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A HIGHLY SELECTIVE VEHICLE CLASSIFICATION UTILIZING DUAL-LOOP INDUCTIVE DETECTOR

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Abstract

In general, currently employed vehicle classification algorithms based on the magnetic signature can distinguish among only a few vehicle classes. The work presents a new approach to this problem. A set of characteristic parameters measurable from the magnetic signature and limits of their uncertainty intervals are determined independently for each predefined class. The source of information on the vehicle parameters is its magnetic signature measured in a system that enables independent measurement of two signals, i.e. changes in the active and reactive component of the inductive loop impedance caused by a passing vehicle. These innovations result in high selective classification system, which utilizes over a dozen vehicle classes. The evaluation of the proposed approach was carried out for good vehicles consisting of 2-axle tractor and a 3-axle semi-trailer.

Keywords: inductive loop detectors, magnetic signature, vehicle classification

1. Introduction

The inductive-loop detectors (ILD) have become the most utilized sensor in traffic detection systems. The ILD has the form of several turns of insulated wire installed in a slot sawed in the pavement. It is supplied with alternating current with frequency of several kHz to 100 kHz.

Two solutions of detection systems utilizing inductive-loop detectors are used. In the first solution the inductive-loop detector is connected in the generator resonant circuit. A change in the detector inductance caused by a vehicle passing over the detector results in a change in the generated signal frequency. In the second solution the directly measured quantity is the change in the detector's impedance due to the same cause. The change in the frequency or in the detector's impedance components, as a function of time or the distance travelled by a vehicle, is termed the magnetic signature of a vehicle.

Vehicles categorized into different classes generate in a measuring system employing an inductive-loop detector their magnetic signatures that differ in amplitude, duration, frequency spectrum and statistical parameters. This signal (signature) is further processed by the vehicle classification algorithm. The subject literature presents various algorithms for processing magnetic signatures and various vehicle classification algorithms. In consequence they differ in their resolution (the capability differentiating among a larger or smaller number of vehicle classes) and the classification effectiveness (a relative number of correctly classified vehicles). In general, currently employed algorithms can distinguish among only a few vehicle classes.

Publication [1] presents a vehicle classification algorithm based on the vehicle velocity and duration of the recorded magnetic signature. The system utilizes two inductive-loop detectors

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installed a short distance apart. This enables determining the vehicle velocity. The attained effectiveness of classification was rather low.

In [2] a new approach to vehicle classification is proposed; it consists in the magnetic signature analysis rather than measuring its duration. Vehicles were categorized into four classes: 1) passenger cars, 2) delivery vans, 3) goods vehicles, 4) buses. The classification effectiveness achieved in this solution was 0.83.

Publication [3] employs a self-organizing feature map (SOFM) for the purposes of the magnetic signature analysis and vehicle classification. Seven vehicle classes have been distinguished: 1) passenger cars, 2) sport utility vehicles (SUVs) and pickups, 3) vans, 4) limousines, 5) buses, 6) two-axle trucks, 7) goods vehicles with a number of axles greater than two. The average effectiveness of classification was 0.80.

Publication [4] discusses the influence of the inductive-loop detector length (in the vehicle motion direction) on the shape of magnetic signatures obtained for vehicles belonging to diverse classes. According to the presented results a signature obtained from a very short loop (10cm) allows axle counting and axle spacing measurement. The results show that such loop may substitute a system with two load sensors used as axle detectors.

In publication [5] author utilizes the data fusion method employing fuzzy measures with triangular and Gaussian membership function to solve the problem of vehicles classification using their magnetic signatures. The input data have been gathered from a road measurement site equipped with a single inductive-loop detector and two piezoelectric axle load detectors. The vehicle classification algorithm was tested solely with respect to two-axle vehicles. The best results were obtained for the Gaussian membership function. The effectiveness of classification was 0.94 for passenger cars and 0.92 for delivery vans.

In [6], using back-propagation neural networks (BPNN), authors have returned to the idea of vehicle classification based on the length of magnetic signature using for that purpose a single inductive-loop detector. Vehicles were categorized into four classes with respect to their length. For each class was designed and configured a specific neural network. The work does not provide information about the classification effectiveness. Authors, however, conclude that better results were achieved when the neural network was tuned to current measurement data in order to take into account changes in traffic at the given measuring point.

In [7] authors combined methods employed in former works and proposed a new classification algorithm. The average effectiveness of classification was 0.915.

In [8] authors proposed the use of BPNN with preliminary processing of measurement data. The processing consisted in clearing the disturbances from measurement data using discrete Fourier transform (DFT). The cleared data were transformed into the principal component analysis (PCA) domain. As a result, the classification effectiveness for five initially defined vehicle classes was 0.942.

The above summary of recent research shows that the crucial problem of magnetic signature application to vehicle classification is its resolution, which is limited to only a few classes. It is therefore purposeful to improve the resolution to the extent that enables even recognition of a particular vehicle in traffic stream and, consequently, tracing the vehicle route, as well as credible and continuous estimation of the travel time.

In this work we propose a novel solution for the vehicle classification problem based on vehicles magnetic signatures. It provides an opportunity to define a larger number of vehicle classes. Achieving this goal requires taking actions in three fields, these are:

- design and construction in conjunction with seeking for such dimensions of loop detectors that allow detecting geometrical details of a vehicle undercarriage,

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- design and construction related to the conditioning system interoperating with the loop detector,
- seeking algorithms for processing measurement signals that enable to separate information about vehicle structure details, useful for the vehicle classification process.

The work provides research results concerning selection of a loop detector dimensions and the proposed classification algorithm.

The results illustrating the proposed approach have been obtained from magnetic signatures recorded at the measurement site installed in the national road Dk 81 in Gardawice, Poland. For various vehicles were recorded magnetic signatures from five loop detectors with lengths in the vehicle motion direction 0.1m, 0.3m, 0.5m, 1.0m and 3,0m; dimension of all detectors in the direction transverse to the traffic lane was the same - 2.0m.

With each loop-detector was connected a conditioning system designed for this purpose. The conditioning system supplies the detector with AC current of selected frequency, filters, amplifies signals and works out the measurement signal according to the adopted measurement principle.

Simultaneously the video image, vehicle velocity and number of axles from piezoelectric detectors have been recorded.

The paper is organised as follows: chapter 2 concerns the conditioning systems applied for ILD detectors. The system allowing measurement of two independent output signals that are proportional to changes in the real part (*R* component) and imaginary part (*X* component) of the loop detector impedance, respectively, is presented. Chapter 3 presents the analysis of the loop detector dimensions influence on the vehicle parameters measurement uncertainty. In chapter 4 the proposed approach to the vehicle classification is presented. It should allow to distinguish over a dozen vehicle classes. In chapter 5 the evaluation results of the proposed approach are presented. This analysis was caried out for good vehicles consisting of 2-axle tractor and a 3-axle semi-trailer. Chapter 5 contains the final conclusions.

2. Magnetic signature measurement systems

The loop detector is supplied with AC sinusoidal current. As a consequence, an alternating electromagnetic field is produced around the loop. The interaction of a metal object with the electromagnetic field generates eddy currents in the metal object elements. This causes observed variation in the detector equivalent parameters, i.e. an increase in the resistance and decrease in the inductance. At the same time ferromagnetic components of the object (e.g. steel wheel rims that are in the immediate vicinity of the detector) act like a magnetic core increasing the detector equivalent inductance.

The resultant effect of these phenomena is a change in the detector impedance parameters. The objective of the sensor circuit, whose component is the loop detector, is to achieve a linear dependence between changes in the detector parameters and the voltage signal over a possibly wide frequency range [9]. The sensor circuit output signal is amplitude modulated.

The conditioning system applied by the authors allows measuring the detector impedance changes caused by a passing vehicle. Two system solutions, shown in Fig. 1, are used. The solution applied by authors in former works [2, 4, 9] employs an AC bridge (Fig. 1a). The bridge is automatically balanced when no vehicle is passing over the detector. The occurrence of a vehicle unbalances the bridge and a time-varying unbalance signal is regarded as the vehicle magnetic signature.

The measuring system utilized in this work is shown in Fig. 1b. The sensor circuit is supplied with sinusoidal voltage U_0. Its output voltage U_{out} is applied to two synchronous demodulation circuits while signals controlling demodulators $D1$ and $D2$ are generated in the *SIN/COS* block which ensures their phase shift with the supply voltage U_0 is 0° and 90°, respectively. Therefore from both demodulation paths U_R and U_X are obtained two independent output signals that are proportional to changes in the real part (R component) and imaginary part (X component) of the loop detector impedance, respectively.

Changes in both components (combined) as a function of the distance travelled by a vehicle are termed the vehicle magnetic signature.

Separation of the detector impedance components stems from the authors' confidence, based on their research, that each component contains information about different vehicle features: the R component provides information on the undercarriage geometry, including the vehicle length, and the X component provides information on the number of axles and their spacing. The separate analysis of both components should, therefore, improve the classification process resolution.

The shape of recorded signal (magnetic signature) depends on a vehicle undercarriage dimensions, i.e. distances of the undercarriage components, vehicle axles and wheel rims from the detector surface and is characteristic for a given vehicle class.

Depending on how far the electromagnetic field extends, the decisive influence upon the magnetic signature shape have wheel rims and axles or the whole undercarriage of a vehicle. In the case of goods vehicles, the information on axles is relatively easily available whereas it is much more difficult to acquire details about the undercarriage geometry because of its height above the detector. On the other side, only a complete knowledge about the vehicle's parameters, including its length, axle spacing and undercarriage geometry, can be the basis for a high-resolution vehicle classification.

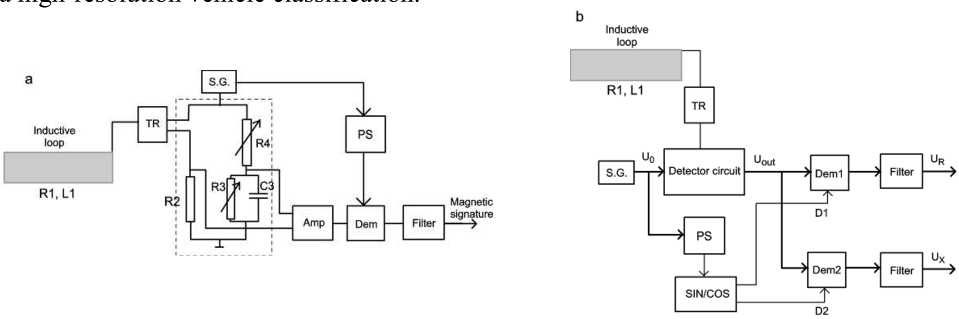

Fig. 1. Magnetic signature measuring systems: a) the bridge system, b) the system with separation of the detector impedance components. TR – transformer, S.G. – supplying generator, PS – phase shifter, Amp – amplifier, Filter – low-pass filter, Dem, Dem1, Dem2 – phase-sensitive demodulators, SIN/COS – signal generator, R1, L1 – resistance and inductance of the loop.

3. Analysis of the loop detector dimensions influence on the vehicle parameters measurement uncertainty

The length of a loop detector, measured in the direction of vehicles traffic is one of key factors deciding on the detector's electromagnetic field extent. The magnetic field range of very short detectors, with length of e.g. 0.1m is 0.2 – 0.3m. As a consequence, such detectors are used for axle detection [9].

Figure 2 shows changes in both impedance components (R and X) of the ILD detector, recorded for the vehicle consisting of a 2-axle tractor and a 3-axle semi-trailer (TT(2+3) class vehicle) passing over detectors with lengths of 0.1m and 0.3m. On the basis of magnetic signatures shown in Fig. 2 it can be concluded that:

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- vehicle axles can be clearly distinguished only in the X component of the loop detector with length of 0.1m,
- for both lengths of the detector, the component X does not allow determining the overall vehicle length because the signal may assume both positive and negative values, particularly for the 0.1m detector,
- the overall length of a vehicle can be exclusively determined from changes in the R component using the 0.3m detector.

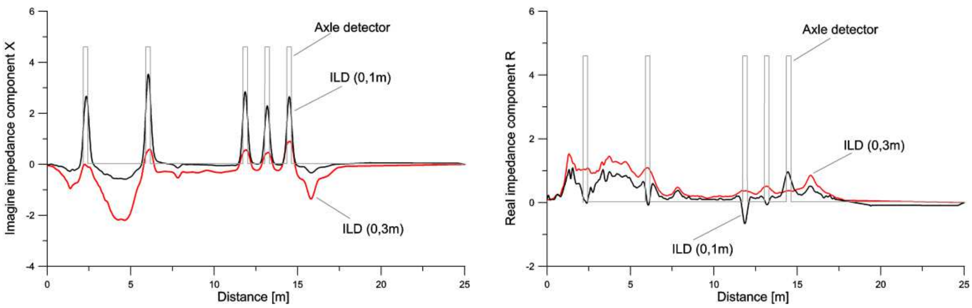

Fig. 2. Changes of the imaginary (X) and real (R) components of the ILD detector impedance as a function of the distance travelled by a TT(2+3) class vehicle.

In order to obtain complete information on the vehicle's length and its axles (the number and spacing) from X and R components they are processed using algorithms (1) and (2).

$$y\_axle(x) = a1 + a2 \cdot R(x) + a3 \cdot X(x) + a4 \cdot R^2(x), \tag{1}$$

$$y\_body(x) = b1 \cdot R(x) + b2 \cdot X(x), \tag{2}$$

where:
x - the distance travelled by a vehicle,
$y\_axle(x)$ - model used for axles detection and axle spacing measurement,
$y\_body(x)$ - model used for the vehicle length measurement,
$R(x), X(x)$ - the real and imaginary component of the loop detector impedance, respectively,
$a1 \div a4, b1, b2$ - models' coefficients, determined individually for each detector.

The form of algorithms (1) and (2) and their coefficients values are selected individually for each pre-defined vehicle class.

Figure 3 shows the results of processing X and R components of a magnetic signature recorded from the 0.3m detector.

As a result of applying algorithms (1) and (2) were obtained model signals: *y_axle* and *y_body*, that contain information about the number and spacing of vehicle axles and the vehicle length.

The key advantage of axle detection using the vehicle magnetic signature — compared with the use of axle load detectors, is that it enables detection of axles' positions with respect to specific points of a vehicle, e.g. its front (front overhang) or end (rear overhang) and detection of lifted retractable axles.

A set of 244 pairs of X and R signals was processed. The signals were acquired under traffic conditions for a class of five-axle goods vehicles: 2-axle tractor + 3-axle semitrailer, further designated as TT(2+3), on site equipped with different loop detectors and piezoelectric axle counter. The goal of tests was to determine the measurement uncertainty of various parameters that characterize such a vehicle class and are measurable using its magnetic signature.

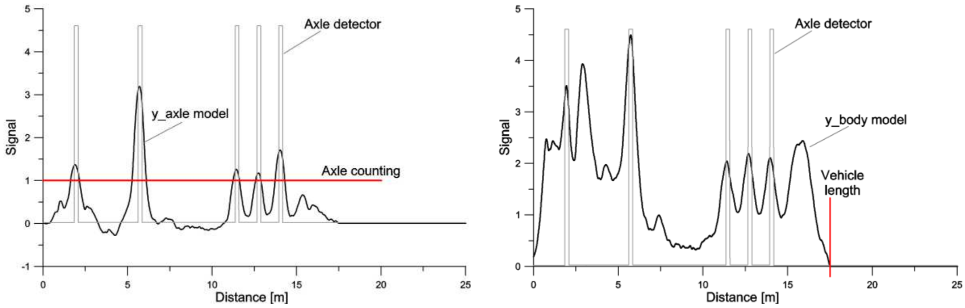

Fig. 3. Signals of models *y_axle* and *y_body* determined for 0.3m detector with illustration of the axle counting and vehicle length estimation algorithms.

The following characteristic parameters have been taken as into account:
- the number of axles,
- the overall length of a vehicle,
- spacings between subsequent axles,
- the distance between the vehicle's front edge and the first axle (front overhang).

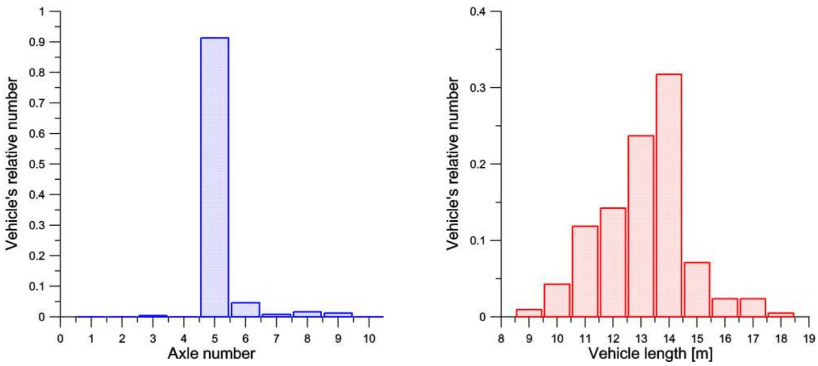

Fig. 4. The distribution of results of axle counting and vehicle length measurement for the 0.1m detector.

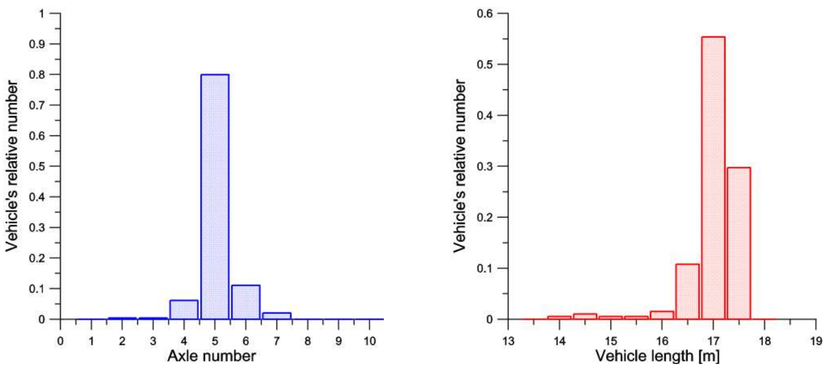

Fig. 5. The distribution of results of axle counting and vehicle length measurement for the 0.3m detector.

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Figures 4 and 5 show distribution of results of axle counting and vehicle length measurement acquired from 0.1m and 0.3m detectors, respectively.

Table 1. The mean value and standard deviation of axle spacing measurement results obtained for 0.1m and 0.3m detectors and of results acquired by the Polish Road Transport Inspection (ITD).

Detector axle distance	0.1 [m]		0.3 [m]		ITD	
	mean [m]	std [m]	mean [m]	std [m]	mean [m]	std [m]
1 – 2	3.78	0.17	3.82	0.30	3.70	0.20
2 – 3	5.59	0.23	5.47	0.30	5.04	0.98
3 – 4	1.31	0.06	1.37	0.50	1.31	0.007
4 – 5	1.29	0.06	1.30	0.12	1.31	0.006

Table 1. summarizes the values of statistical parameters that characterize uncertainty of axle spacing measurement using detectors with lengths of 0.1m and 0.3m.

Figure 6 shows the results of the front overhang measurement obtained for 0.1m and 0.3m detectors, respectively.

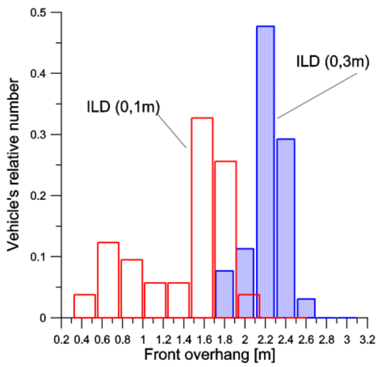

Fig. 6. Distribution of the front overhang estimation result based on the magnetic signatures acquired from different inductive detectors.

For other detectors, i.e. those with lengths of 0.5m – 3.0m, only the variation of axle counting and length measurements have been evaluated. The results are presented in graphic form in Fig. 7. Due to high uncertainty of axle counting, observed in the case of these detectors, the analysis of axle spacing measurement results is groundless.

The histograms shown in figures 4 – 6 and the results contained in table 1 and presented in figure 7, enable to evaluate uncertainty intervals of chosen parameters for various detectors. Knowledge of these intervals is necessary for parameterisation of the vehicle classification algorithm operating on these parameters measurement results.

Conclusions from the above results are explicit: detection and correct counting of vehicle axles is exclusively possible using the shortest detectors, i.e. those with lengths of 0.1m or 0.3m. An increase in the detector length results in significant increase of the axle counting measurement bias and the width of the measurement results uncertainty interval.

The result of the vehicle length measurement obtained using the shortest detector is highly uncertain. Other detectors (0.5m to 3.0m) ensure a much lower, and comparable between detectors, uncertainty of the measurement result.

Where the measurement goals are the number of axles, their position with respect to the vehicle body characteristic points and the vehicle length, the use of 0.3m detector is a comprise choice.

Magnetic signatures obtained from 0.3m detector, recorded for different vehicle classes were the basis for testing the effectiveness of the developed classification system.

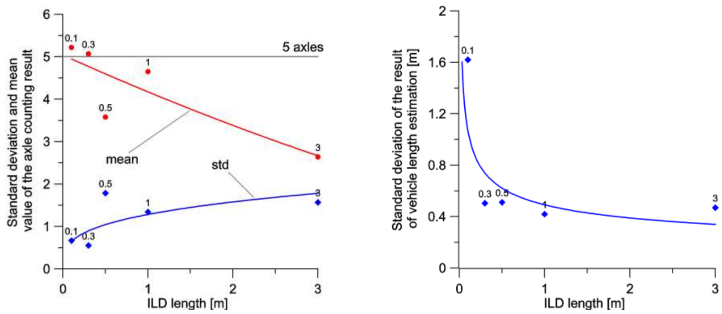

Fig. 7. Standard deviation and mean value of the results of axle counting and standard deviation of vehicle's length estimation as a function of inductive detector length.

4. Classification system

The vehicle classification system has been developed basing on the analysis of vehicle magnetic signatures and a certain number of vehicle classes predefined depending on the classification process goal. The idea of this system consists in that for each predefined vehicle class is developed a separate algorithm, which decides whether a vehicle should be categorized into a given class or not. The decision-making scheme may be different for each of these algorithms. Each algorithm utilizes a different set of parameters and different ranges of their variability, and different vehicle features determined from its magnetic signature. Execution of each algorithm is ended either by classification a vehicle into the class "supported" by this algorithm or a vehicle remains unclassified by the algorithm. Signatures of vehicles unclassified by one algorithm are processed according to algorithms developed for subsequent classes. The vehicle that was not classified by any algorithm is considered as unclassified. The idea of the developed classification system is illustrated in Fig. 8.

Such classification system differs considerably from those being currently in use, in which signatures of all vehicles are processed by one algorithm, the same set of characteristic features is taken into account, and the result of classification depends exclusively on the fact whether these parameters and features fall into intervals with limits that have been defined individually for each class.

The advantage of the proposed new approach to the problem of vehicle classification is that it enables to define a much greater number of classes than the traditional approach allowed. One has now at disposal not only the variability intervals of parameters (though the number of these intervals is limited by the measurement uncertainty of each parameter) but for each class can be considered a different set of vehicle parameters.

Fig. 9 shows an example of classification algorithm developed for the goods vehicles class TT(2+3). The algorithm utilizes vehicle parameters and characteristic features that are measurable with a satisfactorily low uncertainty level on the basis of magnetic signature acquired from inductive loop detector with length of 0.3m, and can be regarded as characteristic for the vehicle class TT(2+3).

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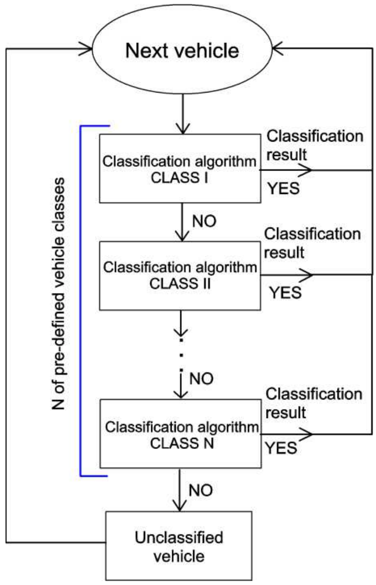

Fig. 8. Block diagram of the classification system.

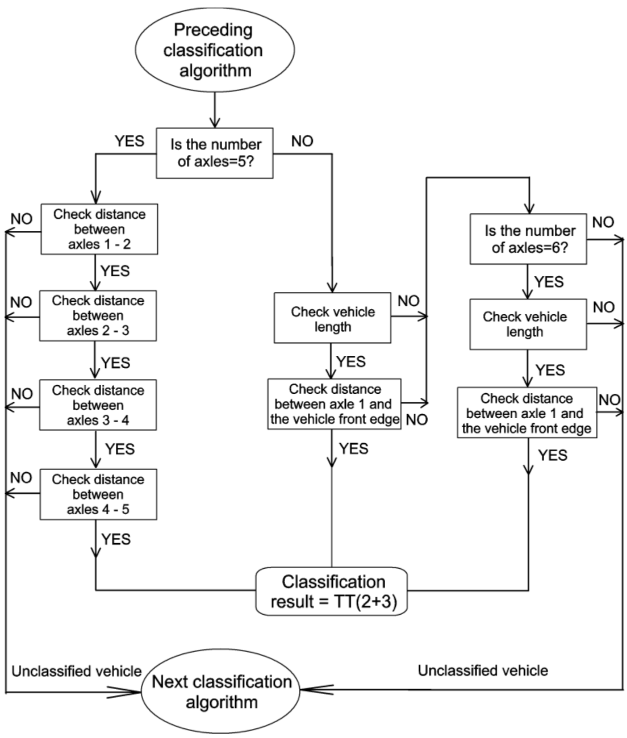

Fig. 9. Classification algorithm for TT(2+3) vehicle class.

The vehicle classification algorithm contains three parallel decision-making paths. Each of these paths utilizes knowledge about different vehicle parameters. If the number of axles equals 5 the decision on classification a vehicle into to the goods vehicles class TT(2+3) is made on the basis of measured spacings between successive axles (the left path in the diagram in Fig. 9). For each pair of axles has been defined the uncertainty interval resulting from characteristics shown in table 1. A vehicle will only be categorized into class TT(2+3) when results of measurement of all distances fall into uncertainty intervals defined for them.

However the execution of the magnetic signature based algorithm for axle detection and counting is not error-free. If the number of detected axles differs from 5, the decision on classification result is made in the middle path. Classification in this path is based on measurements of the vehicle length and the distance between the vehicle's front and the first axle (front overhang). If both measurement results fall simultaneously into uncertainty intervals defined for them, the decision on categorizing the vehicle into class TT(2+3) is made.

In some vehicles of the TT(2+3) class a front bumper support structure causes that the loop detector generates an artefact, which is interpreted as an additional axle (Fig. 10). In the case of this class the number of counted vehicle axles is 6, assuming the other axles were correctly counted, but the first axle (the false one) is evidently closer to the vehicle front edge (c.a. 0.9m) the actual first axle (c.a. 2.2m). The decision on classification the vehicle into TT(2+3) class is made on the basis of the axles number, vehicle length and the false first axle distance from the vehicle front edge (the right path in the diagram in Fig. 9).

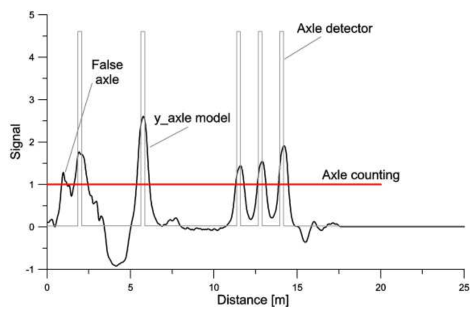

Fig. 10. An artefact caused by front bumper as a reason of incorrect axle counting.

5. Evaluation of classification effectiveness

The evaluation of effectiveness of road vehicles classification based on their magnetic signatures has been carried out for goods vehicle class TT(2+3). The classification utilizes both components (R and X) of magnetic signatures obtained from a loop detector with length of 0.3m in the vehicle motion direction, processed according to algorithms (1) and (2).

For that purpose 14 groups of vehicles were selected, among them 4 groups (table 2, rows 1 - 4) comprised vehicles belonging to the selected class. The classification result should be unambiguously positive, i.e. an ideally working classification algorithm should classify vehicles from these 4 groups as class TT(2+3) vehicles. In that case the relative number of correctly classified vehicles, that expresses the classification effectiveness, should equal 1.0.

As can be seen from table 2, the result of classification obtained using the tested algorithm is not an ideal one. The achieved classification effectiveness is contained within the interval 0.78 - 0.93, depending on the vehicle group. The resultant classification effectiveness for these four vehicle groups is 0.90. That means 10% of vehicles that actually belong to class TT(2+3) have not been categorized into this class by the tested algorithm.

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Table 2. Estimation of the classification effectiveness.

No.	Vehicle group	Relative number of vehicles classified as belonging to TT(2+3)
1	Two-axle tractor with three-axle semi-trailer - TT(2+3) class	0.93
2	Two-axle tractor with three-axle semi-trailer, one axle lifted - TT(2+3) class	0.78
3	Two-axle tractor with three-axle semi-trailer and additional cabinet mounted under the carriage - TT(2+3)	0.89
4	Two-axle tractor with three-axle semi-trailer and additional cabinet mounted under the carriage, one axle lifted - TT(2+3) class	0.83
Total	**TT(2+3) class**	**0.90**
5	Two-axle tractor with three-axle semi-trailer for sand transportation	0.02
6	Two-axle tractor with three-axle semi-trailer for sand transportation, one axle lifted	0.0
7	Two-axle tractor with three-axle tank	0.33
8	Two-axle tractor with three-axle tank, one axle lifted	0.25
9	Two-axle tractor with three-axle tank for granular substances transportation	0.05
10	Two-axle tractor with three-axle tank for granular substances transportation, one axle lifted	0.0
11	Heavy Good Vehicle (HGV)	0.0
12	HGV with trailer	0.07
13	Two-axle bus	0.0
14	Three-axle bus	0.0
Total	**Buses, HGV and tractors with different trailer types**	**0.03**

The purpose of these tests was to determine also the second type of classification error, which consists in classifying to the selected class vehicles that actually do not belong to that class. In order to do that were selected 10 groups of very similar vehicles with comparable structures, number of axles or lengths (table 2, rows 5 - 14). Due to high similarity of these parameters this type of error is more probable than in the case of other vehicles. From the summary results provided in table 2 it can be concluded that mean level of this type classification error is 0.03. The highest value the error attains for tanker trucks. Vehicles in this group are most similar to class TT(2+3) vehicles (similar length, the same number of axles and their spacing).

In case of groups No. 1 – 4 (Table 2), the mean value 0.90 means the total number of vehicles classified as belonging to TT(2+3) class, referred to the total number of vehicles included in these four groups, which actually belong to the TT(2+3) class. In case of groups No. 5 – 14, the mean value 0.03 means the total number of vehicles classified as belonging to TT(2+3) class, referred to the total number of vehicles included in these 10 groups, which actually do not belong to this class.

6. Conclusions

The proposed new approach to the vehicle classification problem is based on vehicle parameters that are measurable from magnetic signature. In order to extend the information resource acquired from vehicle's magnetic signature has been employed an independent measurement of both components of the loop detector impedance and the influence of the detector length on uncertainty of acquired measurement information has been analysed.

The proposed approach allows defining a larger number of vehicle classes and therefore improving the classification resolution that depends on uncertainty of individual parameters and the number of vehicle characteristic features acquired from its magnetic signature. Hence seeking for new, more advanced algorithms enabling magnetic signatures analysis becomes particularly significant.

It also seems that the population of a vehicle parameters set can be increased by means of appropriate design of a loop detector, i.e. its shape and dimensions, and adequate selection of algorithm for preliminary processing of recorded magnetic signatures (filtering, sharpening).

The proposed approach to the vehicle classification problem was tested on the 14 highly similar vehicle groups. The obtained results are promising. The future works will be focused on design of full classification system, considering all vehicle classes observed in traffic stream.

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