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6. THE POSSIBILITY OF USING INDUCTION LOOPS AS A SOURCE OF INFORMATION ON VEHICLES

6.1. Introduction

Vehicle Weigh-In-Motion stations provide detailed data on each passing vehicle. The data includes information on vehicle length, number of axles, axle spacing, total weight, individual wheel and axle loads and vehicle class according to the standard adopted by the road authority. As part of the research and development project co-financed by the European Regional Development Fund through the Silesian Centre for Enterprise, APM PRO sp. z o.o. developed the iWIM weighing computer, which processes and analyses data from individual sensors installed, among others, in the road surface. The computer contains a module that enables reading the magnetic profile of a vehicle passing through a station. This module is designed to be a separate unit.

WIM stations are set up to exclude from traffic vehicles that exceed the permitted standards[3]. There are different limitations for various vehicles. There are many configurations of Weigh-In-Motion stations and now they usually do not have a connection to government vehicle databases. Therefore, there is a need to classify the type of vehicle based on data collected by a WIM station.

The loop recorder allows the creation of a classifier based on the signal from a single induction loop, which has the advantage, among other things, of not processing personal data, unlike systems using automatic number plate recognition (ANPR) cameras.

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[3] Raport NIK, Ruch pojazdów przeciążonych na obszarach zurbanizowanych https://www.nik.gov.pl/plik/id,23352,vp,26070.pdf, [accessed in May 2022].

Magnetic signature analysis makes it possible to extract vehicle characteristics such as number of axles and vehicle length, which consequently allows them to be classified.

Two standards are typically used to classify vehicles: COST 323[4] and TLS 8+1[5]. Research into the use of induction loops as sources of vehicle information shows that it is possible to recognise vehicle length[6], number of axles[7] and vehicle class[8] from loop data. Algorithms proposed by various authors enable the extraction of specific vehicle features. In this study, it was decided to investigate the suitability of machine learning algorithms for vehicle feature extraction and classification based on a single induction loop.

6.2. General description of the wim station structure

The Weigh-In-Motion (WIM) station is used for dynamic weighing of vehicles at high speeds while maintaining smooth traffic flow. Weighing at high speeds is possible by suitable sensors embedded in the road surface. The most common types of sensors for measuring weight are strain gauges and piezoelectric quartz sensors. The construction of the measuring station involves installing individual sensors in the road surface. The following are incorporated on the approach side (respectively): induction loops, load cells (strain gauges or quartz piezoelectric), piezoelectric sensors and, optionally, another two sets of load cells. ANPR cameras, 3D scanners, a weather station and CCTV cameras are located on the gantry structure, which is just behind the last load cells. Induction loops are responsible for detecting the approach and activating the measuring track of the weighing station and the 3D scanner. When a vehicle approaches the induction loop, images from ANPR and CCTV cameras are also taken.

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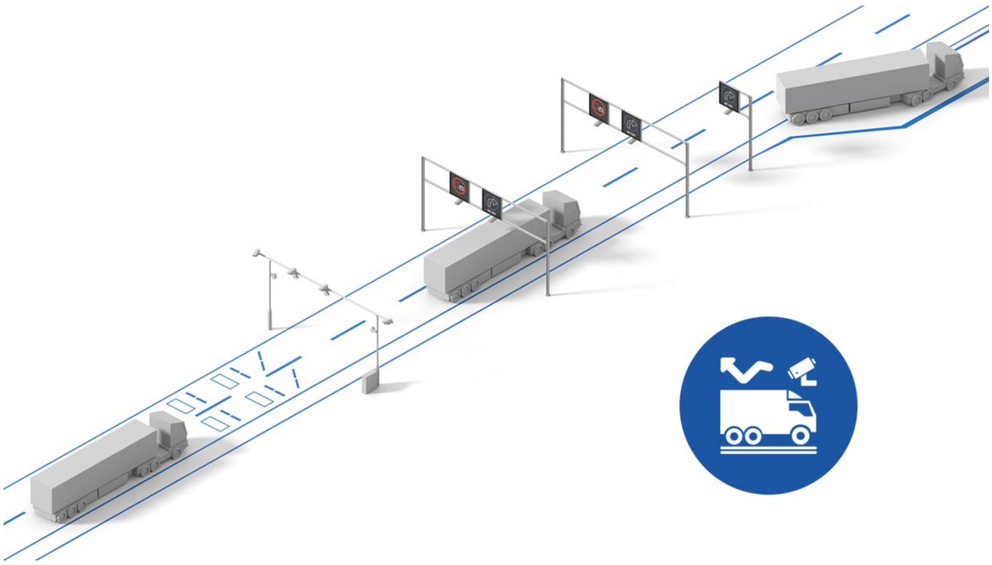
[4] Jacob B., O'Brien E., Jehaes S.: COST 323 Weigh-in-Motion of Road Vehicles, 1999. http://www.is-wim.org/doc/wim_eu_specs_cost323.pdf, [accessed in May 2022].

[5] TLS2012, Technische Lieferbedingungen für Streckenstationen. BAST, 2012. https://www.bast.de/BASt_2017/DE/Publikationen/Regelwerke/Verkehrstechnik/Unterseiten/V5-tls-2012.pdf?__blob=publicationFile&v=1, [accessed in May 2022].

[6] Gajda J., Sroka R.: Vehicle classification by parametric identification of the measured signals, XVI IMEKO World Congress, Vienna, Austria, 2000.

[7] Marszalek Z., Zeglen T., Sroka R., Gajda J.: Inductive loop axle detector based on resistance and reactance vehicle magnetic profiles, Sensors, 2018.

[8] Burnos P., Gajda J., Piwowar P., Sroka R., Stencel M., Zeglen T.: Measurements of road traffic parameters using inductive loops and piezoelectric sensors, Metrology and Measurement Systems, 2007, Vol. 14, No. 2, pp. 187–203.



Rys. 6.1. Stacja ważenia pojazdów w ruchu – schemat ogólny
Fig. 6.1. Vehicles Weigh in Motion station – general scheme
Source: Company materials.

6.3. Method used

6.3.1. Features selection and extraction

The proprietary iWIM system was installed for the first time at a test station located on national road 44 in the Silesian Voivodship, Mikołów County. 1799 records for the learning set were retrieved from the test station, and then additional 118 records as the test set. The datasets were selected in such a manner that the number of records from each class was similar.

The first step in preparing the learning set was to analyse the signals received to determine their statistical measures – including mean, weighted mean and median. Also, the individual peaks from the signal distributions using the Fast Fourier Transform and the chirp Z-transform were included in the feature vector.

There were 64 features in the vector created to develop a classifier to recognise vehicle category. A vector of 141 features was used to create a regressor that identifies vehicle length, while a vector of 167 features was used to identify the number of vehicle axles.

6.3.2. Vehicle length recognition

For the regressor recognising vehicle length, a method was chosen in which the data were standardised so that the mean value was 0 and the standard deviation was 1. In this case, the standardisation procedure achieved better results than with unstandardised data. Next, a factor analysis was performed using the Factor Analysis algorithm to find the vector features that had the greatest impact on the correct prediction of vehicle length. The use of this algorithm also made it possible to reduce computational complexity. The final stage was to test several classification algorithms in terms of the accuracy of the results obtained. The following algorithms were verified: random forest regressor, decision tree regressor, voting classifier (composed of random forest regressor and logistic regression), support vector machine and logistic regression. The random forest regressor showed the highest accuracy, averaging 85% for the 10 cross-validation results.

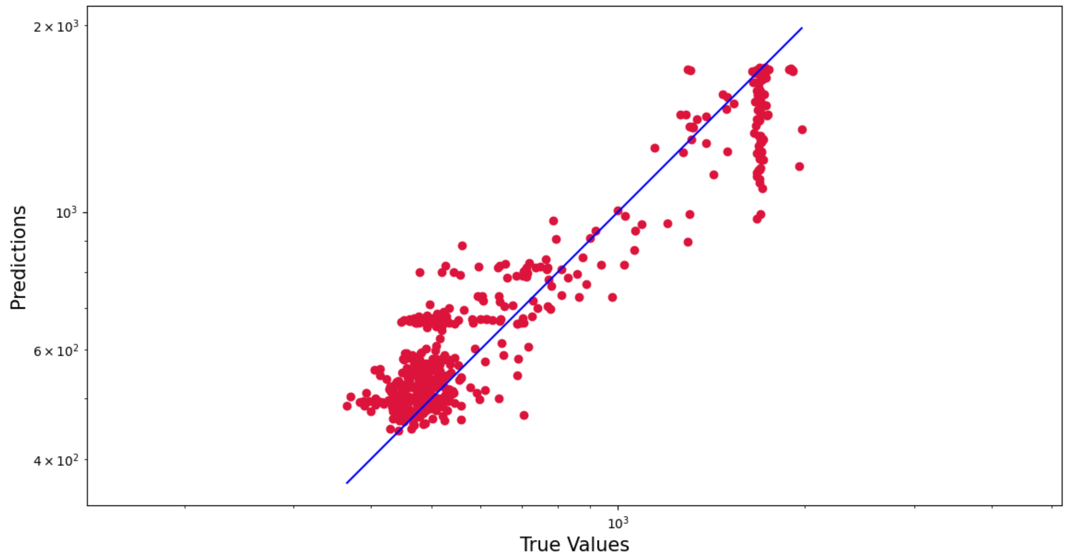


Fig. 6.2. Values estimated by regression to measured values of vehicle length
Rys. 6.2. Wartości estymowane przy pomocy regresora do wartości zmierzonych długości pojazdu

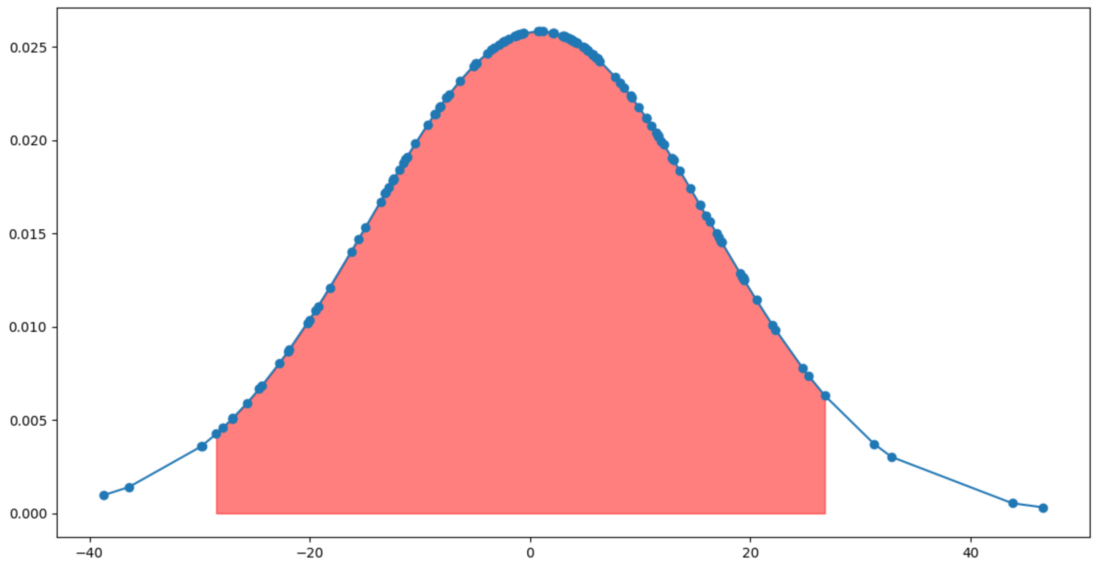


Fig. 6.3. Percentage distribution of deviations of the regressor-estimated value from the measured vehicle length value

Rys. 6.3. Procentowy rozkład odchyleń wartości estymowanej przy użyciu regresora od wartości zmierzonej długości pojazdu

A Shapiro-Wilk normality test was performed for the set of vehicle length results obtained. The value of the statistic was 0.99 and the p-value was 0.36 (for a random data set other than the teaching and test set). No grounds were shown for rejecting the hypothesis of normality of the data distribution. Using the properties of the normal distribution, it was found that 95.5% of the estimated values assume an accuracy of +/-26%. This estimation does not allow the obtained values to be taken as actual information about the passing vehicle but is sufficient to provide a general indication of whether the vehicle length was within one of four ranges: short (3–5 metres), medium length (7–9 metres), long (11–13 metres) or very long (15–19 metres).

Recognition of the number of axles on the vehicle

In the case of a classifier that determines the number of axles, the best results were obtained when standardising the vector of vehicle features. Then, after testing multiple classifiers, a random forest was selected as giving the best results. In this case, the use of factor analyses (after testing PCA, FA and ICA) was abandoned because they did not improve the detection of the number of axles. The random forest-based classifier gave the best results and showed over 99% accuracy on the test set in detecting the number of vehicle axles.

Table 6.1

Classification results for the number of vehicle axles

Actual number of axles	Classification accuracy	Number of samples in the test set	Number of misclassified	Number of samples in the learning set
2	100%	14	0	30
3	100%	14	0	30
4	100%	14	0	30
5	100%	14	0	30

6.3.4. Vehicle category recognition

The results of the classifiers discussed above could be used to create a very simple classifier dividing vehicles into four classes, as described in "Measurements of Road Traffic Parameters Using Inductive Loops and Piezoelectric Sensors"[9]. However, it was decided to explore the possibility of using the obtained data to develop a classifier that would classify vehicles according to the TLS 8+1 standard. The data vector was fed with results from the two classifiers described above. The dataset was then standardised for a standard deviation of 1 and a mean value of 0, this method in this case increased the effectiveness of the classification. No factor analysis algorithm was used (ICA, PCA and FA were tested) as this did not positively influence the classification results.

As before, several classifiers were tested: a support vector machine, logistic regression, decision tree, random forest, and a voting classifier composed of logistic regression and random forest.

The highest accuracy was obtained using the voting classifier, which gave an average of 98% efficiency for the ten cross-validation results. The results for each class are shown in the table.

[9] Burnos P., Gajda J., Piwowar P., Sroka R., Stencel M., Zeglen T.: Measurements of road traffic parameters using inductive loops and piezoelectric sensors, Metrology and Measurement Systems, 2007, Vol. 14, No. 2, pp. 187–203.

Table 6.2

Classification test results

Actual classes determined by the expert	Classification accuracy	Number of samples in the test set	Number of misclassified	Number of samples in the learning set
2	97%	70	2	251
3	96%	55	2	251
5	100%	61	0	251
7	99%	72	1	251
8	100%	78	0	251
9	97%	66	2	251
10	100%	15	0	42
11	99%	67	1	251

The small number of samples in the learning and test set for category 10 (motorbikes) is because, relative to the other vehicle categories, there is little motorbike traffic (there were only a few dozen journeys over several months of signal recording). Much of the data from motorbike journeys was not suitable for analysis because the induction loop does not cover the entire width of the lane, being in its centerline – many TLS Class 10 vehicles (motorbikes) passed outside the loop, preventing recording. The lowest classification accuracy was obtained for class 3 (trucks), 9 (truck tractors with semi--trailers) and 2 (cars with trailer) according to the TLS standard. As further work, it is planned to continue developing the classifier by applying fuzzy logic.

6.4. Results

Induction loops are embedded in the road surface. The vehicle approaching the loop triggers the whole measuring track of the weighing station. However, this is not the only function of induction loops. Passing through the loops allows the recording of vehicle's magnetic profile.

The placement of loops in the road, their layout and size are determined by the relevant standards among others TLS. The TLS standard allows for the construction of unified vehicle classification stations. It standardizes the classification of vehicles by class: 8 (trucks with trailer), 9 (truck tractors with semi--trailers), 7 (cars), 5 (buses), 3 (trucks), 2 (cars with trailer), 10 (motorbikes).

Data obtained from induction loops can be used to classify vehicles. There are devices available on the market that determine the vehicle category based on data obtained from two induction loops.

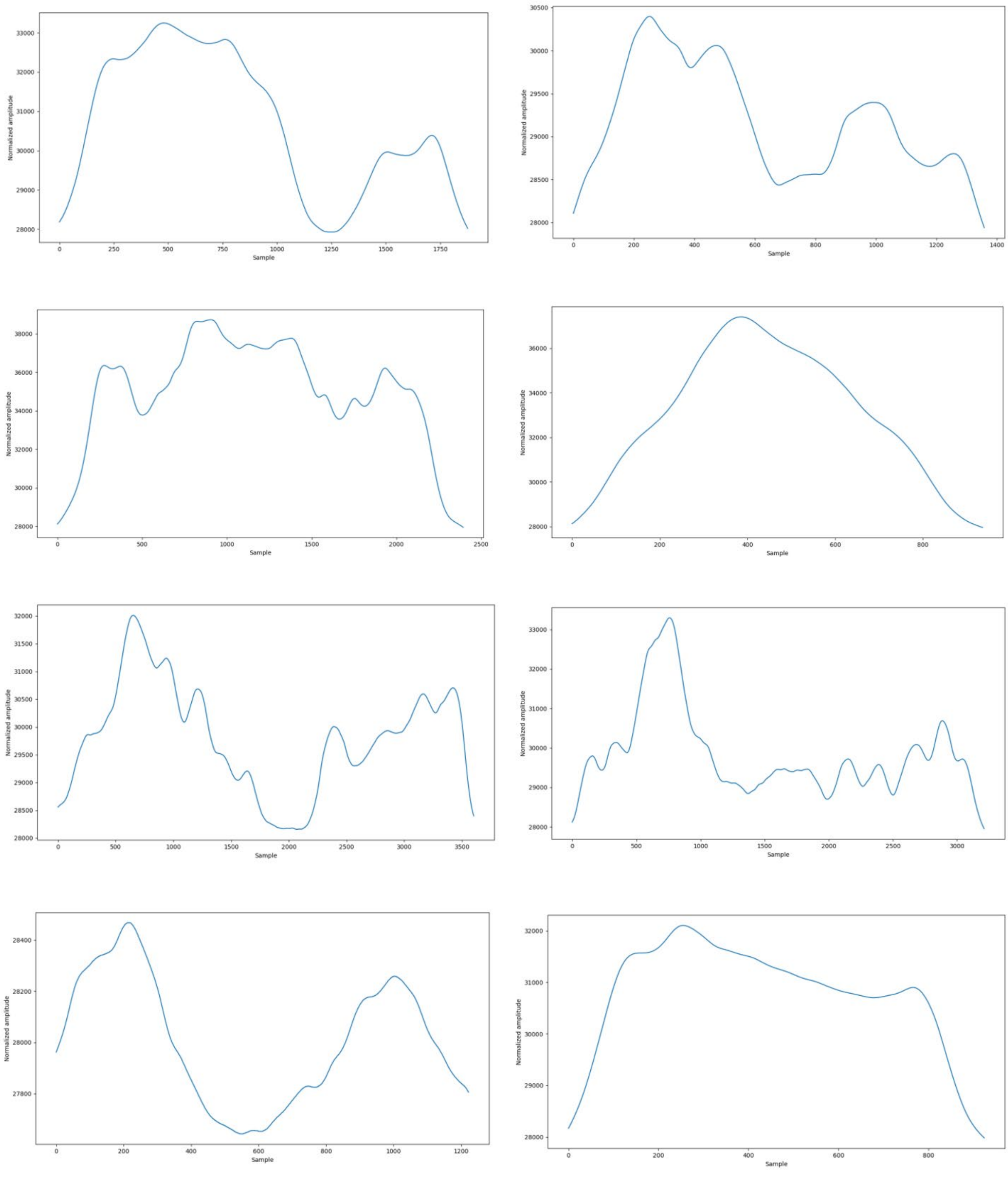


Fig. 6.4. Magnetic profiles of vehicles for classes (according to TLS 8 + 1): 2, 3, 5, 7, 8, 9, 10, 11
Rys. 6.4. Profile magnetyczne poszczególnych klas pojazdu (według TLS 8+1): 2, 3, 5, 7, 8, 9, 10, 11
Source: Own elaboration.

The research resulted in the development of a high-performance classifier. Using the Python programming language, a web service was created. The program processes the signal from the induction loop as an input parameter, then subjects it to a classification, this way obtaining vehicle class. The time from sending data to the web service to receiving a response with the vehicle class is approximately 500ms, which is sufficient for use in an industrial environment.

The designed classifier was deployed in a production environment when the iWIM weighing computer was first installed. This computer has a module for reading data from an induction loop at the aforementioned test station in Mikołów on National Road 44. Classification data is processed and stored in a database. Additionally, camera images are collected to verify the correctness of the classification by the classifier. The currently designed vehicle classification system obtains an accuracy of approximately 96%.

Based on the research, we conclude that it is possible to create a high accuracy classifier based on a single inductive loop. Such a solution in the future may replace more complex two-loop systems or those requiring additional sensors.

6.5. Discussion

Based on the magnetic profile, we can recognise: the number of axles of the vehicle, the vehicle length, and the vehicle classification. However, the described are computational methods that do not find deep connections as in the case of machine learning algorithms, hence the new approach proposed by the authors to the topic of recognition of individual vehicle features and classification, based on machine learning algorithms.

The literature proposes the application of classifiers that use two induction loops. However, it has been shown through research that data obtained from only one loop using the proposed method can give similar results. The use of a single loop for classification enables a significant reduction in the cost and installation time of the solution and may therefore allow widespread use of the solution on roads. The application of the developed vehicle classification method can also help in the creation of traffic structural maps, which improves road infrastructure management, road capacity and traffic safety.

The use of the induction loop as a source of vehicle information requires further research. In the course of the research, it was noted that the shape of the loop affects the signal and presumably also the information that is contained in the signal.

Acknowledgments

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