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ALTERNATIVE AUTOMATIC VEHICLE CLASSIFICATION METHOD

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Abstract

The paper deals with the new method of automatic vehicle classification called ALT (ALTernative). Its characteristic feature is versatility resulting from its open structure, moreover a user can adjust the number of vehicles and their category according to individual requirements. It uses an algorithm for automatic vehicle recognition employing data fusion methods and fuzzy sets. High effectiveness of classification while retaining high selectivity of division was proved by test results. The effectiveness of classification of all vehicles at the level of 95% and goods trucks of 100% is more than satisfactory.

Keywords: automatic vehicle classification, ITS, weigh-in-motion, WIM, fuzzy sets, data fusion.

1. Overview of existing classification schemes

Vehicle weighting, and particularly automatic weigh-in-motion (WIM) systems, require a concurrent and unique classification of the weighed vehicle in terms of both its type and the undercarriage characteristics. These needs result from legal regulations determining the permissible axle loads depending on the axles configuration and spacing.

Recent works resulted in developing several classification schemes and algorithms for automatic classification. The schemes differ in the number of vehicle categories that are based mainly on the vehicle functional features and its gross weight, and mostly ignore the undercarriage characteristic. The information on the number of axles and their spacing is utilized solely by the automatic vehicle classification algorithms.

Practical applications employ at least several vehicle classification schemes and a large number of specific methods developed for individual end-users. The most popular are: the American FHWA [1] classification and European EURO-13 and COST 323 [2] classifications. The COST 323 solution is the least selective one; it comprises only 8 vehicle categories: one category of passenger cars, one of buses and 5 categories of goods trucks . For instance, two-axle and three-axle road tractors with single-axle or two-axle semi-trailers are categorized into one group. The EURO-13 classification is more detailed and a given category comprises vehicles of similar gross weight and overall dimensions. However, this classification ignores the categorization according to the undercarriage type and therefore renders this scheme impracticable. The FHWA classification seems to be the most selective in respect to the axle configuration. It differentiates two-axle vehicles into cars, delivery vehicles and lorries, and three-axle single vehicles are distinguished from vehicle combination. However, articulated vehicles are divided in a manner that precludes their unique classification; moreover, this scheme includes also vehicles which can be hardly found on European and Polish roads.

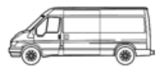
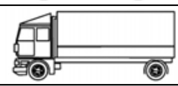
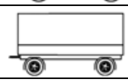
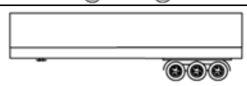
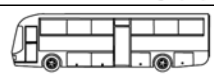
Having in mind that vehicle outlines are differentiated not only by their functional design but, first of all the number and configuration of axles, it can be concluded that the above classification schemes do not meet the selectivity requirements. A coarse categorization is sufficient for analysis of traffic parameters, long term forecasting, or sizing the road pavement structure. Enforcement low-speed weigh-in-motion scales and, in the near future, enforcement WIM systems, require more selective and reliable automatic vehicle classification methods. Unfortunately, developing a single universal classification scheme, which would satisfy expectations of various user groups, is difficult or often infeasible because of a macro-scale diversity of vehicles. The traffic structure in Europe varies with the geographical situation and is dissimilar in various countries. Therefore a universal vehicle classification should not have a closed structure and should be characterized by:

– high selectivity – associated with the applied vehicle classification scheme;
– high effectiveness – associated with the algorithm employed;
– high flexibility, *i.e.* capability to adjust vehicle categories to the traffic characteristic in a given area.

2. ALTernative vehicle classification

In order to satisfy the requirements for vehicle classification laid down for automatic weighing purposes the author proposes a novel solution based on the ALT classification and the algorithm for automatic vehicle recognition employing data fusion methods and fuzzy sets. The basis for the ALT classification is the configuration of vehicle units (a single vehicle, articulated vehicle or vehicle combination) and the number and configuration of axles [3]. First, 8 basic groups of vehicle units have been selected. Some of them can occur only singly, *e.g.* cars, and some, like trailers, can only be coupled with other units. Each group is denoted by a letter symbol.

Table 1. Basic group of vehicle component units.

Vehicle type:	Category designation:	Outline:
Motorbike	M	
Car	C	
Delivery vehicle	D	
Lorry	L	
Tractor	T	
Trailer	R	
Semi-trailer	S	
Bus	B	

The vehicle symbol is supplemented with the number of vehicle axles, *e.g.* a three-axle lorry is denoted 3L, and two-axle semi-trailer is denoted 2R (see Figure 1).

Table. 2. The ALT vehicle classification .

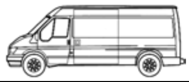
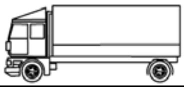
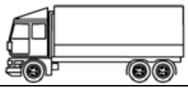
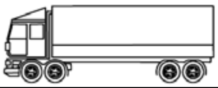
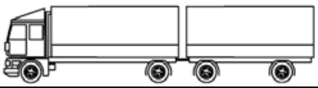
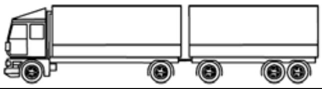
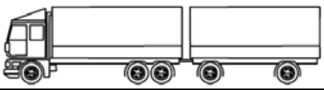
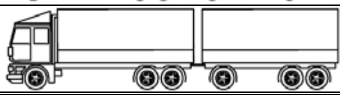
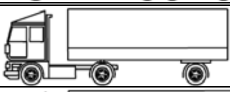
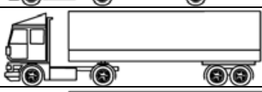
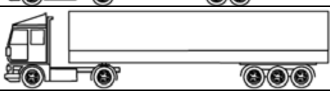
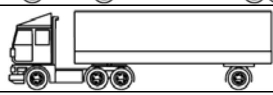
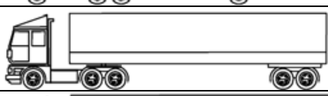
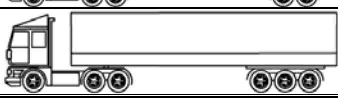
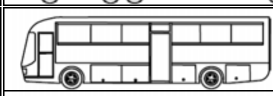
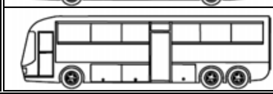
Vehicle type	Category Number	Category Symbol	Outline
Single vehicles	1	M	
	2	2C	
Vehicle combinatio n	3	2C+1R	
	4	2C+2R	
Single vehicles	5	2D	
	6	2L	
	7	3L	
	8	4L	
Vehicle combination	9	2L+2R	
	10	2L+3R	
	11	3L+2R	
	12	3L+3R	
Articulated vehicles	13	2T+1S	
	14	2T+2S	
	15	2T+3S	
	16	3T+1S	
	17	3T+2S	
	18	3T+3S	
Single vehicles	19	2A	
	20	3A	

Fig. 1. Vehicle designation according to the number of axles.

Next, basing on the analysis of the vehicle types structure in Poland, the elements from Table 1 were grouped into suitable combinations corresponding to vehicle outlines of the most frequent occurrence The symbols corresponding to selected categories are formed. in that manner. For example, an articulated vehicle, which consists of a two-axle tractor and three-axle semi-trailer is classified into category 2T+3S, and a vehicle combination of two-axle lorry and two-axle trailer is categorized as 2L+2R. Twenty vehicle categories most frequently found in Poland are listed in Table 2.

The resultant categories uniquely characterize a vehicle for a given configuration of component units and the number of axles. The number of categories is not fixed and can be modified according to the given area traffic if required, what is an evident advantage of this method.

3. Automatic vehicle classification systems

The automatic vehicle classification processes utilize the functionality potential of the presented classification methods. The basis for a vehicle classification process is the measurement of vehicle characteristic parameters, such as the number of axles, their spacing, gross vehicle weight or the vehicle magnetic profile that form the so-called characteristic parameters vector. The number of measured parameters depends on the structure and the intended purpose of a given automatic classification system. The decision whether a vehicle falls into a given category is taken by comparing the characteristic vector with the vector being the model of this category. The simplest case is a coarse division into large and small vehicles, based on measuring of only one parameter, *i.e.* their length. The selectivity can be improved by increasing the number of parameters; *e.g.* in the case of division according to the number of axles, better selectivity is achieved by measuring the second parameter, *i.e.* their spacing. The classification process is then a multi-stage and hierarchical one. Once a vehicle is qualified into the group of vehicles with the given number of axles, the second parameter, *i.e.* the axle spacing is compared with the model assumed a priori. The decision is taken on the grounds of classical logic ("should" or "should not") what, as will be demonstrated, is the reason for a low effectiveness of such classification algorithms. Despite of its drawbacks this algorithm is extensively used in automatic classification systems employing the EURO-13 and FHWA schemes.

3.1. Classical logic and fuzzy sets

In the domain of classical logic the known algorithms for automatic classification are based on the definition of the conventional set, which can be written as a set of pairs:

$$A = \{(x, \varphi_A(x))\}, \tag{1}$$

where:

– $X = \{x\}$ – is a certain wider set of values (in this case: the distance between axles or the vehicle length);

– $\varphi_A(x): X \to \{0,1\}$ – is referred to as the classical membership function that to each element of the space X assigns the number "0' which means non-membership or "1" – the membership.

The group of vehicles with same number of axles various types of vehicles with similar axle spacing can be specified. It is therefore not possible to define the disjoint criteria, and inferring the vehicle membership to a given category on the basis of classical logic has no meaning, as illustrated in Fig. 2 for the parameter x_{12} – the axle spacing 1–2.

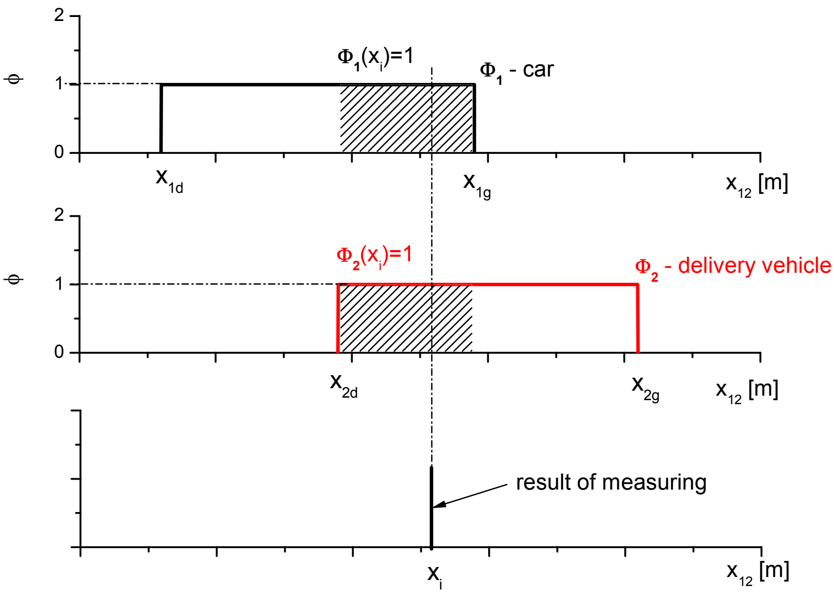


Fig. 2. An example illustrating the formulation of vehicle category models for rectangular (classic) membership functions and the procedure in the event a new result of measuring x_i is obtained.

The classical approach lowers the effectiveness of classification, which in the presented form does not exceed 60–70%. Such result is intolerable in weighing systems because taking an erroneous decision on the vehicle category may result in unfounded penalty levied against a hauler. Since unique assignment of an element to the set does not apply here, the fuzzy logic should be employed as a measure of fuzzy, multiple-valued and imprecise concepts. The fuzzy set B defined on X can be represented as the set of pairs [4]:

$$B = \{(\mu_B(x), x)\} \qquad \forall x \in X \tag{2}$$

where:

– $X = \{x\}$ – as in (1);

– $\mu_B : X \to [0,1]$ – is the membership function which to each element from space X assigns a degree of membership in the given fuzzy set: from non-membership ($\mu_B(x) = 0$) through partial membership ($0 < \mu_B(x) < 1$) to full membership ($\mu_B(x) = 1$).

In the fuzzy sets theory the transition from non-membership to membership is gradual rather than abrupt as in non-fuzzy sets. The shape of the membership function depends on the problem being considered, and may take form from a simple analytic function (triangle MF, Gaussian MF, *etc.*) to complex relations that are combination of many simple functions [5]. At the same time there are no exact rules for choice of the optimum shape of the membership function; the procedure is largely subjective and non-formalized. For the purposes of the algorithm for automatic vehicle classification the triangular (3) and trapezoidal (4) shape of the membership function were selected.

$$\mu_{Tri}(x) = \begin{cases} 1 - \dfrac{|x-\mu|}{\alpha \cdot \sigma} & for \quad |x-\mu| < \alpha \cdot \sigma \\ 0 & for \quad |x-\mu| \geq \alpha \cdot \sigma \end{cases} \tag{3}$$

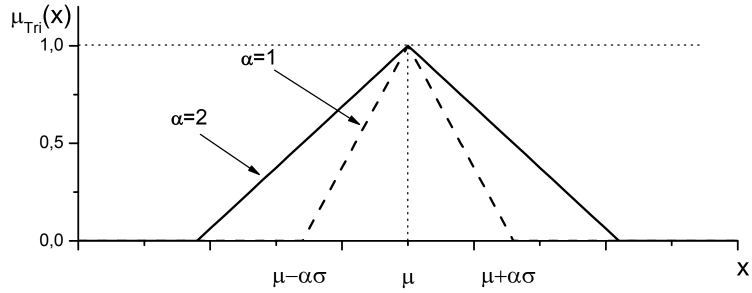


Fig. 3. Interpretation of the triangular MF parameters.

$$\mu_{Tra}(x) = \begin{cases} 0, & for \quad x \leq a \\ \dfrac{x-a}{b-a} & for \quad a \leq x \leq b \\ \dfrac{d-x}{d-c} & for \quad c \leq x \leq d \\ 0, & for \quad d \leq x \end{cases} \tag{4}$$

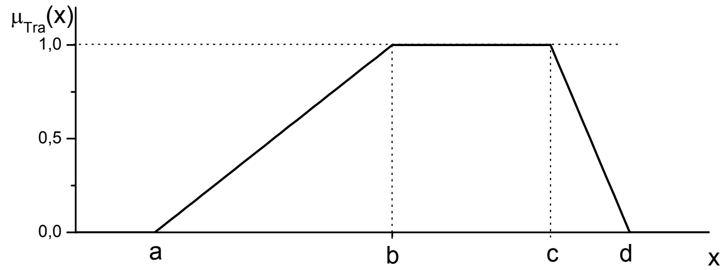


Fig. 4. Interpretation of the trapezoidal MF parameters.

Aside from the “membership – non-membership” alternative, characteristic for classical logic, the cases of partial membership also occur. An example of the triangle membership function of the fuzzy set “axle spacing” – x_{12} is shown in Fig. 5. Practically the notion of a fuzzy set is equated with its membership function and this convention has been adopted by the author further in this work.

The use of triangular membership functions eliminated the ambiguity characteristic to non-fuzzy sets. The membership function values μ_1 and μ_2 obtained in this example should be interpreted as the measure of membership of a vehicle with the axle spacing x_{12} in one of the two categories: a car or delivery vehicle. The value ($\mu_1(x_i) = 0.65$) > ($\mu_2(x_i) = 0.25$) indicates that the vehicle with measured axle spacing of x_i, “better” matches the category of delivery vehicles than that of cars. The above considerations can be generalized to an arbitrary number k of vehicle categories and number N of measured parameters.

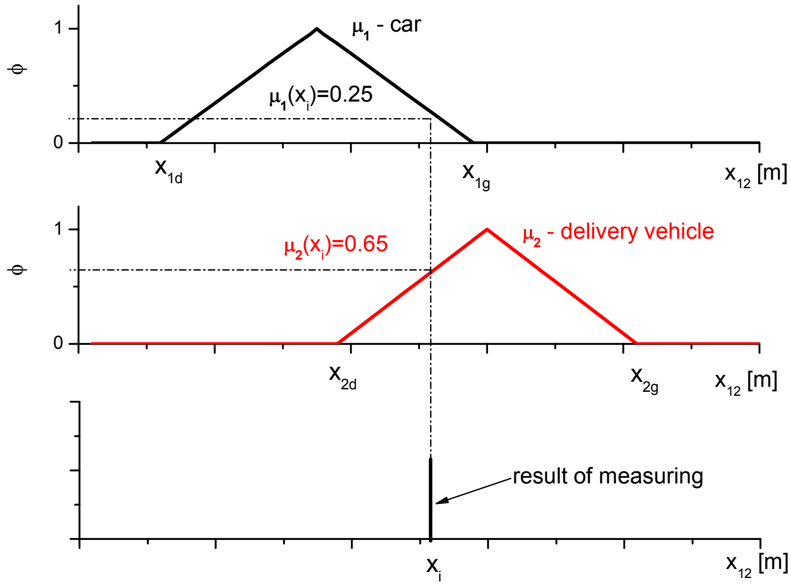


Fig. 5. An example illustrating the formulation of vehicle category models for triangular membership functions and the procedure in the event a new result of measuring x_i is obtained.

Each function should adequately represent the relation between the parameter value and the degree of membership, constituting the model of a given vehicle category. The models were formulated utilizing the reference data from three sources:

a) vehicle manufacturer specifications – passenger vehicles and two-axle and three-axle lorries;
b) the Committee for Road Transport – results of measurements and dimensions of lorries (mainly five-axle);
c) the data acquired from the WIM system – results of axle spacing measurement and the electrical equivalent length of a vehicle.

The model of the *k*-th category consists of a group of three membership functions determined for 3 selected parameters of a vehicle:

– axle spacing;
– length;
– the difference between the vehicle length and the distance between two outermost axles.

The coefficients of functions (3) and (4) are determined by means of statistical analysis methods applied to the reference database and in that way the models for each category of vehicles were formulated.

3.2. Data fusion

Measurements of several parameters of a vehicle allow constructing diverse scenarios for execution of the classification algorithm. Firstly, the information contained in the measurement of each parameter can be analyzed separately, and decisions on a vehicle membership in a given category can be taken solely on that basis. However, as formerly demonstrated, such procedure is both unselective and inefficient. The alternative approach is two-stage classification that consists in vehicle selection according to the number of axles, and next, according to one of the measured parameters: the vehicle length or axle spacing. The classification selectivity increases but its effectiveness, in the case of classical identification algorithms, remains unsatisfactory. The third option consists in the use of the data fusion method. This notion will be understood as a set of operations whose purpose is to combine data from various sources in order to reach decisions, or achieve results better, in qualitative or quantitative terms, then those obtained from an individual analysis of each source data separately [6]. The use of common information, "hidden" in the original measurement data, allows obtaining new or more comprehensive results that cannot be achieved by other methods. Data aggregation in the process of data fusion seems to be a particularly suitable method to be applied in automatic vehicle classification.

The vector of characteristic parameters, obtained from the measurement has the length N that depends on the number of vehicle axles:

$$parameters=[\, d_l\,,\ d_{xl}\,,\ x_{12}\,,\ x_{23}\,,...,]_{(1\mathrm{x}N)},$$

where: d_l is the vehicle length, x_{12} is the distance between axles 1 and 2, x_{23} between axles 2 and 3, etc. and d_{xl} is the difference between the vehicle length and the distance between the two outermost axles. The first stage of classification is the qualification of a vehicle into the group with a given number of axles. Next, the results of measurement of N parameters are compared with K membership functions that constitute the models for particular categories. As the result of the comparison we obtain N values of the membership function for each of K categories:

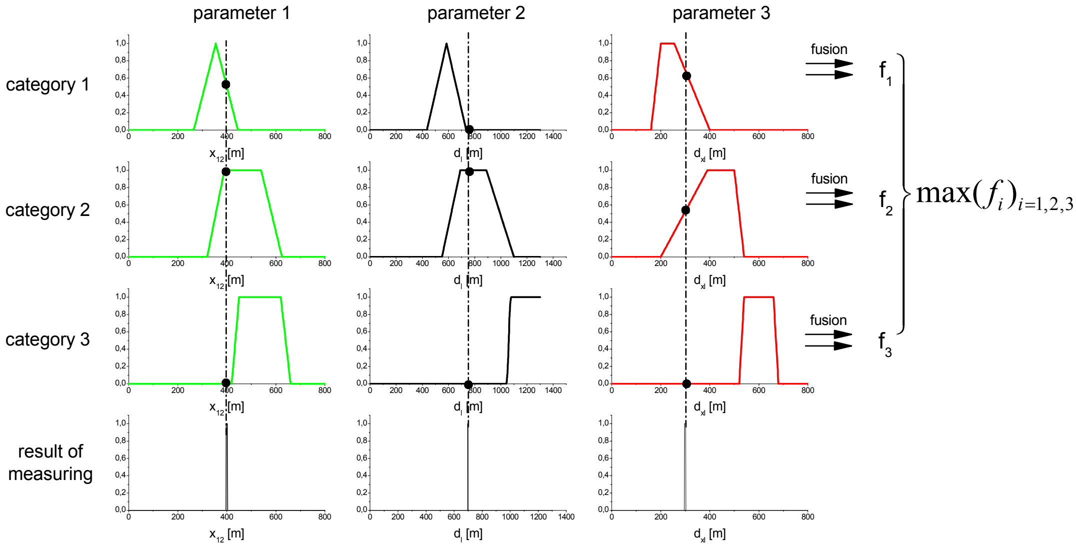


Fig. 6. An example illustrating models of three categories of vehicles, the procedure in the case of obtaining a new result, and data fusion.

The N values of the membership function obtained for a given category are combined by means of functions executing the data fusion. Two functions yielding the best results were found by testing:

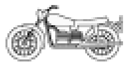
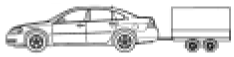
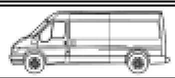
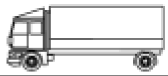
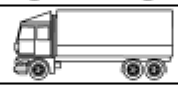
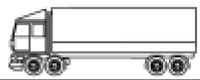
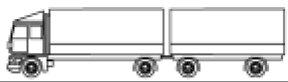
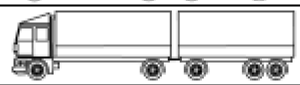
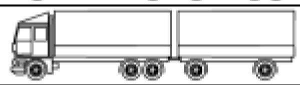
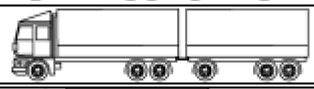
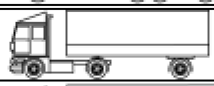
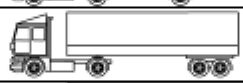
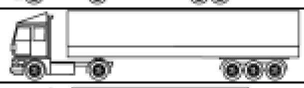
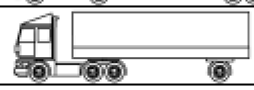
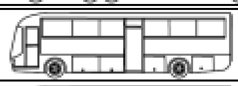
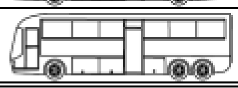
$$f_1 = \frac{1}{N}\sum_{i=1}^{N}\mu_i\left(x_i\right), \tag{5a}$$

$$f_2 = \bigcap_{i=1}^{N}\mu_i\left(x_i\right) = \min\left(\mu_1,\mu_2,...,\mu_N\right). \tag{5b}$$

The choice of the function depends on the vehicle number of axles. As the result of fusion we obtain one number for each category being considered. The largest value indicates the category to which the considered vehicle shall be assigned.

4. The tests results

Table 3. Classification effectiveness.

Vehicle type	Category Number	Outline	Effectiveness [%]: ALT	Effectiveness [%]: FHWA	No. of vehicles
Single vehicles	1		-	-	0
	2		99.26	98.8	673
Vehicle combination	3		100	80.0	5
	4		100	0	3
Single vehicles	5		75.6	76.9	156
	6		89.7	43.8	57
	7		100	100	14
	8		100	0	7
Vehicle combination	9		100	No category	8
	10		100	No category	1
	11		100	No category	5
	12		-	No category	0
Articulated vehicles	13		-	-	0
	14		100	0	45
	15		100	100	109
	16		-	-	0
	17		100	0	1
	18		100	100	2
Single vehicles	19		72.7	90.9	11
	20		-	-	0
	Total of correctly classified vehicles:		95.0	85.0	total: 1097
	Total of not classified vehicles:		0.0	9.0	

The aim of the tests was comparison of effectiveness of two algorithms for automatic vehicle classification:

– classical classification algorithm employing the FHWA scheme;
– the algorithm employing data fusion methods and fuzzy sets for ALT classification.

For the purposes of comparison measurement data were used from the 16-sensor MS-WIM installed on road No. 81, in Gardawice. The system is provided with piezoelectric load sensors, evenly spaced at a distance of 1m from each other (as follows from the modeling research [7]). Each pair of load sensors is encompassed by a single inductive loop sensor, and two temperature sensors situated at the beginning and the end of the WIM station. The arrangement of piezoelectric sensors allows for measuring the following parameters: number of axles and their spacing, axle load, vehicle gross weight and speed. The use of induction loops also enables measuring the vehicle magnetic profile – associated with the undercarriage form, and electrical equivalent length of a vehicle. The number of 1097 vehicles was recorded and, basing on visual assessment, assigned to appropriate categories. The recorded data were processed employing the classification methods described above. The result of automatic classification was compared with the result of visual assessment of a vehicle. The ratio of the number of correctly classified vehicles to the total number of vehicles being tested in a given category was used as a measure of effectiveness.

The effectiveness of the algorithm based on fuzzy measures and data fusion is significantly better than that of the classic algorithm. It should be particularly noted that no vehicles remained non-classified, whereas in the case of FHWA they count for almost 10% of all results. Moreover, despite the fact that the ALT classification is more selective than FHWA, the overall effectiveness of ALT classification is 10% higher than that of FHWA. This proves the rightness of the concept of employing fuzzy logic and data fusion for automatic vehicle classification.

5. Conclusion

The work presents an alternative scheme of vehicle classification ALT. Its characteristic feature is versatility resulting from its open structure. A user can adjust the number of vehicles and their category according to individual requirements. Supplementing the ALT classification method with the algorithm based on fuzzy measures and data fusion enables high effectiveness of classification while retaining high selectivity of division, as proved by tests results. The effectiveness of classification of all vehicles at the level of 95% and goods trucks of 100% is more than satisfactory. The simplicity of the method (measuring the distance between the axles and vehicle length), its versatility and at the same time high effectiveness, allow for its implementation in autonomous WIM systems.

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