selected independent variables. In case of the analysed work, discriminant analysis was applied in order to determine which variables distinguish (discriminate) different classes of vehicles, which allows for assigning object to the proper class at minimum classification error.

In the first step of the presented methods authors have performed discriminant analysis for the entire data set. As a result of analysis, the two eigenvectors DA1 and DA2 with the highest eigenvalue were obtained, which explains over 90% of the variance. The correlation of particular vehicle parameters with the DA1 and DA2 vector is shown in figure 2.

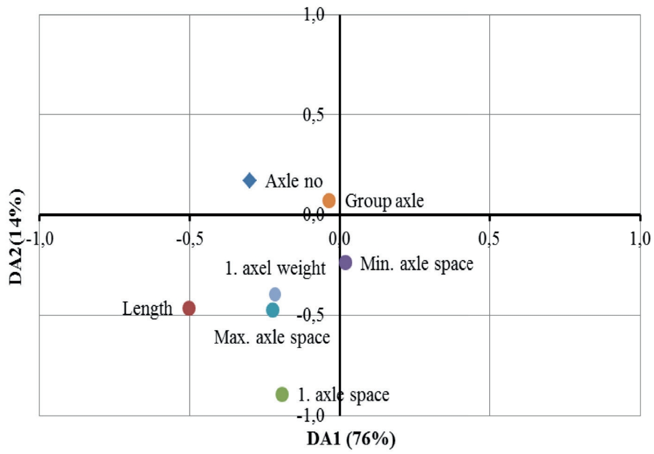

Fig. 2. Correlation coefficient for DA1 and DA2 [own study]

Analysis presented in figure 2 indicates the highest correlation of DA1 vector with the length of the vehicle. The number of axles, the maximum wheelbase and the vehicle first axle load are significantly important. In case of DA2 highest correlation value obtained with the spacing between the first and second axle and the maximum wheelbase. Distribution of objects in the area of two main vectors DA1 and DA2 is shown in figure 3.

As can be seen in figure 3, discriminant analysis made it possible to obtain high distinctions of classes 10, 9, 8 and 2. For classes 3, 5, 7, 11 sets of calculated values form a common area with a clear overlap between classes 3/5, 3/11 and 11/7. Accordingly, in the presented method authors assumed that those classes form a common set of data which will be distinguish in the next analysis step.

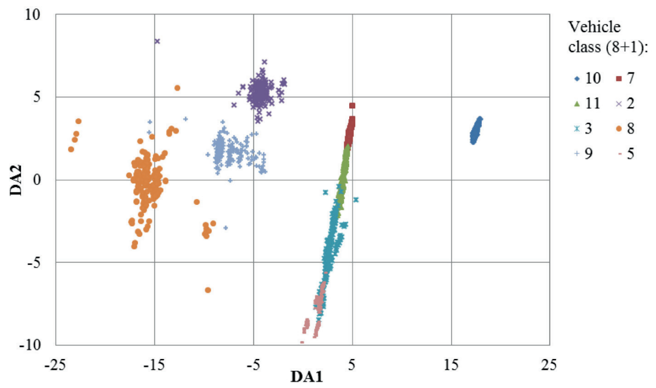

Fig. 3. Distribution of objects in space of the first two eigenvectors for the entire data set [own study]

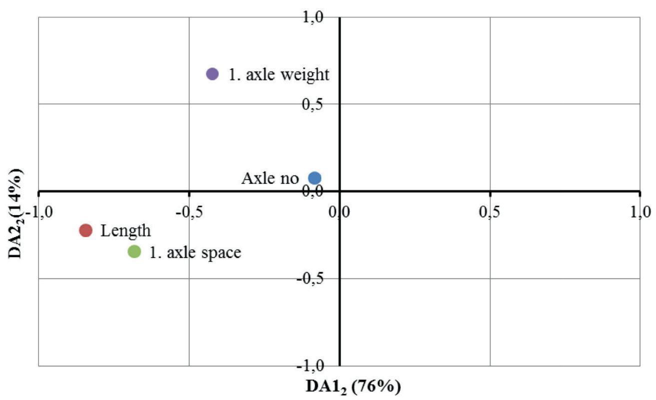

Fig. 4. Correlation coefficient for DA1$_2$ and DA2$_2$ [own study]

Analysis of a common set of data for classes 3, 5, 7 and 11 were also made using the discriminatory method. For the purposes of analysis, taking into account the parameters of analysed vehicles in particular classes, authors reduced the data set by using only the number of axles, vehicle length, spacing between the first and second axle and the first axle load. As a result of such analysis, authors obtained two eigenvectors DA12 and DA22 with the highest eigenvalue, which explains over 99% of the variance. The correlation of particular vehicle parameters with the DA12 and DA22 vector is shown in figure 4.

Presented in figure 4 –data indicates the highest correlation of vector DA12 with the length of the vehicle. Also significantly important are the spacing between the first and second axle and the first axle load. In case of DA22, the highest correlation value is obtained with the first axle load. Distribution of objects in the area of two main vectors DA12 and DA22 is shown in figure 5.

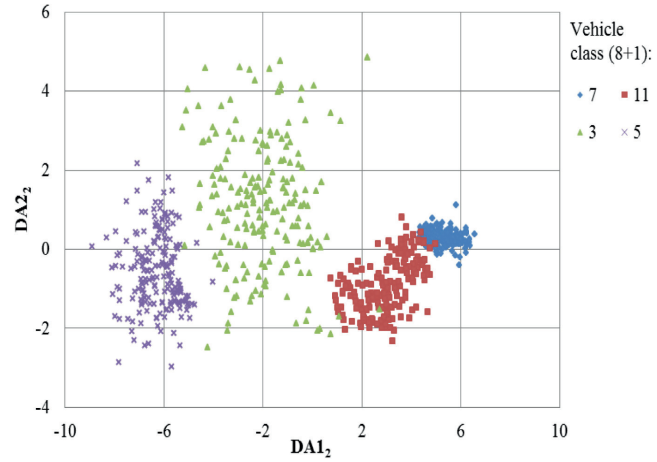

Fig. 5. Distribution of objects in space of the first two eigenvectors for a set of classes 3, 5, 7, 11 [own study]

2.3. Evaluation of the methods effectiveness

In order to evaluate the effectiveness of the proposed method, authors verified the efficiency of the classification with respect to the training set. The allocation of the vehicle to the proper class, basing on the DA vector values, is made using the minimum of Mahalanobis distances from centroid of class area to the vehicle DA vectors. The process can be described using the equation:

$$d_i = (M - m_i)S_i^{-1}(M - m_i)^T + ln|S_i| - 2\,ln\,P_i \qquad \textbf{(1)}$$

where:
S_i - covariance matrix for i-th class,
m_i - centroid of i-th class,
P_i - a-priori class probability,
$(M - m_i)S_i^{-1}(M - m_i)^T$ - Mahalanobis distance between M and i-th centroid.

The results were compared with the classification of vehicles made by an expert. The results of the classification efficiency for the iteration are shown in table 2 for the first one, and in table 3 for the second one.

Table 2. The effectiveness of the classification for the entire data set [own study]

The class specified by an expert	The effectiveness of classification	The class specified by DA method				
		2	8	9	10	3,5,7,11
2	99,5%	199	1	0	0	0
8	98,5%	0	202	3	0	0
9	98,1%	0	4	206	0	0
10	100,0%	0	0	0	173	0
3,5,7,11	100,0%	0	0	0	0	800
Total	99,2%	199	207	209	173	800

Table 3. The effectiveness of the classification for the set 3, 5, 7, 11 [own study]

The class specified by an expert	The effectiveness of classification	The class specified by DA method			
		3	5	7	11
3	93,0%	186	7	0	7
5	100,0%	0	201	0	0
6	100,0%	0	0	199	0
11	90,0%	0	0	20	180
Total	95,8%	186	208	219	187

3. Conclusion

The method of vehicles classification presented in the work is a completely new, original proposal. The major advantage of it is the high efficiency of classification, even for difficult to identify class 3 (van-type vehicles). It can be used for each WIM station, regardless of the specific technology used at the station.

The high efficiency of the method is achieved by using a number of parameters that characterize the type of vehicle (independent variables), including those that are usually overlooked in other methods of classification e.g. the first axle load. The use of two-stage procedure allows rapid determination of the classes 10, 9, 8 and 2. Further analysis, using additional more detailed independent variables, is carried out only for classes 3, 5, 7, 11. This approach increases the efficiency of computational methods.

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