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Metrol. Meas. Syst., Vol. XXI (2014), No. 4, pp. 619–630.

METROLOGY AND MEASUREMENT SYSTEMS
Index 330930, ISSN 0860-8229
www.metrology.pg.gda.pl

AUTOMATIC VEHICLE CLASSIFICATION IN SYSTEMS WITH SINGLE INDUCTIVE LOOP DETECTOR

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Abstract

The work proposes a new method for vehicle classification, which allows treating vehicles uniformly at the stage of defining the vehicle classes, as well as during the classification itself and the assessment of its correctness. The sole source of information about a vehicle is its magnetic signature normalised with respect to the amplitude and duration. The proposed method allows defining a large number (even several thousand) of classes comprising vehicles whose magnetic signatures are similar according to the assumed criterion with precisely determined degree of similarity. The decision about the degree of similarity and, consequently, about the number of classes, is taken by a user depending on the classification purpose. An additional advantage of the proposed solution is the automated defining of vehicle classes for the given degree of similarity between signatures determined by a user. Thus the human factor, which plays a significant role in currently used methods, has been removed from the classification process at the stage of defining vehicle classes. The efficiency of the proposed approach to the vehicle classification problem was demonstrated on the basis of a large set of experimental data.

Keywords: inductive loop detector, magnetic signature, vehicle classification, classification algorithm.

1. Introduction

Currently used vehicle classification systems employ several types of sensors and the classification process is based on different vehicle characteristics. The number of distinguished classes varies from several to over ten (FHWA vehicle classification scheme F). Usually vehicles are classified according to the number of axles and the distance between them, utilizing the so-called vehicle magnetic signature measured by means of inductive loop detectors (ILDs), or on the basis of information from video cameras monitoring a traffic lane. Some known solutions are based on the analysis of the acoustic signal generated by a vehicle [1, 2].

Vehicle classification systems utilizing information about the number of the vehicle axles are more expensive compared to those equipped with inductive loops. They utilize information from axle detectors, which respond to the force exerted by axle on the road surface, or from inductive loop detectors of special construction [3, 4].

In return such systems allow defining above ten vehicle classes [5]. This method of classification is used in Weigh-In-Motion (WIM) systems.

The systems utilizing inductive loops have five considerable advantages over other systems:

- they can be operated independently from a WIM system since they do not require information from load sensors,
- they are remarkably cheaper than other solutions,

Article history: received on Mar. 06, 2014; accepted on Jun. 06, 2014; available online on Dec. 15, 2014; DOI: 10.2478/mms-2014-0048.

- they allow avoiding gathering unnecessary information about the given vehicle route and the driver as is the case with vision systems,
- the road network is usually equipped with a considerable number of inductive loop detectors operated in a single-sensor or dual-sensor system; it is therefore sufficient to equip these systems with a software processing the acquired measurement information,
- they operate independently from weather conditions (rain, fog) and the time of the day.

These advantages justify research on further development of vehicle classification methods and systems utilizing loop detectors and magnetic signatures. The research has begun in late 1980s and is currently continued. The basic line of research was determined by the development of equipment used for classification systems. Such an equipment allows using more complex algorithms for acquiring information contained in magnetic signatures and enables real time operation.

Recent literature sources describe substantially different methods for use of magnetic signatures in vehicle classification. Some solutions are based on the signature parameterisation, e.g. the signature duration and maximum, mean and minimum values. Classification of a given vehicle is based on the values these parameters take on for its signature. These solutions allow arbitrarily define 5-8 classes based on the functional characteristics of vehicles (e.g. cars, vans, heavy goods vehicles, etc.) [6].

Another approach consists in analysing the vehicle signature regarded as a time-variable signal or as a function of the distance travelled by the classified vehicle. The tools used in this analysis are: artificial neural networks (ANN), self-organizing feature map (SOFM), data fusion methods, Principal Component Analysis (PCA) [7−12].

In some applications the magnetic signature is subject to a pre-processing procedure (e.g. low-pass filtering) in order to suppress interferences and artefacts, before being processed by a classification algorithm [13].

The subject of the research is also the influence of the inductive loop dimensions on the possibility of defining some additional parameters of the classified vehicle (e.g. the number of axles and axle spacing) [14, 4].

There are also attempts to estimate the vehicle speed from the magnetic signature obtained from a single inductive loop. The information about the vehicle speed in connection with the signature duration provides information about the vehicle length that may be utilized in the classification process [15].

Currently also multi-loop vehicle classification systems are being developed [16].

As follows from the above literature review the classification methods may be divided into two groups. The methods based on the vehicle length measurement require an assessment of the vehicle speed (determined in a dual-loop system or, using more complex algorithms, in a single-loop system). Parallel research is aimed to developing methods, in which the magnetic signature is regarded as a two-dimensional image and the classification process consists in comparing this image to reference images that represent a priori defined vehicle classes.

Both approaches share a common feature, i.e. the same approach to defining vehicle classes. Determination of vehicle classes is based on the observation of vehicle silhouettes and takes into account vehicle functional properties. Hence, 3−8 classes are usually distinguished, including motorcycles, passenger cars, delivery vehicles, SUVs, buses and coaches (optionally small and large ones may be distinguished), goods vehicles and heavy goods vehicles. Then, for each class specific features of the magnetic signature or intervals of variation of parameters determined from these signatures, are defined.

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In our opinion this approach is erroneous: the method of defining vehicle classes and the method of assigning vehicles to the given class are inconsistent, because different features of a vehicle are taken into account. Due to the similarity of construction or even use of the same components (e.g. a floor panel), a visual observation of a vehicle (which takes into account the vehicle intended purpose rather than its structure) may indicate a different vehicle class than that ensuing from its undercarriage construction and, therefore, from its magnetic signature. This, consequently, leads to classification results deemed to be erroneous, e.g. a delivery van is classified as a SUV, whereas, according to the magnetic signature analysis, the classification is correct because their magnetic signatures are very similar.

The proposed vehicle classification method allows treating vehicles uniformly at the stage of defining the vehicle classes, as well as during the classification itself and assessing its correctness. The sole source of information about a vehicle is its magnetic signature. This approach allows defining a large number (even several thousand) of classes comprising the vehicles with similar magnetic signatures, according to the assumed criterion with a precisely determined degree of similarity. The decision about the degree of similarity and, consequently, about the number of classes, is taken by a user depending on the classification purpose. An additional advantage of the proposed solution is automated defining of vehicle classes for the determined by a user degree of signature similarity. This approach allows eliminating the human factor involved at the stage of defining the vehicle classes as it takes place in the currently used methods.

The vehicle classification may have several purposes:

- gathering information about a traffic structure for the road infrastructure and traffic management purposes,
- re-identification of vehicles and tracking their routes,
- continuous, automated estimation of travel duration,
- accurate estimation of the vehicle speed using the magnetic signature obtained from a single ILD (the values of the estimator parameters depend on the vehicle class and are selected according to the result of the vehicle classification result - in such a case the classification algorithms utilizing information about the vehicle speed cannot be employed).

The number of distinguished vehicle classes depends on the classification purpose. For traffic management purposes it is sufficient to distinguish several to over ten classes, taking into account the vehicle intended purpose and its functional properties. In other cases it is necessary to distinguish the vehicle type or even a specific item. In such a situation the number of distinguished vehicle classes is large and classes should be homogenous, i.e. comprise vehicles having similar magnetic signatures (in order to identify a specific vehicle, e.g. for its re-identification, or to develop a speed estimation algorithm). In these applications the vehicle functional properties are of minor importance.

The large number of classes ensures a high resolution of the classification process. It means that the system is capable to distinguish vehicles having very similar but not the same signatures. The smaller are differences detected by the classification system, the higher is the system resolution.

Considering the results of the classification carried out according to the proposed method there is no question of an erroneously classified or not classified vehicle. Each vehicle with its magnetic signature similar, at least to a minimum degree specified by a user, to the magnetic signatures of vehicles within a given class, will be categorized into that class. If the degree of similarity is too low, the vehicle signature will initiate defining a new class.

Given the specific approach to the problem of defining vehicle classes, the correctness of the classification system operation can be exclusively made from the viewpoint of the homogeneity of defined classes, i.e. the degree of similarity of constructional characteristics of vehicles categorized into the same class. The authors suggest that the homogeneity should be investigated at the stage of testing the classification system. It is proposed that the measure of homogeneity should be the deviation of a given parameter of vehicles categorized into the same class. For instance, the parameters utilized for that purpose could be the distance between two adjacent axles or the length of a vehicle. Such investigations can be exclusively carried out at the test site, additionally equipped with a vehicle speed measuring system.

The paper is divided into four chapters. The proposed method of defining vehicle classes and the classification process are presented in chapter 2. Chapter 3 provides the results of this method investigations carried out on the set of 114,000 magnetic signatures, recorded at the measurement site. Chapter 4 provides the summary of the research results.

2. Defining vehicle classes and the classification process

Building up the classification system consists primarily in defining a set of classes and creating standards representing these classes. At furthers stages a criterion according to which a classified object is categorized into the given class should be defined, followed by verification of correctness of the whole system operation.

The proposed approach to the vehicle classification problem is fundamentally different from those currently utilized and described in the cited literature. This approach consists in automated defining of vehicle classes, based exclusively on vehicle magnetic signatures, and employs no visual information about vehicle silhouettes. There are no separate stages of the class defining process and the classification process. Both processes are carried out concurrently and automatically. The sole basis for classes defining and vehicle classification are magnetic signatures of vehicles passing through the measurement site.

The process is carried out in the following way:

- Magnetic signatures of vehicles are recorded at a selected location on a road. All signatures are normalised with respect to their values and time and then re-sampled, so that the normalised value of all signatures equals to a unity, the normalised duration equals to a unity, and all signatures will contain the same number of samples and be synchronously sampled.
- The first recorded signature corresponds to the first vehicle class; it is regarded as the reference signature representing this class.
- Each subsequent signature is compared to the reference signature representing the already defined class. The distance between the analysed signature and the reference one is computed with respect to a specified measure. Depending on the predefined threshold value the comparison results can be of two kinds: a signature is sufficiently similar or the degree of similarity is insufficient, when assessed using the specified measure.
- A vehicle with a signature satisfying the specified condition for similarity is included into the class represented by the given reference signature (classification). A signature, which does not meet the similarity condition, becomes the reference signature of a new class (defining a new class), thus increasing the number of vehicle classes. A signature, which satisfies the similarity condition for more than one class, is categorized into the class in which it is best fitting.
- Each subsequent signature is compared to reference signatures representing the already defined classes. Thus the number of classes varies during the classification process and their final number depends primarily on the minimum required value of similarity between signatures.

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The proposed method for defining vehicle classes and the classification process is illustrated on the diagram shown in Fig. 1.

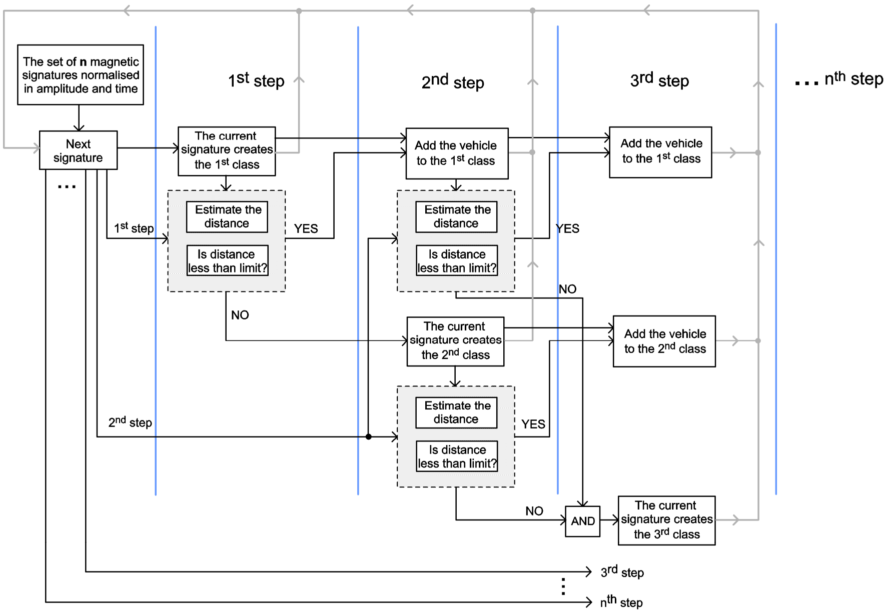

Fig. 1. A diagram of the proposed method for defining vehicle classes and the classification process.

The distance between compared signatures is assessed using the normalised correlation coefficient described by the relation (1), which takes on values from the interval $[0 \div 1]$.

$$r = \frac{\sum_{i=1}^{p} \left(x^{(i)} - \overline{X}\right)\left(\overline{x}_k^{(i)} - \overline{X}_k\right)}{\sqrt{\sum_{i=1}^{p} \left(x^{(i)} - \overline{X}\right)^2} \sqrt{\sum_{i=1}^{p} \left(\overline{x}_k^{(i)} - \overline{X}_k\right)^2}}, \tag{1}$$

where:

$\overline{x}_k^{(i)}$ - *i*-th sample of the reference signature representing the *k*-th class,

$x^{(i)}$ - *i*-th sample of the currently processed magnetic signature,

$\overline{X} = \frac{1}{p}\sum_{i=1}^{p} x^{(i)}$ - the mean value of the currently processed signature,

$\overline{X}_k = \frac{1}{p}\sum_{i=1}^{p} \overline{x}_k^{(i)}$ - the mean value of the *k*-th class reference signature,

p - total number of samples of the signature after re-sampling.

The number of distinguished classes, their population size and homogeneity depend directly on the value of the coefficient (1), above which a vehicle is regarded as belonging to the vehicle class represented by the given reference signature.

3. Experimental investigations

The experiment lasting 60 days was carried out on the national road Dk81 (Poland). The magnetic signatures of 170,000 vehicles were recorded; 114,000 of them were utilized in the tests.

The magnetic signatures used for the purposes of this work were recorded by means of the measuring system shown in Fig. 2.

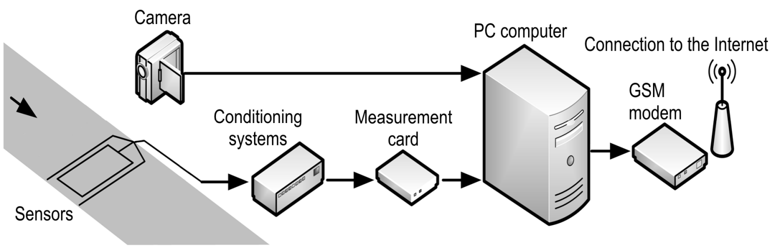

Fig. 2. Diagram of the measuring system.

The measuring system comprises an inductive loop sensor with dimensions 1.2m x 2m (2m is the loop width perpendicular to the traffic lane) and two piezoelectric axle detectors. All detectors are connected to their conditioning systems. The system is provided with a camera recording images of passing vehicles. Vehicle axles are counted by a system co-operating with axle detectors. The GSM module enables online tracking of the system operation. The measuring system was installed in one traffic lane.

Figure 3 illustrates the dependence of the number of defined vehicle classes on the threshold value r_{limit} of the correlation coefficient. Selecting the r_{limit} =0.6 resulted in defining 43 vehicle classes, whereas selecting r_{limit}=0.98 resulted in defining 9,698 vehicle classes comprising representatives from the set of 114,000 recorded signatures.

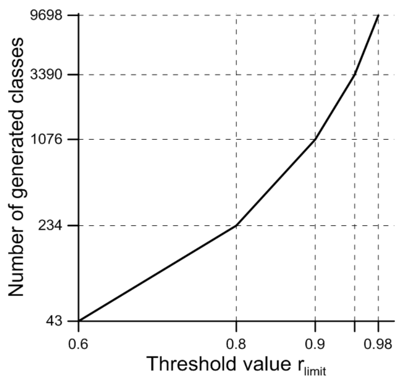

Fig. 3. The dependence of the number of defined vehicle classes on the threshold value r_{limit} of the correlation coefficient. The characteristics was obtained using the set of signatures of 114,000 vehicles.

A large number of defined classes entails a small number of vehicles categorized to certain, "uncommon" classes and their high homogeneity that manifests itself in a very high similarity of magnetic signatures of vehicles categorized into the same class.

Despite the large volume of recorded profiles (114 thousand vehicles), as many as 6,800 classes defined for r_{limit} =0.98 contain only a single vehicle. Populations of individual classes

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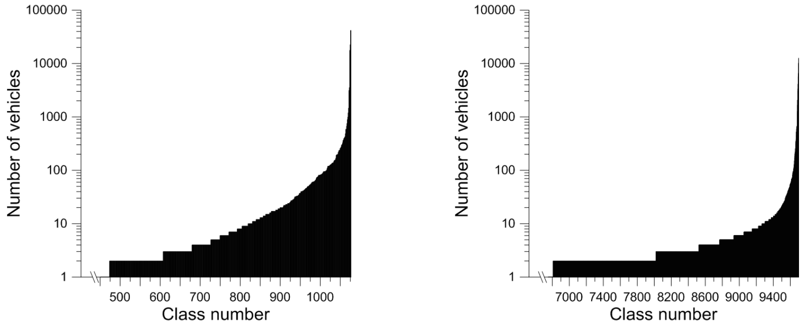
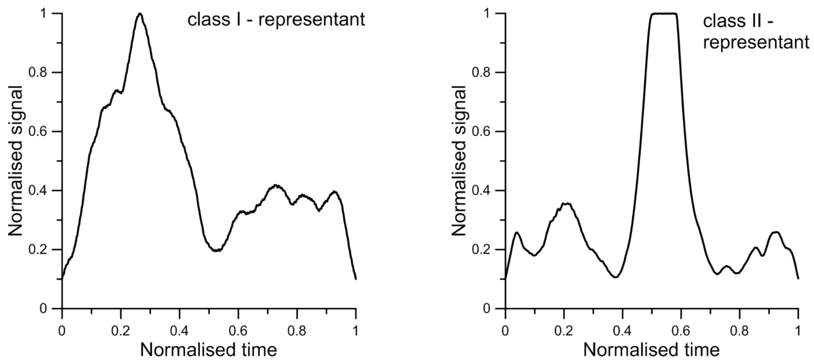
for r_{limit} =0.90 and r_{limit} =0.98 (numbers of defined classes are 1076 and 9698, respectively) are shown in Fig. 4.



A B

Fig. 4. Populations of vehicle classes defined for different threshold values r_{limit}:
A - r_{limit}=0.90 and B - r_{limit} =0.98.

The influence of the parameter r_{limit} on the homogeneity of classes is illustrated in figures 6 and 7. Investigations were carried out for two selected classes defined using magnetic signatures shown in Fig. 5.

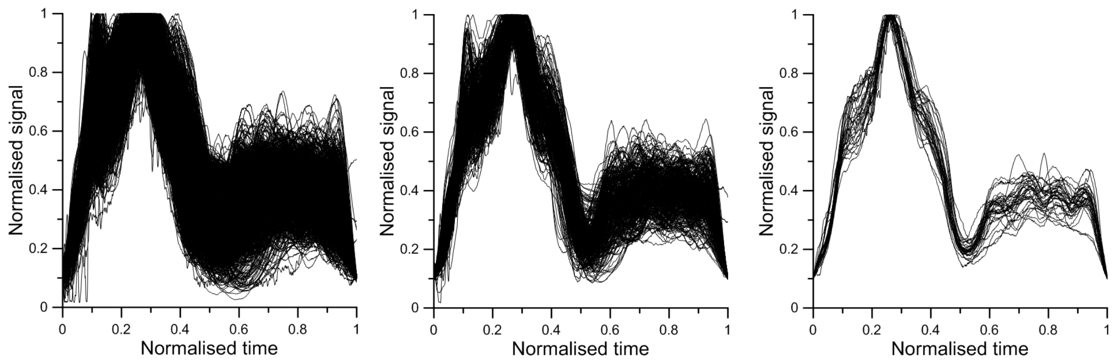


a) b)

Fig. 5. Reference magnetic signatures of two vehicles: a) – class I; b) - class II.

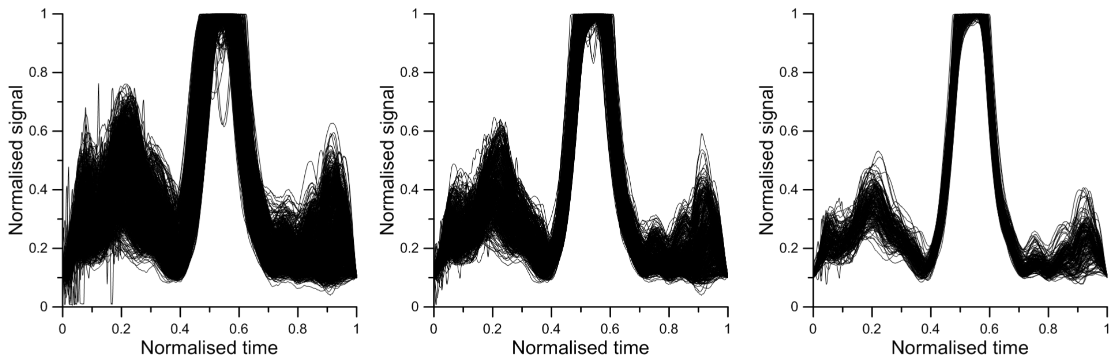
Due to the method of vehicle classification, the homogeneity of classes depends on the correlation level of magnetic signatures categorized into the same class. The user decides upon the homogeneity of a given class by selecting the value of the parameter r_{limit}. But here we assess the homogeneity of the generated class, taking into account constructional parameters of vehicles categorized into this class. Thus we refer to vehicle classification systems, known from literature, where vehicle classes are defined using constructional parameters of vehicles (e.g. length, number of axles) or vehicle functional characteristics (car, delivery vehicle, etc.). Hence, the standard deviation of spacing between the first and the second axle of a vehicle was taken as the measure of homogeneity.

The sets of magnetic signatures of vehicles qualified into classes I and II, respectively, corresponding to different values of the coefficient r_{limit} are shown in Figures 6.



a) b) c)

Fig. 6a. Magnetic signatures of vehicles qualified into classes I for different values of the coefficient r_{limit}: a) - r_{limit}=0.90, b) - r_{limit}=0.95, c) - r_{limit}=0.98.



a) b) c)

Fig. 6b. Magnetic signatures of vehicles qualified into classes II for different values of the coefficient r_{limit}: a) - r_{limit}=0.90, b) - r_{limit}=0.95, c) - r_{limit}=0.98.

Fig. 7 shows the relative standard deviation of spacing between the first and second axles (with respect to the average value) of vehicles qualified to classes I and II as a function of the parameter r_{limit}.

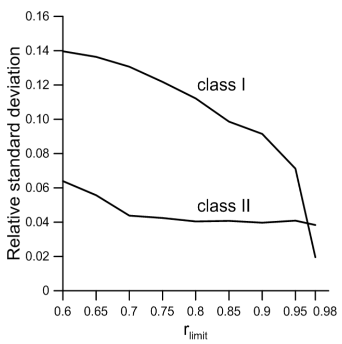


Fig. 7. The relative standard deviation of spacing between the first and second axle vs. the parameter r_{limit}.

Lower values of the coefficient r_{limit} lead to higher diversity of magnetic signatures, therefore entirely different vehicles are categorized into the same class (Fig. 6). This is confirmed by a considerable variability of axle spacing (Fig. 7). An increase in the coefficient

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r_{limit} value causes categorization of vehicles with similar signatures into the same class. Thus, the class becomes homogeneous. Consequently, the deviation of axle spacing is significantly reduced.

This thesis is confirmed by the results that characterize structures of the class I and class II provided in tables 1 and 2, respectively. Magnetic signatures were recorded jointly with the photographs of the passing vehicles and the information about the number of axles acquired from piezoelectric axle detectors, what enabled further comparative analysis of vehicles categorized into one class. Such an analysis was carried out for different values of the parameter r_{limit} from the point of view of the number of axles of vehicles categorized into class I and class II, respectively.

Table 1. The structure of class I in terms of the number of axles of classified vehicles, depending on the parameter r_{limit}.

r_{limit}	0.60	0.65	0.70	0.75	0.80	0.85	0.90	0.95	0.98
Number of axles	Number of vehicles								
2	7078	5618	4230	3150	2276	1420	612	24	0
3	507	451	384	304	228	141	63	8	0
4	1766	1666	1514	1334	1101	755	345	58	6
5	7143	6874	6378	5603	4455	2901	1227	241	25

Table 2. The structure of class II in terms of the number of axles of classified vehicles, depending on the parameter r_{limit}.

r_{limit}	0.60	0.65	0.70	0.75	0.80	0.85	0.90	0.95	0.98
Number of axles	Number of vehicles								
2	54	33	16	5	0	0	0	0	0
3	25	15	5	2	2	2	1	0	0
4	395	372	346	315	258	208	157	69	20
5	1533	1493	1436	1332	1223	1072	878	444	153

Due to a small value of the r_{limit} parameter (0.6) vehicles with different numbers of axles were categorized into one class. Heavy goods vehicles and two-axle passenger cars were qualified into the same class. The reason for mixing up different vehicles is normalisation of signatures, which is necessary when there is no information about the vehicle speed. However, increasing the value of the parameter r_{limit} allows rejecting two-axle and three-axle vehicles. Thus only four-axle and five-axle vehicles remained. It was established from photographs that this class includes five-axle heavy goods vehicles, some of them with the trailer retractable axle lifted.

A higher homogeneity of defined classes allows achieving a higher resolution of the vehicle classification. This means the capability for distinguishing very similar, but not identical, vehicles. The required resolution depends on the classification purpose. The classification can be carried out for the purposes of vehicles re-identification, tracking their routes, continuous, automated estimation of travel time, measuring the speed of a given vehicle, etc. In such applications the highest achievable resolution is required, which - in an extreme case - enables to identify a specific vehicle. The second area of classification result applications is the road infrastructure management. For this purpose a coarse categorization of vehicles into several, or a dozen, classes is sufficient. The attained resolution can be controlled by changing the r_{limit} parameter, as is evident from Fig. 6.

From the practical point of view the excessive number of classes occurring due to the parameter r_{limit} value being close to unity, may pose a problem. The analysis of characteristics in Fig. 4 shows a large number of classes with a small population of vehicles. It means the share of these vehicles in traffic over the given area is negligibly small. Thus removing the classes with small populations the number of classes may be considerably reduced. With this aspect in view, the authors propose the following procedure. All classes defined for an assumed value of r_{limit} are arranged in order of increasing population. Next, starting from the first class, all classes containing in total a specified percent of vehicles from the training set (*cut_off_level*) are rejected. The method is illustrated in Fig. 8.

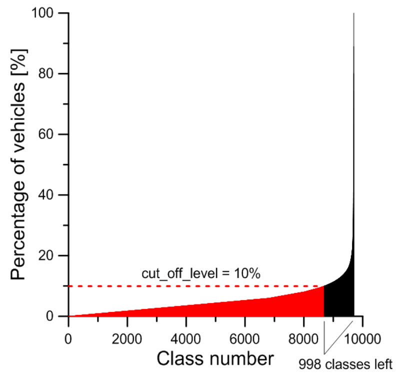

Fig. 8. The method for limiting the number of classes by rejecting classes with a small population of vehicles, for the *cut_off_level* = 10% of recorded vehicles and r_{limit}=0.98.

As follows from the characteristics in Fig. 8, the rejection of classes containing in total 10% of vehicles allows almost ten times reduction in the number of classes: from 9698 to 998.

The influence of a selected value of the *cut_off_level* on the resulting number of vehicle classes (for the considered set of 114,000 signatures) is shown in Fig. 9.

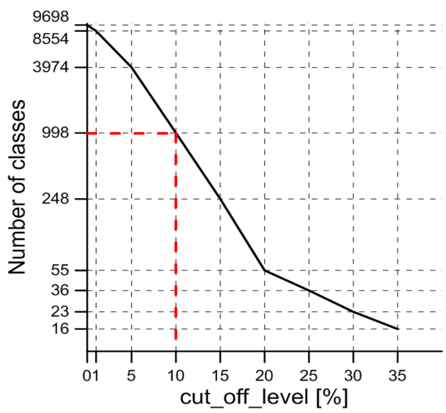

Fig. 9. The influence of the *cut_off_level* value on the resulting number of vehicle classes for r_{limit}=0.98.

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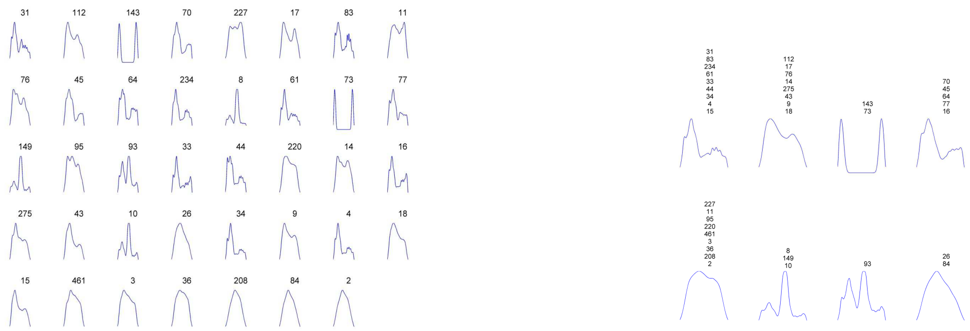
However, this method has also some negative effects. The rejection of classification results from a certain number of classes comprising total 10% of vehicles that passed through the measurement site means that 10% of vehicles were not classified.

Another way of solving the problem of excessive number of vehicle classes is to "combine" together similar classes. This process consists in finding reference classes similar to each other (the degree of similarity is assessed using the correlation coefficient (1)) and combining them into a single, aggregated class. This procedure enables to maintain a high selectivity of classification and presents the results in a more concise form.

In the example that illustrates the proposed method of "combining" vehicle classes and creation of aggregated classes for r_{limit} =0.90, 1076 vehicle classes were defined (Fig. 10). In effect of rejecting the classes with small populations of vehicles and assuming the *cut_off_level* = 10%, the number of remaining classes is 39. The reference signatures of these classes are shown in Fig. 10A, their original numbering from the set of 1076 classes has been preserved. The "combining" of similar classes selected for r_{limit} =0.85 resulted in creation of 8 aggregated classes. Their reference signatures are shown in Fig. 10B, given the numerical designations of classes from which the aggregated classes were created.



a) b)

Fig. 10. Illustration of defining aggregated vehicle classes: a) - reference signatures of primarily defined classes; b) - reference signatures of aggregated classes.

Classes denoted by numbers 143 and 73 contain erroneously recorded signatures. Two passenger cars separated by a small distance between them have passed at high speed through the measurement site. Both signatures were recorded in a single data set what resulted in creation of a class of non-existent vehicles containing erroneously recorded signatures. This is an additional advantage of this method since it does not require browsing through several thousands of signatures and verification of their correctness. The vehicles with erroneously recorded signatures will create separate classes that can be eliminated after the classification.

4. Conclusions

The paper presents a new approach to the vehicles classification problem based on vehicle magnetic signatures in systems equipped with a single inductive loop detector. The result of classification depends on the correlation between the vehicle signature and the reference signature of a given class. The processes of selecting and classifying reference signatures are carried out simultanously and are based exclusively on information contained in magnetic signatures. The subject of investigations was the influence of a minimum correlation coefficient between signatures r_{limit} defined by a user on both the number of classes and their homogeneity. On the basis of experimental data it was demonstrated that vehicle classes determined for the correlation coefficient $r_{limit} = 0.98$ exhibit sufficient homogeneity to comprise vehicles with same number of axles, and the relative standard deviation of spacing between selected axles is of the order of 2% of the mean value (the uncertainty of the axle spacing measurement by means of piezoelectric sensors is c.a. 0.3%).

A method for eliminating classes with small population of vehicles was proposed and its efficiency was demonstrated. Also, a method for aggregating classes, e.g. in order to present the results in a brief form, was proposed.

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