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DATA FUSION APPLICATIONS IN THE TRAFFIC PARAMETERS MEASUREMENT

In the paper the problem of measuring road traffic parameters using systems with complex algorithms for measurement data processing is discussed. A characteristic feature of these systems is utilising there data fusion methods. This way a possibility has been created of linking the knowledge of measuring with an initial knowledge on the measurement object. The authors have shown that these methods allow to decrease measurement uncertainty, increase measurement reliability or limit the influence of the disturbing factors.

Keywords: data fusion, vehicle classification, Weigh-In-Motion, WIM calibration

1. INTRODUCTION

Each cognitive process is connected with information processing. Information can be acquired from various sources and a measuring experiment is one of them. The quality of the cognitive process is dependent on the amount and quality of the information collected from the measurement object, resources of the *a priori* knowledge about this object, and the quality of processing. Independent of the measurement object and the purpose of the cognitive process is the basic principle saying that the richer and more complete information is gained from the object, the more reliable effects of the cognitive process are. The enrichment of the measurement information gained from the object can be achieved not only by increasing the measuring accuracy but also through measuring a greater number of appropriately selected object variables. At the stage of information processing, it is possible to join the measurement (experiment) knowledge with the *a priori* knowledge, which may considerably increase the effectiveness of the cognitive process. Joining knowledge from various sources is called data fusion. Depending on the type of information and the structure of the system in which the fusion takes place, it can be realized at the level of unprocessed data, features or decision. Depending on its purpose, the fusion can be the cooperation, competitive or complementary fusion [1, 2, 3]. These problems are presented for the case of measuring the parameters of moving vehicles.

In particular, these systems classify and weigh moving vehicles (Weigh-In-Motion systems, WIM). Also, the problem of using data fusion in the calibration process of WIM systems was discussed.

2. VEHICLE CLASSIFICATION

Classifying an automotive vehicle means determining to which of the selected classes the vehicle belongs. Classification methods are dependent on the vehicle parameters that can be determined in a given measuring system and on the classification purpose.

The simplest classification method, often used in practice, is based on measuring the vehicle length. Not more than three classes are then defined. The method can be applied in a very simple measuring system, e.g., in a single-sensor system with an inductive loop utilizing only the signal of vehicle occurrence above the sensor.

When the necessity of defining more (four or five) classes arises, it is possible to use a system with inductive sensor and process the obtained magnetic profile of the vehicle. The profiles generated by different vehicles differ in shape, amplitude, frequency spectrum, statistical parameters, etc. One method out of the magnetic profile preprocessing methods consists in transforming the profile into the vehicle length domain [4]. This operation results in that the profile contains the combined information on the shape and length of the primary profile, which enables a more selective classification to be made (Fig. 1). To carry out such transformation the information on vehicle speed is also necessary. This transformation is therefore an example of data fusion. Also, amplitude standardization can be abandoned, gaining in this way additional information on the vehicle suspension height.

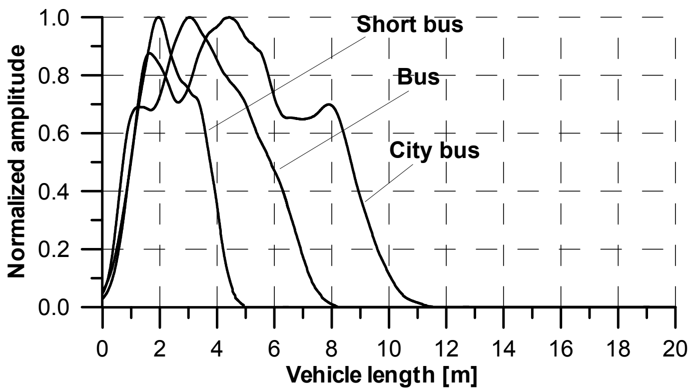

Fig. 1. Bus magnetic profiles in the vehicle length domain.

Nonparametric classification methods consist in comparing directly the profile generated by the vehicle being classified (after transformation) with the reference profiles representing each of the defined classes. Depending on vehicle class, the effectiveness of such classification ranges from 67% to 100%.

Parametric methods consist in comparing the profile parameters of the vehicle being classified and those of a reference vehicle. The effectiveness of the classification based on individual profile parameters is unsatisfactory [5, 19] (depending on the selected parameter, the effectiveness gained is 60% –70% for one of the classes and considerable worse for the others).

Combined utilization of various parameters is much more effective: the classification effectiveness in all classes under consideration is then increased and equalized [5, 6]. Such action is called decision fusion. It can be implemented basing on voting or weighted voting methods, or hierarchical methods. Depending on the class, the classification effectiveness of the voting methods is in the interval of 50% to 97%. The classification effectiveness of the hierarchical methods ranges from 77% to 96%.

Describing reference data with fuzzy measures is another approach to the classification problem. A model of any class consists of a set of membership functions (similarity measures) defined for selected parameters. The membership functions are determined using statistical analysis (mean and standard deviation) of a selected parameter. Both simple logical functions operating on fuzzy sets (OR and AND, fuzzy set normalized power), and more complex functions enabling weighting coefficients to be taken into account are selected as functions realizing data fusion [7, 8]. In this case, the classification effectiveness depends on the set of selected parameters, adopted shape of fuzzy measures (triangular, gaussian), and on the functions realizing data fusion. The method's classification effectiveness reaches 92 - 94% for five selected magnetic profile parameters and four defined vehicle classes.

It is also possible to join the parametric and nonparametric methods. In [9] an algorithm is presented which utilizes a neural network to fuse the features obtained from the profile and the samples of this profile. A classification effectiveness of 89% was reached for five defined vehicle classes.

Vehicle classification can also be effected by measuring the number of vehicle axles. It is particularly important in vehicle weighing systems. To decide on exceeding the allowable load values, it is necessary to combine the obtained result of weighing and the result of classification. However, such classification may be not selective enough. It is then necessary to measure the inter-axle distances. Taking into account this parameter improves considerably the classification selectiveness although requires the vehicle speed to be measured. In such a system also vehicle length (treated as a parameter auxiliary to the classification process) is measured and a trailer is detected. So the measuring system must cooperate with different-type sensors and realize the fusion process (complementary fusion, increasing the completeness of object description) of the data acquired from these sensors and the possessed *a priori* knowledge.

Typical measurement signals from a system with complementary fusion implemented are presented in Fig. 2. Such a system allows to differentiate between 13 - 14 vehicle classes [10].

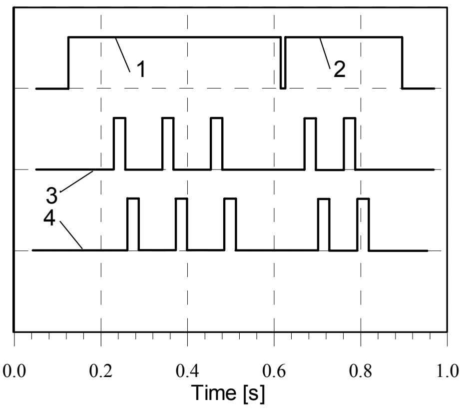

Fig. 2. Measurement signals from a multi-sensor system with complementary fusion implemented taken from a three-axle vehicle with two-axle trailer. 1 - vehicle presence signal; 2 - trailer presence signal; 3, 4 - signals from axle load sensors.

Complementary fusion can also be realized having a single detector and an inductive loop only. Depending on the shape and size of the loop, the range of the electromagnetic field generated by the loop will be different. The resulting measurement signal (magnetic profile) will contain different information on the vehicle that moved above this loop (Fig. 3).

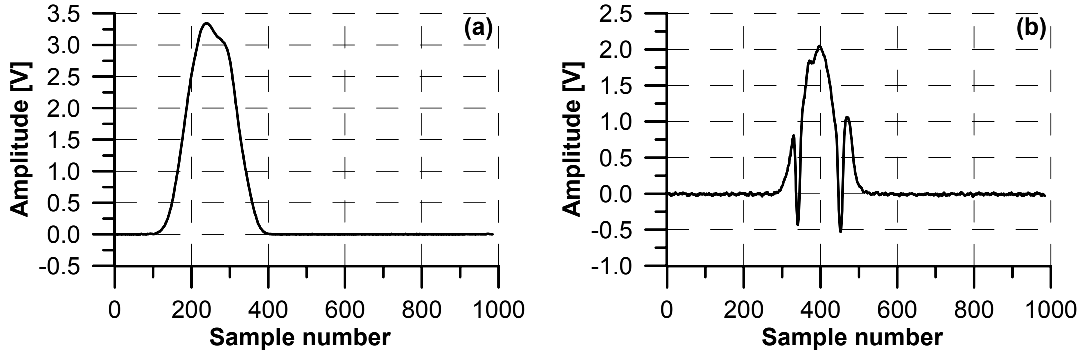

Fig. 3. Passenger vehicle profile acquired from sensors of a) 150 cm, b) 10cm width.

A thin loop enables detection and vehicle axles counting to be carried out. The mechanism of complementary fusion realized at the sensor's level can be explained with the fact that the measuring sensors react simultaneously to many different physical quantities. This makes it possible to collect greater an amount of information on the object with a single sensor provided that the user can extract from the measurement signal the information relevant to each measured quantity or can utilize the combined information.

3. WEIGH IN MOTION

The term *weigh-in-motion* (WIM) means a process of measuring the dynamic wheel forces of a moving vehicle onto the road and estimating the corresponding static loads or total weight. The lack of significant limitations posed on the vehicle speed is a characteristic feature of such weighing systems. In general, the WIM systems complement the static vehicle weighing stations, playing the role of preselection systems.

Classic WIM preselection systems are based on an inductive sensor and two load sensors. Such system configuration allows to estimate static loads of individual axles, total weight and classify a vehicle based on the number of its axles. Also, the pavement temperature is measured as this is necessary for correction of weighing results which depend on the thermal and mechanical properties of the pavement and sensors. In such a system the data fusion is realized to make the description of the object under consideration complete and to ensure the high possible measuring accuracy. The High Speed WIM preselection systems provided with two load sensors can determine the total weight of a moving vehicle with an error not less than 10 - 15%. The main reason is the occurrence of the dynamic component in the signal of vehicle load on the road surface (Fig. 4). The amplitude of this component depends on the pavement quality and vehicle speed and may achieve even up to 40% of the static load value [11].

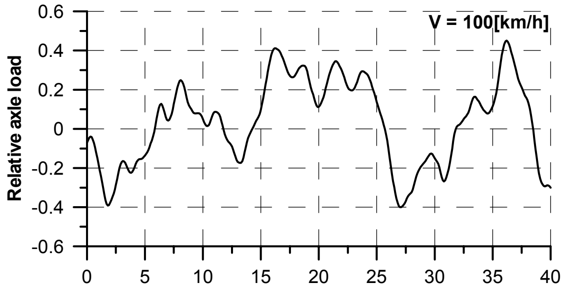

Fig. 4. Relative changes of the vehicle instantaneous axle load at the speed of 100 km/h.

Weighing vehicles with an accuracy of 1% or 2% is now possible with static or low-speed (up to 6 km/h) scales only. The improvement of measuring accuracy of the total weight and static axle loads of vehicles moving with a road speed up to the accuracy of low-speed scales is possible through building multi-sensor weigh-in-motion systems (MS-WIM), developing static load estimation algorithms, and applying suitable methods for calibrating such systems. Based on the analysis of pavement models [11, 17] and selected models of vehicle suspension, it was found that the following relationship is a good approximation of the signal of the force the vehicle wheels exert on the pavement during vehicle motion:

$$F(t) = F_0 + \sum_{k=1}^{M} F_k \sin(2\pi f_k t + \varphi_k), \tag{1}$$

where: F_0 - static load exerted on the road by a stationary vehicle, $\sum_{k=1}^{M}[\bullet]$ - dynamic components occurring during vehicle motion, F_k, f_k, φ_k - parameters of the dynamic load components: amplitude, frequency and phase angle, respectively.

Depending on the required modelling accuracy and suspension construction in the vehicle under consideration, different numbers M of dynamic components (usually $M = 1$ or $M = 2$) [12, 18, 20] are defined in the model. Frequencies f_1 and f_2 in this model describe the vertical oscillation of the suspended vehicle mass and wheel hopping (oscillations of unsuspended mass), respectively. Depending on the vehicle class and vehicle total weight, these frequencies are $f_1 = 1.5 \div 4.5\text{Hz}$ and $f_2 = 8 \div 15\text{Hz}$, respectively. The amplitudes of individual dynamic components are significantly dependent on the vehicle speed.

To solve the problem of estimating the axle static load, F_0, the following estimates are used [10]:

- **mean value**, usually calculated from the results of instantaneous load on successive **maximum likelihood estimator (ML)**. It allows to determine the components of state vector (containing three ($M = 1$) or five coefficients ($M = 2$) $[F_0 \quad F_1\sin\varphi_1 \quad F_1\cos\varphi_1 \quad F_2\sin\varphi_2 \quad F_2\cos\varphi_2]$, depending on the model assumed). Assuming the frequencies f_1, f_2 are known, the values of model coefficients (state vector components) are sought that maximise the likelihood function [23]. As in practise the frequencies of dynamic components are not known *a priori*, the solution to the problem is being determined for each pair (f_1, f_2) of frequencies selected after searching with the assumed step the variability intervals assumed for each of these frequencies. The final result of identification are such values of the sought coefficients which produce the maximum value of the likelihood function. Quantization of the obtained frequency estimates f_1, f_2 is the basic cause limiting the accuracy of this estimation method.
- **nonlinear least-squares estimator (NLS).** The method consists in determining such signal model coefficients for which the least-squares criterion adopted as the measure of the distance between the measurement results and the model (1) reaches minimum. With a nonlinear relationship between model response and the coefficients, the minimisation can be carried out only approximately, according to an iterative algorithm. The high sensitivity of such an algorithm to the coefficient initial value is one of the cumbersome disadvantages of the algorithm. Because of high variability of weighed vehicle parameters (speed, total weight, frequency and amplitude of suspended and unsuspended mass fluctuation), the accuracy of this algorithm with no additional modification is not satisfactory.
- **nonlinear Kalman filter (NKF).** The operating of the Kalman filter may be interpreted as algorithms of prediction and correction alternatively repeated implemented to

successive measurement signal samples and the calculated model response (1). Each sensor installed into a MS-WIM system is assigned one load signal sample. In each cycle, the successive improved estimates of the state vector are determined, taking into account the axle load measurement results collected successively by the individual load sensors during the travel of the weigh vehicle. This estimator has good properties which are available, however, for a relatively high (compared to other estimators) sampling frequency and large number of measurement signal samples. For this reason, the estimator is not suitable for processing signals from such MS-WIM systems where no more than twenty load sensors are used.

- **modified nonlinear least-squares estimate (MNLS).** The modification consists in connecting the ML estimator, generating an initial estimate of the parameters to be determined, with the NLS estimator. The NLS estimator allows to determine more accurate estimates, quantization error eliminated. At the same time this modification solves the problem of selecting starting values for the NLS iterative algorithm.
- **artificial neural networks** (usually of back propagation type) [13, 14]. The implementation of this algorithm may be difficult under real conditions because large (of order of several thousand) teaching and test sets have to be collected for each considered class and vehicle type, which may be very difficult for WIM systems.

To assess and compare the above mentioned estimators, the following characteristic was applied:

$$Pr(\delta) = 1 - P(\delta), \tag{2}$$

where: $\delta = \left| \left(\hat{F}_0 - F_0 \right) / F_0 \right|$ is the absolute value of the relative estimation error of the static component F_0, $\hat{F}_0$ is an estimate of the static component, $P(\delta)$ is the cumulative probability distribution function of error δ.

This characteristic specifies the occurrence probability of error greater than δ and is called reliability function. Measuring systems with 16 load sensors distributed uniformly every 1.7 m distance, and non-uniformly with distance between successive sensors decreasing linearly were considered. The distance of 1.7 m between the first sensors was decreased for each sensor by 0.1 m. In Fig. 5 typical characteristics allowing to compare the described estimators are presented.

From the characteristics presented in Fig. 5 it follows that the probability of exceeding the weighing error of 0.02 depends on the applied estimation algorithm and equals 0.18 for the MNLS estimator, 0.22 for ML estimator, and 0.49 for simple averaging (Mean). Applying a non-uniform layout of sensors allows to reduce considerably this probability for the MNLS estimator. For the other two estimators, this probability increases considerably. The choice of the estimation algorithm depends mainly on the speed at which the weighed vehicle is moving. The characteristics shown in Fig. 6 confirm the possibility of a significant improvement of weighing accuracy by adaptive selection of load estimation algorithms depending on the speed of a weighed vehicle.

The architecture of the MS-WIM systems is usually organized in such a way that the successive pairs of load sensors are operated by the individual sub-systems. Their task is to preprocess signals. After processing is over (so in an asynchronous way), each of these sub-systems sends its measurement results. The data received by a host system must be properly associated because of the fact that more than one vehicle may be present on the measurement site. Next, the data must be aligned in regard to the vehicle occurrence time at the successive sensors (this is required by the load estimation algorithms). Both stages are an important element of the data fusion process realized at the central level. After these initial operations are done and the non-exceedance of imposed limitations (e.g., the variability of vehicle speed during travelling through the measuring site, data completeness) is checked, measurement data processing can be carried out according to the relevant estimation algorithm (whose selection realized on line will depend on vehicle speed, vehicle classification, etc.) (see Fig. 6). In such a multi-sensor data fusion process, the a priori knowledge plays an important role and is taken into account through applying the appropriate number of load sensors and their optimum distribution. This knowledge is acquired from the experience of other constructors, model studies, measurements of vehicle stream parameters at the WIM site location and the resulting parameters of acquisition and signal preprocessing, limitations of various types, etc.

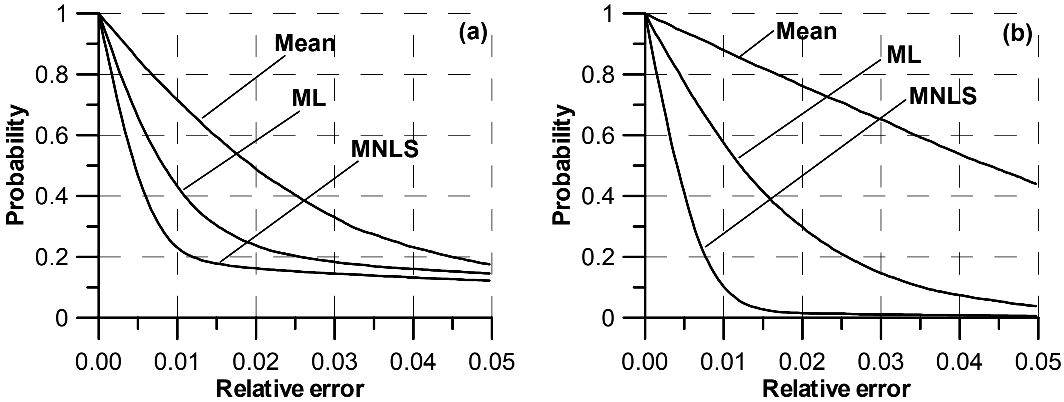

Fig. 5. Characteristics (2) for $M = 2$ and three comparable static load F_0 estimation algorithms for: a) uniform; b) non-uniform distribution of 16 sensors.

The number of load sensors applied is usually limited by economic reasons, although in [13] there has been shown that this number can be limited because of the properties of the applied estimation method and the lack of its accuracy improvement after exceeding a certain number of sensors.

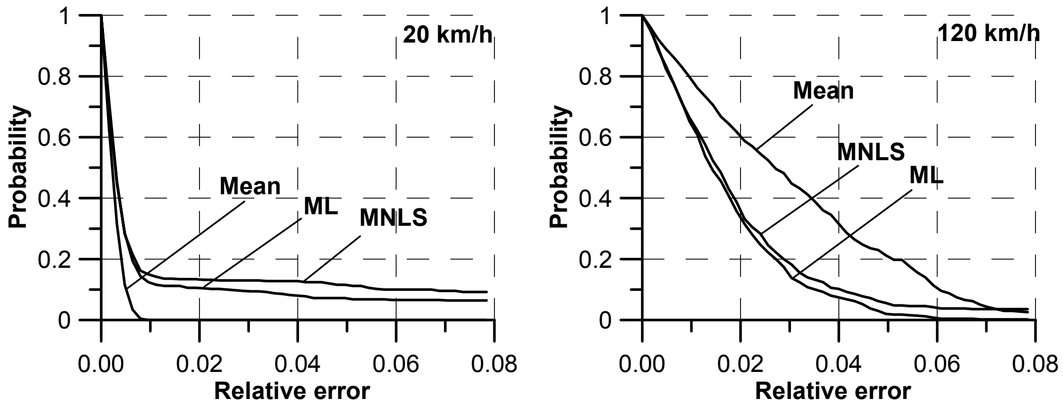

Fig. 6. Characteristics (2) for $M = 2$, uniform distribution of 16 sensors, different speeds and three comparable static load F_0 estimation algorithms.

4. CALIBRATION OF WIM SYSTEMS

The aim of calibrating a WIM system is to determine experimentally the system transfer constant C which allows to determine the axle static load of a weighed vehicle and the vehicle total weight according to (3).

$$Ws = \frac{1}{C} Wd \ , \tag{3}$$

where: *Ws* - calibrated weighing result, i.e., the vehicle total weight or the static load of a selected axle; *Wd* - non-calibrated weighing result, i.e., the result of processing of load signal from WIM system sensors.

The calibration of a WIM system can be carried out using several different methods: with the use of static or dynamic force setters, using pre-weighed vehicles or an instrumented vehicle, i.e., a vehicle where a possibility exists to continuously record its dynamic axle loads exerted on the road surface during travel [15, 16]. All these methods have both advantages and disadvantages. Main disadvantages include high costs of implementation of these methods and their high time consumption. On the other hand, the nonstationarity of WIM systems require that their calibration should be often repeated according to the rule: the more frequent calibration the more accurate system.

A new calibration method consisting in data fusion has been designed. The current measurement results in the WIM system are combined with an *a priori* knowledge about the axle loads of a selected class of vehicles moving along a given road and adopted as the reference vehicles.

A characteristic feature of the proposed autocalibration method is determining the current estimate of the system constant after passing of any vehicle recognized as the reference one. Thanks to this, the system acquires the possibility to react automatically to the changes of many factors affecting its operation, such as the variation of temperature, humidity, sensor sensitivity, etc.

A sufficiently small random variability of a parameter to be measured over the whole population of reference vehicles should be their characteristic feature. A necessity of precisely identifying a selected vehicle class is an additional requirement.

Five-axle units consisting of two-axle truck-tractor and three-axle trailer are a characteristic vehicle class. As the WIM systems can measure also the inter-axle distance (with a resolution not worse than 10 mm), this allows to detect easily the vehicles belonging to this vehicle class. Moreover, a characteristic feature of the five-axle units is small random variability of the load exerted by the first axle within the widely understood variability range of the vehicle total weight. In Fig. 7, estimates of probability density functions are presented describing the variability of weighing results for this class obtained from low-speed vehicle scales. The size of measurement result population was limited by technical reasons and equalled 82.

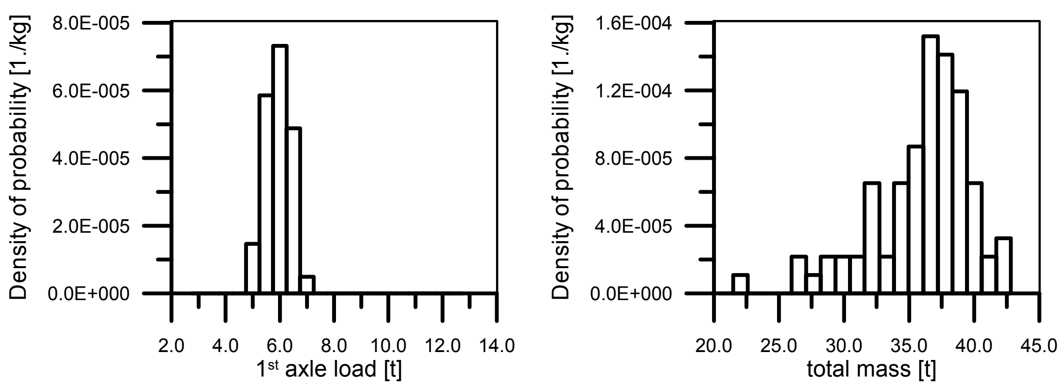

Fig. 7. Probability density functions of the five-axle unit front-axle loads and the unit total weight determined using a low-speed vehicle scales.

The results presented in Table 1 show that the front-axle load is not only of the smallest random variability ($\sigma^2 = 0.0053$) but also is the least correlated with the variability of the loads of the other axles and with the vehicle total weight (cov = 0.0018 to 0.0040). The observed correlation is 3 to 5 times smaller than for the other axles. Based on these premises, the front-axle load of this vehicle class was accepted as the reference value. The mean front-axle load is $\overline{w}$ = 61677 N.

Table 1. The covariance matrix of the 5-axle vehicle static weighing results. 1 through 5 - statistical parameters of successive axle load measuring results, 6 - statistical parameters of vehicle total weight measuring results.

i \ k	1	2	3	4	5	6
1	**0.0053**	**0.0036**	**0.0018**	**0.0039**	**0.0040**	**0.0038**
2		0.0222	0.0041	0.0060	0.0077	0.0101
3			0.0376	0.0266	0.0171	0.0159
4				0.0299	0.0255	0.0176
5					0.0480	0.0197
6						0.0134

Because of the continuous character of a calibration process, the estimation of the transfer constant C is made in an iterative way, e.g., according to an algorithm with an exponential forgetting [21].

According to this algorithm, the successive estimates $\hat{C}_n$ of the forgetting constant are described by Eq. (4).

$$\hat{C}_n = \hat{C}_{n-1} + K_n \left(Wd_{n-1} - \overline{w}\hat{C}_{n-1} \right), \tag{4}$$

$$b_n = 1./\left(\overline{w}P_{n-1}\overline{w} + \lambda\right), \tag{4a}$$

$$K_n = P_{n-1}\overline{w}b_n, \tag{4b}$$

$$P_n = \left(P_{n-1} - K_n\overline{w}P_{n-1}\right)/\lambda, \tag{4c}$$

where: λ - the forgetting constant, $\lambda \leq 1$, n is the iteration number corresponding to the number of the successive reference vehicle which passed the station under calibration.

The dynamics of this system is characterised by the so called forgetting constant λ. The time intervals between the moments of determining the successive estimates correspond to the moments at which the successive reference vehicles pass the WIM station.

In the case of systems significantly nonstationary, too large time distance between the successive reference vehicles may force using the algorithm with a small value of the λ coefficient. In consequence, this will cause high random variability of transfer constant estimates, and therefore of weighing results. Although accepting the values of the coefficient λ close to unity will decrease this random variability, it will cause that the dynamic properties of the estimation algorithm would be very bad. The necessity of a compromise between both limitations causes that the discussed calibration method may be used on the roads with a large number of reference vehicles passing through the calibrated station during a time unit.

In order to solve the above problem, a modification to the transfer constant estimation algorithm may be introduced that consists in making the forgetting constant λ dependent on the time interval between the successive reference vehicles [22] according to the rule that the smaller value the coefficient λ assumes, the longer the expecting time for the next vehicle.

Based on simulation study, a comparison was made between the basic (λ = *const*) and modified (λ = *var*), algorithm operation, and the results are presented in Fig. 8. The nonstationarity of the system was simulated making the measurement transfer constant variable.

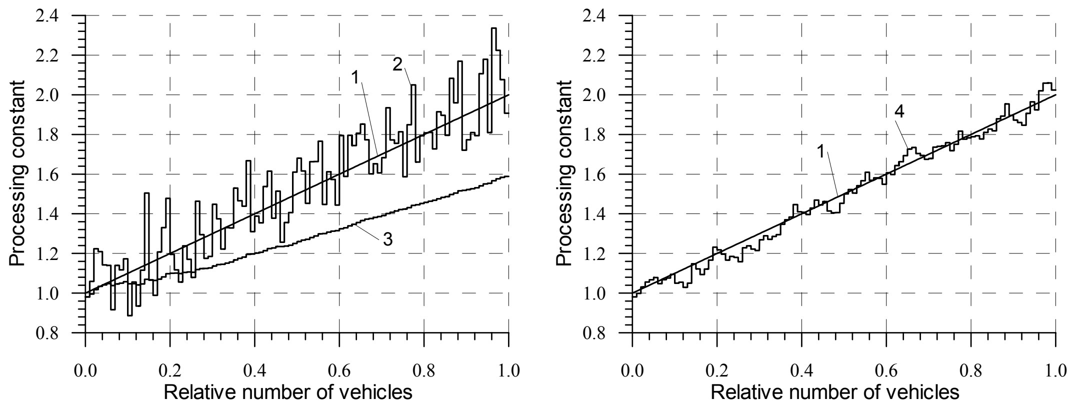

Fig. 8. Linear time relationship of the WIM system transfer constant (1) and the results of its estimation: 2 - algorithm (4), λ =0.1; 3 - algorithm (4), λ = 0.9; 4 - algorithm (4) with modification λ = *var*.

Algorithm (4) with also in case modification is valid of step change of system parameters which is pictured in Fig. 9. Such a situation may occur in reality e.g., in the case of a load sensor failure.

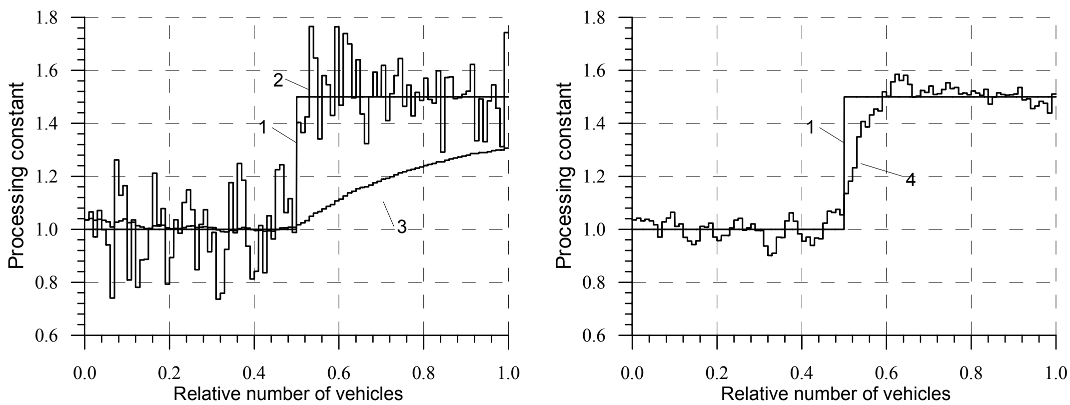

Fig. 9. Step variability of the WIM system transfer constant (1) and the result of its estimation: 2 - algorithm (4), λ = 0.1; 3 - algorithm (4), λ = 0.9; 4 - algorithm (4) with modification λ = *var*.

The modified WIM system transfer constant estimation algorithm allows to make current calibration of nonstationary systems with the simultaneous minimisation of the random variability of weighing results.

5. CONCLUSIONS

Selected problems of applying data fusion to measuring vehicle-in-motion parameters are presented in the paper. The approach was taken from two aspects: increasing the description completeness of the object undergoing measurement, and achieving the highest possible measurement accuracy of object parameters, or classification effectiveness.

These purposes were realized through the adequate selection of the number and type of sensors, their construction parameters, systems of their cooperation, and also of through initial operations on signals (e.g., by transforming into the vehicle length domain, parameterisation, association, alignment, etc.). Another not less important problem was the selection of the vehicle classification method (parametric, nonparametric) and vehicle axle load estimation and calibration methods.

In regard to the measurements presented, data fusion was applied both at the level of sensors, features, and decisions. Examples of complementary and cooperation data fusion were presented. It was shown that in each of these cases the quality or quantity of the results were better than when no data fusion would have been applied.

The presented study results point at the possibility of utilising data fusion and applying the presented WIM system autocalibration method to eliminate both the slow trend and jump changes of the transfer constant values of the WIM system. The structure of traffic stream observed on Polish roads meets the requirements demanding for the application of this calibration method. However, still open remain the problems of estimating the vehicle weighing uncertainty in the system calibrated according to the discussed method and of the assessment of the parameter influence of both the traffic stream (frequency of occurrence and the number of reference vehicles) and the WIM site (type and number of the sensors used, the amount of nonstationarity) on this uncertainty.

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ZASTOSOWANIE FUZJI DANYCH W POMIARACH PARAMETRÓW RUCHU DROGOWEGO

Streszczenie

Praca dotyczy zagadnienia pomiaru parametrów ruchu drogowego przy użyciu systemów realizujących złożone algorytmy przetwarzania danych pomiarowych. Cechą charakterystyczną omawianych systemów i algorytmów jest wykorzystanie w nich metod fuzji danych. W ten sposób stworzona została możliwość łączenia wiedzy pomiarowej z wiedzą wstępną posiadaną na temat obiektu pomiarowego. Autorzy wykazali, że metody te pozwalają zmniejszyć niepewność wyniku pomiaru, zwiększyć jego rozdzielczość lub ograniczyć wpływ czynników zakłócających. W pracy przedstawiono problemy związane z klasyfikacją pojazdów, ważeniem pojazdów w ruchu oraz kalibracją systemów ważących.