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ORIGINAL ARTICLE

Recognition of Moving Tracked and Wheeled Vehicles Based on Sound Analysis and Machine Learning Algorithms

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ABSTRACT – The paper presents results of a preliminary study on verification of the possibility to establish simple methods to process acquired sound signals that were generated by a vehicle in motion; to determine its characteristic features for classification as a wheeled or tracked one. The analysis covered 220 signals acquired from real experiment and pre-processed with the use of power spectral density estimation (PSD) and linear prediction coding (LPC). The signal processing methods were used to generate features for which applicability in the classification process was assessed using a statistical method. The set of features was then optimised to reduce the dimensionality of data. Results of recognition obtained with the proposed non-iterative procedures for solving linearly separable problems were compared with results from standard methods, including SVM and k-NN. The developed features as well as selected methods of classification were proposed with respect to the possibility to implement them in low computational power computers for embedded applications.

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INTRODUCTION

An efficient vehicle traffic management requires location and classification of vehicles in motion on paved surfaces in civilian applications as well as on tracks, field and forest ways in military applications. Civilian applications may include identification of an overloaded vehicle [1], whereas military applications may require identification of the vehicle type (class), i.e. light, heavy, tracked and wheeled [2]. Identification of the military vehicle type may be used in selecting proper warfare agents and neutralisation methods. There are solutions that are currently being developed for intelligent transport systems including supervision of traffic control and measurement of traffic stream characteristics [3].

'Recognising' devices can measure different signals generated by the vehicle in motion: the sound emitted, base vibrations, heat, magnetic field [4-8]; advanced systems usually use multiple signals simultaneously [9,10]. Vehicle identification is a multi-stage process that in many cases should be carried out in real-time. The format of the recorded signals and the processing methods must be simple to reduce the time required for making proper decisions. The process includes the following stages: recording signal generated by the vehicle, finding its relevant representations, determining characteristic features, and assigning the resulting feature vector to a specific object class. Commonly known methods of pre-processing in recognition include Fourier transform [11,12], short-time Fourier transform [13,14] or wavelet transform [15,16].

The current study focuses on sound signals generated by vehicles with different masses and drive system designs, that can be divided into two broad categories, namely tracked and wheeled ones. Sound signals seem to be very attractive for the inconspicuous recognition as they can be easily acquired by relatively simple and low energy consumption devices in contrast to image signals. The scope of the research was to find out if also simple methods of sound data processing can be successfully used for the recognition task. Such methods could be then applied in a network of intelligent sensors based on low cost and low energy consumption microcontrollers to meet the requirements of environmental sustainability in recognition [17]. Designing low-cost networks of sensors are nowadays possible with the use of single board computers, just like Raspberry or BeagleBone [18,19]; mostly because of their ability to run an embedded operating system that makes the resulting intelligent sensor accessible and adaptable. Integration of high-level software and low-level electronics including web connectors opens the possibility for making decisions by individual sensors that can be organised in distributed networks for remote monitoring of wide areas. However, simple methods of feature generation, as well as simple methods of recognition, are particularly required because computational capabilities of such devices are still limited. The algorithm of recognition should be as simple as possible not only in the phase of classification of new cases but also in the phase of its design and training. Such property would enable sending new patterns to sensors and performing the retraining process directly on the chip. Figure 1 shows the stages of processing assumed in this work to disclose information necessary to recognise the vehicle type in motion.

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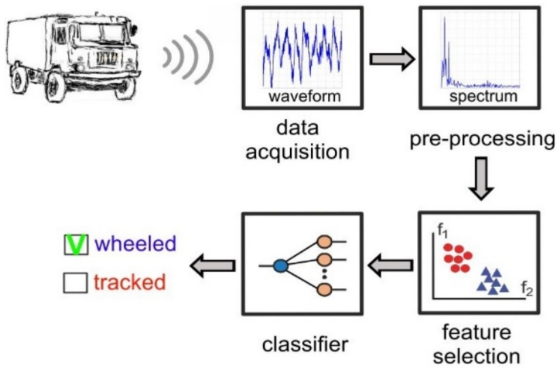


Figure 1. Diagram of the process to recognise the vehicle type in motion.

The first and the most crucial stage of the vehicle type recognition process is to select the parameters constituting a vector that is characteristic for a specific category. The vector can be neither too long nor too short since in both cases it affects the efficiency of the process in real-time. Relevant information must be prior selected when using the recorded signals in recognition. In this study, the pre-processing was based on commonly known power spectrum density – PSD. The representation is generally suited for stationary signals. However, short-duration signals treated as quasi-stationary can also be processed to reveal their spectral content. The motivation to use it in this work was the simplicity of estimation in contrast to spectrogram or a wavelet transform. The users of the aforementioned single board computers can find many libraries for built-in Python interpreters ready to use with the included Fourier procedures for PSD and those based on linear predictive coding LPC [20,21].

The process to assign an object into the corresponding category can be carried out using different methods of machine learning. The most common method is to use the position of the characteristic feature vector of a signal that comes from a new case in relation to the vectors determined for known patterns in a multi-dimensional feature space, assuming that the boundaries, which explicitly separate the feature vectors for different categories can also be found. The position of the boundaries is usually obtained using the trainable artificial neural network. However, less complex methods can also be used, especially when there is a demand to implement them in a processor with low computational power. This study deals with binary classification between wheeled and tracked vehicles and algorithmically efficient, non-iterative methods of finding the hyperplane separating them were proposed and compared to other standards, however more computationally complex methods, including SVM and k-NN classifiers.

DATA POOL

The tests were carried out by recording sound signals generated by real vehicles moving at two pre-determined speeds on an unsurfaced road (15 km/h and 30 km/h). The experiment covered eight different wheeled vehicles (marked from W1 to W8) with different sizes, designs and masses ranging from 2200 kg to 26000 kg as well as four different tracked vehicles (marked from T1 to T4) with masses ranging from 13000 kg to 44000 kg. They were military trucks, combat transporters and tanks. The position of the wide-band microphone in relation to the path of movement of the tested vehicles is depicted in Figure 2.

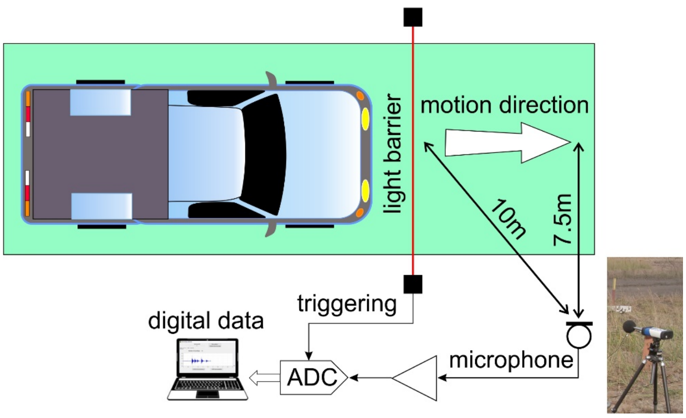


Figure 2. Layout of the test equipment.

The measurements were triggered by the light barrier crossing. The distance from the microphone to the road was dictated by the necessity to reduce unwanted background noise. The database totally included a set of 220 sound signals of 5 s length for both velocities, acquired by a data acquisition card with the sampling frequency of 2 kHz. Figure 3 shows exemplary waveforms corresponding to four different vehicles. The plot was made only for illustrative purposes and the term ‘arb. units’ (arbitral units) means that presented waveforms can be compared only within this study.

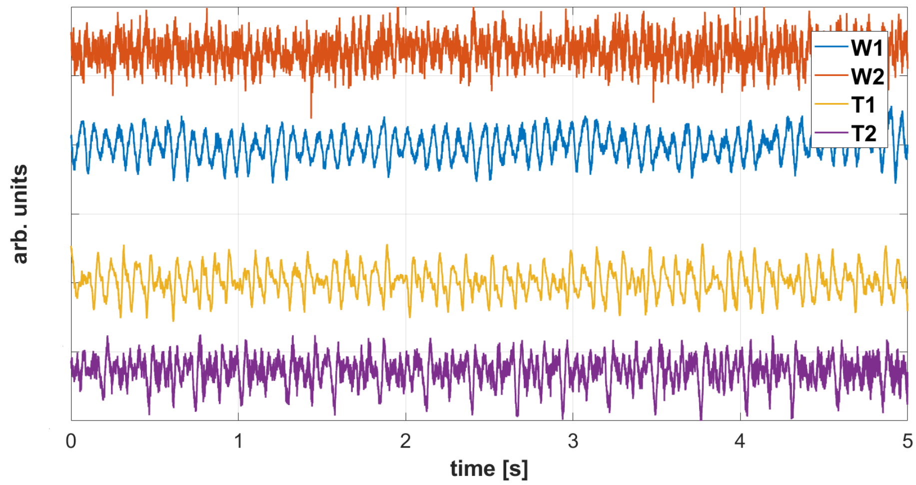
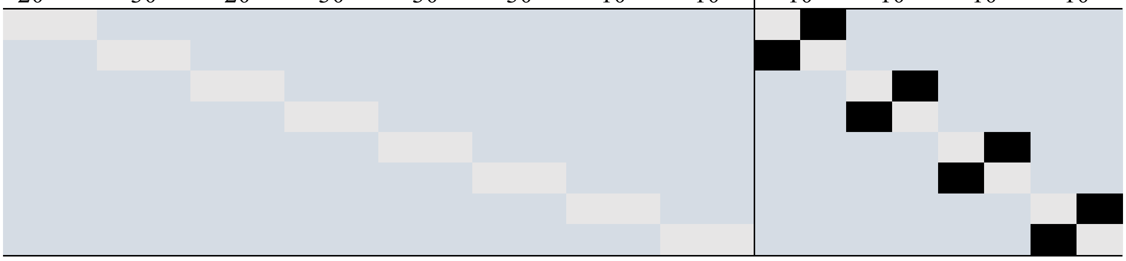


Figure 3. Sound waveforms acquired when two exemplary wheeled vehicles (W1 and W2) and two tracked vehicles (T1 and T2) were crossing the light barrier.

There were 180 signals representing the wheeled vehicles and 40 signals representing the tracked vehicles. The difference between the numbers is caused by the fact that there are more military makes of wheeled vehicles than tracked ones. Table 1 presents the scheme of data splits in the cross-validation used to evaluate the skills of recognition models presented further. The numbers below W1-T4 symbols stand for the number of signals acquired for each vehicle make.

Table 1. The scheme of 8-fold cross-validation used to evaluate the machine learning models together with the number of signals for the vehicle makes.

No. of wheeled vehicles								No. of tracked vehicles			
W1	W2	W3	W4	W5	W6	W7	W8	T1	T2	T3	T4
20	30	20	30	30	30	10	10	10	10	10	10



testing data   training data   excluded data

To build and assess the recognition models, the data should be partitioned into subsets used for training and evaluating the model's performance. The cross-validation is a commonly used strategy to do so without the risk to get too optimistic and unreliable assessments. The strategy usually involves shuffling the dataset randomly and splitting it into K folds. The value of K is often set to 5 or 10, but there is no formal rule [26]. Then each unique fold is treated as testing data and the model is trained on the remaining folds. The process is repeated K-times and thanks to that all data are used in testing and training, however, while tested, they are not used in training. In this research, in order to use testing and training corpora independent on a vehicle, a single fold in cross-validation contained data representing only a separate vehicle make as depicted in the rows of Table 1, where the grey blocks are folds used for testing, the light blue ones are folds used for training and the black blocks represent data excluded from training and testing. In this way, the 8-fold cross-validation is preserved, and the evaluated models are forced to recognise vehicle makes completely unseen in training in each of K=8 repetitions.

NON-ITERATIVE METHODS FOR RECOGNITION

Making a decision is especially simple and computationally effective when there is a plane distinguishing classes in a multidimensional space. In the case of 2-dimensional space of features x_1 and x_2, the plane is described by the dot product in Eq. (1).

$$\boldsymbol{w}^T \cdot \boldsymbol{x} = 0 \tag{1}$$

where vectors $\boldsymbol{w}$ and $\boldsymbol{x}$ are as follows in Eq. (2).

$$\boldsymbol{w} = [w_0 \quad w_1 \quad w_2]^{\,T}, \ \boldsymbol{x} = [1 \quad x_1 \quad x_2]^{\,T}. \tag{2}$$

In spaces with higher dimensions, the description is very similar. Having knowledge of the coefficients (weights) of the plane, i.e. w_0, w_1 and w_2, one can use the following decision rule in Eq. (3) to classify new cases denoted as $\boldsymbol{x}^{\text{new}} = [1\ x_1^{\text{new}}\ x_2^{\text{new}}]^T$. Such rule excludes complex computations and can be easily implemented in an embedded computer.

$$\begin{aligned} \boldsymbol{w}^T \cdot \boldsymbol{x}^{\text{new}} > 0 \quad &\Rightarrow \quad \text{class no. 1 (label } y = 1) \\ \boldsymbol{w}^T \cdot \boldsymbol{x}^{\text{new}} < 0 \quad &\Rightarrow \quad \text{class no. 2 (label } y = -1) \end{aligned} \tag{3}$$

The task to find the coefficients in the problem of two linearly separable classes can be successfully solved in iterative ways based on a single neuron with weights $\boldsymbol{w}$ adjusted by gradient or non-gradient training. However, computationally simpler methods are also available [22]. The first one enables finding the separating hyperplane in such a way that the distance d_1 between each its point and the vector $\overline{\boldsymbol{x}}_1$ representing class 1 is equal to the distance d_2 between that point and the vector $\overline{\boldsymbol{x}}_2$ representing class 2 as depicted in Figure 4. The class representatives maybe just average vectors in each class.

Comparing the distances d_1 and d_2 expressed by Euclidean formulas one can easily find out that simple algebraic equations are used to calculate the weights w_1, w_2 and w_0 – Eq. (4).

$$[w_1 \quad w_2] = [\overline{\boldsymbol{x}}_1 - \overline{\boldsymbol{x}}_2]^T, w_0 = 0.5 \cdot (||\overline{\boldsymbol{x}}_2||^2 - ||\overline{\boldsymbol{x}}_1||^2) \tag{4}$$

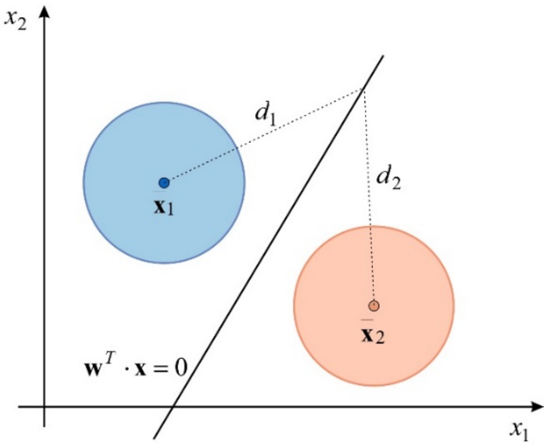


Figure 4. The idea of the non-iterative method based on class representatives.

The method provides good results when the classes are separated well enough in space or when their covariance matrices are equal and diagonal (Figure 4). However, the method may fail when there is a correlation between features as depicted in Figure 5, where the idea of the 2nd alternative approach, is also shown. In this case, the separating hyperplane given by Eq. (1) can be found by the solution of an overdetermined set of equations like those applied in linear approximation – Eq. (5).

$$\boldsymbol{U} \cdot \boldsymbol{w} = \boldsymbol{d} \tag{5}$$

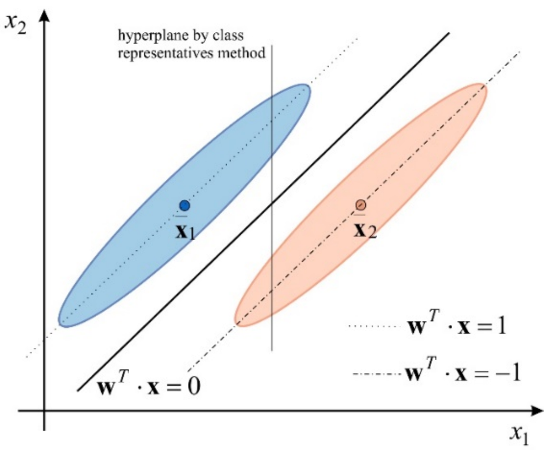


Figure 5. The idea of the non-iterative method based on linear approximation.

The set uses the destination vector $\boldsymbol{d}$ and matrix $\boldsymbol{U}$ of training labelled data and can be written as in Eq. (6).

$$\begin{bmatrix} 1 & x_1^{(1)} & x_2^{(1)} \\ 1 & x_1^{(2)} & x_2^{(2)} \\ \cdots & \cdots & \cdots \\ 1 & x_1^{(n)} & x_2^{(n)} \end{bmatrix} \begin{bmatrix} w_0 \\ w_1 \\ w_2 \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \\ \cdots \\ -1 \end{bmatrix} \tag{6}$$

The LS solution of the set is again given by an algebraic equation – Eq. (7).

$$\boldsymbol{w} = (\boldsymbol{U}^T\boldsymbol{U})^{-1}\boldsymbol{U}^T\boldsymbol{d} \tag{7}$$

and provides good results for classes with similar covariance matrices.

FEATURE SELECTION ALGORITHM

The study was primarily aimed at developing simple methods, so the acquired signals were processed using spectral analysis which, after all, is appropriate in many vibroacoustic diagnostic solutions [3,4,23]. When determining the characteristic features, their applicability in the recognition process was assessed using one of the methods that rank features with some univariate metric reflecting their discriminative power. According to the assumed approach, the significance of the effect of the vehicle type on an individual feature of the sound signal was evaluated using the Student's *t*-test to verify a statistical hypothesis on the equality of average values of two populations. The hypothesis was verified at α significance level by comparing the modulus of the calculated statistic – Eq. (8).

$$t = \frac{\overline{f_W} - \overline{f_T}}{\sqrt{\frac{N_W s_W + N_T s_T}{N_W + N_T - 2}\left(\frac{1}{N_W} + \frac{1}{N_T}\right)}} \tag{8}$$

with the *t*-distribution quantile $t_{1\text{-}0.5\alpha}$, where N_W and N_T are sample sizes for populations of a feature f in the classes W and T and s_W, s_T are corresponding sample variations. The relationship expressed by Eq. (9) indicates that the hypothesis on the equality of average values of an analysed feature found for classes W and T must be rejected.

$$|t| \geq t_{1-0.5\alpha} \tag{9}$$

The analysed feature can then be assumed as an element of a vector differentiating the classes of vehicles – wheeled and tracked ones. The approach is very similar to the Fisher score method [29] but in contrast to that, it selects the features in the terms of statistical significance.

Within the framework of initial data exploration, the following methods of nonparametric and parametric spectral estimation were examined:

i. power spectral density calculated with the use of Welch's method for several dimensions of the Fourier transform (Hamming window and 95% segment coverage were used)
ii. power spectral density obtained via the LPC models of different orders.

The power spectral density by Welch's method was estimated for several segment lengths NFFT to find the optimal value for which the spectra are similar for vehicles in the same category and differ from the spectra for vehicles in the opposite category. The graphs of the *t* statistic were calculated according to Eq. (8) as a function of frequency for several exemplary segment lengths are depicted in Figure 6.

The calculation results enable finding the optimal length of the segment for this specific recognition task between the vehicle types (wheeled and tracked). Both for the short segments (NFFT= 64) and long segments (NFFT=2048 and 4096), the modulus |*t*| reached approximately 8÷10. For the medium segment, i.e. NFFT=128 and 256, modulus |*t*| was higher and reached values at approx. 13-14 showing better potential for good recognition results.

However, the frequency resolution in the Welch's method is limited, especially at low NFFT values. Because of that an alternative method, i.e. the parametric one was also considered to find the power spectral densities. The calculations were carried out for different orders of the linear prediction LPC models at 10, 30, 50 and 150. Figure 7 shows the obtained *t*-statistic graphs as the functions of frequency.

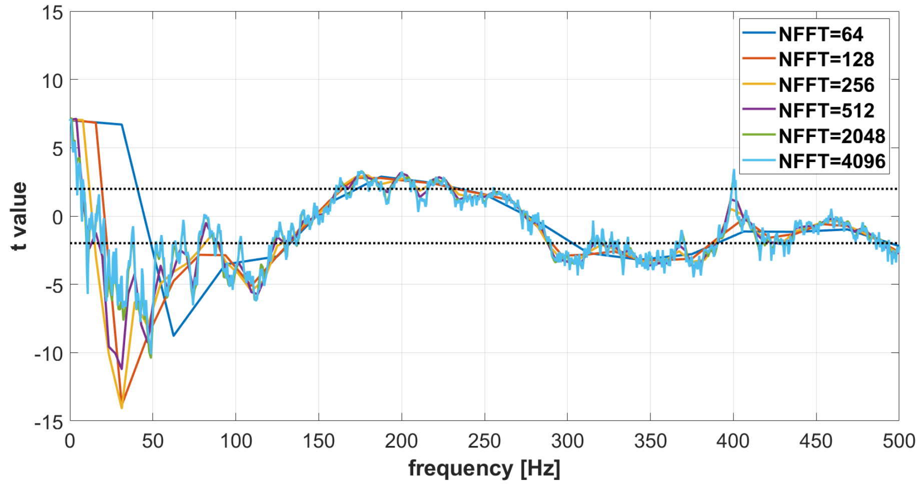


Figure 6. Exemplary results of exploration performed to find the optimal segment length for Welch's method of spectral analysis (the black dotted lines represent the critical values in Student's test at α=5% significance level).

The graphs show higher resolution as compared to Welch's method and similar |*t*| values. Finally, the parametric method was selected as the method to determine the power spectral densities of acquired sound signals. The LPC model of order 10 seemed to be particularly important as the corresponding *t*-value graph showed the widest frequency band in which |*t*| exceeded the critical value of Student's *t*-test. So, the spectrum calculated using this method was adopted as a potentially good tool to differentiate the sound signals under test.

There are many ways to find numerical features describing a spectrum. As the spectra are discrete representations of signals, their values called samples are countable and a number of a sample corresponds to its frequency. So the most natural way for indicating features is just using their numbers, especially these from the frequency range where the |*t*| statistic is high enough.

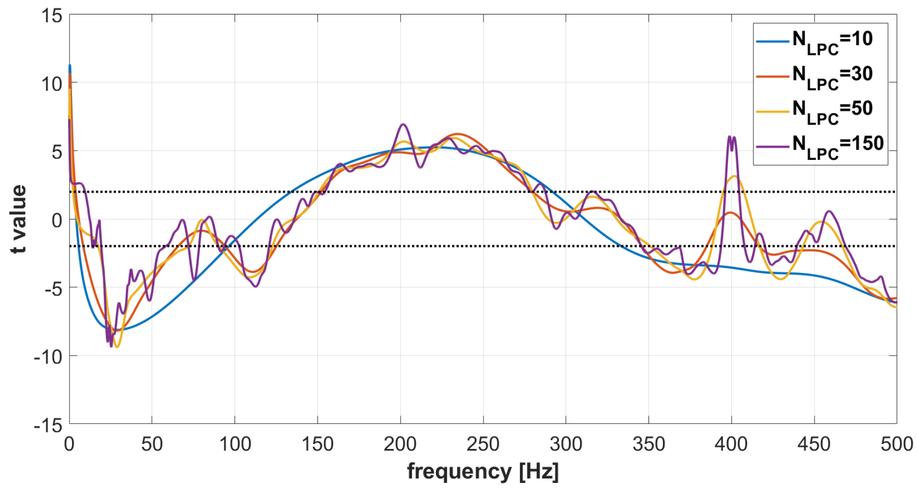


Figure 7. Exemplary results of exploration performed to find the optimal order N_{LPC} for the parametric spectral analysis (the black dotted lines represent the critical values in the Student's test at α=5% significance level).

In this work, the shape of the spectrum was additionally parametrised by spectral moments. Within the approach, the power spectrum *S*(*l*) was normalised as in Eq. (10).

$$S'(l) = \frac{S(l)}{\sum_{l=1}^{N} S(l)} \tag{10}$$

The reason of the normalisation was to obtain a description *S'(l)* that could be treated as a probability distribution of a certain random variable *L*. Thanks to that, the property of the *S'(l)* is expressed by Eq. (11).

$$\sum_{l=1}^{N} S'(l) = 1. \tag{11}$$

Using ordinary definitions of moments, the features of the spectrum can be found as follows:

The centre of spectral gravity – Eq. (12):

$$m_1 = \sum_{l=1}^{N} lS'(l), \tag{12}$$

The measure of spectral width – Eq. (13):

$$m_2 = \sum_{l=1}^{N} (l - m_1)^2 S'(l), \tag{13}$$

The measure of spectral asymmetry – Eq. (14):

$$m_3 = \left(\frac{1}{m_2}\right)^{3/2} \sum_{l=1}^{N} (l - m_1)^3 S'(l), \tag{14}$$

The measure of spectral flatness – Eq. (15):

$$m_4 = \left(\frac{1}{m_2}\right)^{2} \sum_{l=1}^{N} (l - m_1)^4 S'(l). \tag{15}$$

Exploratory data analysis showed that the $|t|$ was particularly high for the product of m_1 and m_3. Its absolute value reached the level of 11.39. The concept behind the spectral moments can be further utilised to find features representing the quantiles of the hypothetic random variable L described by the probability distribution $S'(l)$. A quantile k_p of order p is a measure fulfilling the following equation for probability P.

$$\mathrm{P}\{L \le l_p\}=p. \tag{16}$$

To take the advantage of other features differentiating the vehicle categories within the same framework of calculation, a set of LPC model coefficients was also examined. The results of exploration showed that the highest $|t|$ values were obtained for the LPC model of order of 15 (referred to as LPC15). Figure 8 shows the graph of the statistic as a function of the number of the LPC15 model coefficient; the highest $|t|$ value (approx. 15) was obtained for coefficient no. 4.

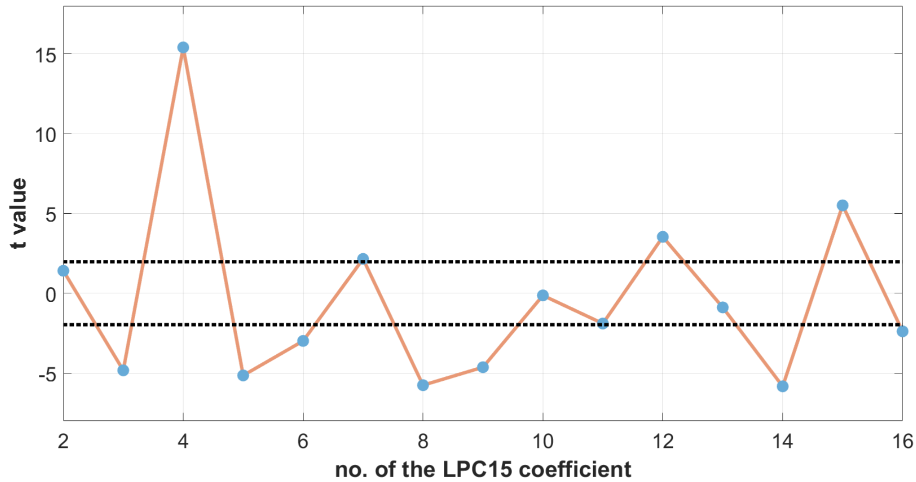


Figure 8. The values of the statistic t for LPC15 model parameters (the black dotted lines represent the critical values in the Student's test at $\alpha = 5\%$ significance level).

Finally, several spectral and linear prediction model parameters as well as their combinations obtained through simple operations were selected. Table 2 shows proposed parameters (characteristic features) together with the corresponding t values showing their possibilities to differentiate between the vehicle categories. However, none of them could be used for error-free recognition alone so they were treated as candidates to be used in differentiating feature vectors based on the above Student's t-test.

In order to avoid ill-conditioned problems in further analysis, each feature was normalised in such a way that its range was in the interval [-1,1] as depicted in Figure 9. The properties of the proposed features can be further explored by means of the data mining techniques used to transform the primary space into space with a lower number of dimensions. The so-called linear discriminant analysis LDA or the Fisher's linear discriminant analysis was used in this study as it meets the criterion of maintaining the maximum of differentiating information required to classify objects. The analysis is discussed in [24] and its usage in the classification process as a feature transform can be found in [25]. In the problem of two classes with the assumption of normal multidimensional distributions of features and identical class covariance matrices, the LDA projection leads to simple equivalent recognition based on threshold analysis of one-dimensional distributions. The distributions obtained after transforming the original set of features are depicted in Figure 10.

Table 2. List of selected primary parameters.

No.	Parameter definition	t value
1	Difference between coefficients no. 3 and 4 for LPC15 model	-12.71
2	Product of coefficients no. 3 and 4 for LPC15 model	11.87
3	Coefficient no. 4 for LPC15 model	15.38
4	Spectrum sample no. 119	-8.05
5	Quotient of spectrum samples no. 119 and 2	-15.42
6	Product of spectrum samples no. 119 and 2	6.05
7	Spectrum sample no. 2	11.27
8	Quantile frequency of order 0.1	-18.15
9	Product of spectral moments no. 1 and 3	-11.39

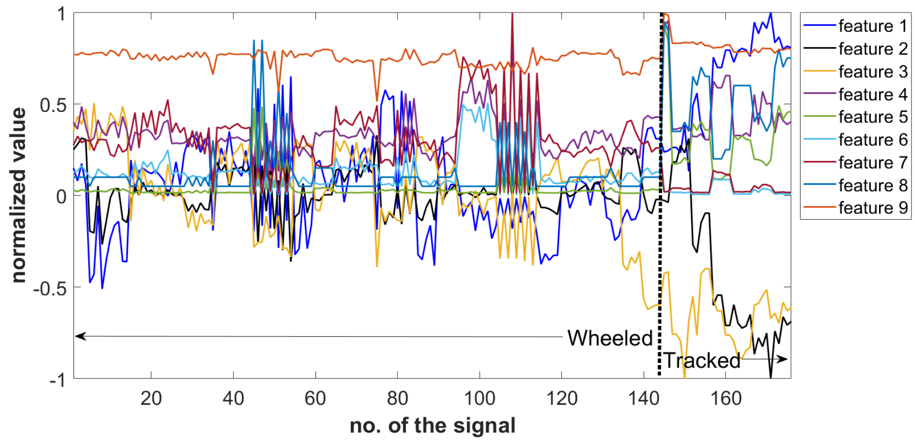


Figure 9. Normalised features for wheeled and tracked vehicles.

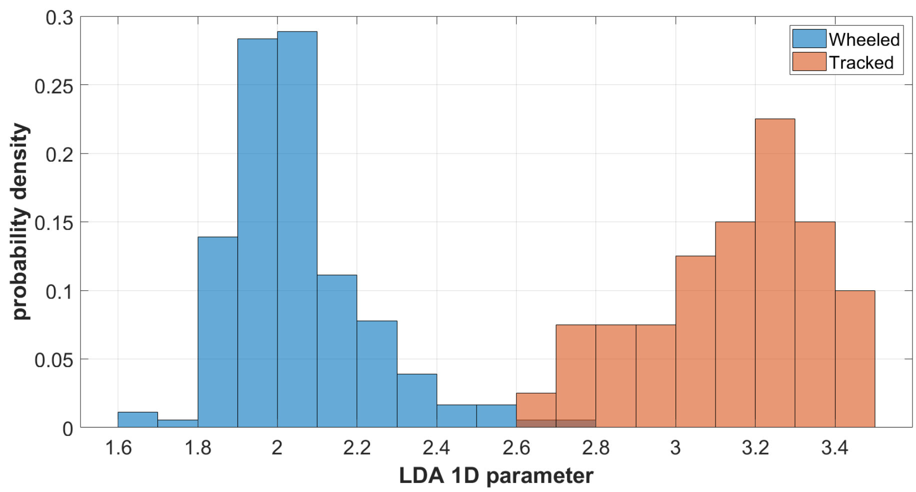


Figure 10. Histograms of the parameter obtained after transformation of the 9-dimensional space into a 1-dimensional space using LDA method.

As can be seen, the distributions are overlapping which excludes the recognition by means of LDA projection into 1-dimensional space. However, the overlap is slight which proves that the vehicle types are well separated in this 9-dimensional space.

RECOGNITION IN SELECTED FEATURE SPACES

The ability of the vector consists of all nine features listed in Table 2 to differentiate the types of vehicles in a computationally effective way was examined with the non-iterative methods that used to classify objects by linear planes (as described earlier. Two other standard methods – support vector machine SVM and nearest neighbours k-NN were also used as references [27,28]. The number of neighbours in the latter was not critical – the same results were observed for odd values of k from 1 to 9. In the SVM procedure linear kernel was used. Because of the limited data sample, the resampling procedure based on 8-folds cross-validation was adopted as described in the section devoted to the presentation of the data pool.

In the assessment of the proposed methods, the concept of confusion matrix [26] was used for describing the performance of a recognition model. This is a simple cross-tabulation of the actual and recognized classes for the data. In general, diagonal cells in a confusion matrix denote the number of objects correctly classified while the off-diagonal cells contain the number of errors. The results of vehicle type recognition in the form of such matrices calculated for the testing data are depicted in Figure 11.

In the matrices, both the number of vehicles and the percentage of the total number of vehicles are presented. Because of the cross-validation, the summations along rows gives the number of acquired signals for each vehicle type. The metrics in the column on the far right represent the percentages of all the vehicles recognized to belong to each class (W or T) that are correctly (green) and incorrectly (red) classified. The metrics in the lowest row show the number of the vehicles that belong (green) and does not belong (red) to each class related to the number of vehicles that are correctly and incorrectly classified to that class. The cell in the bottom right corner shows the overall accuracy and error.

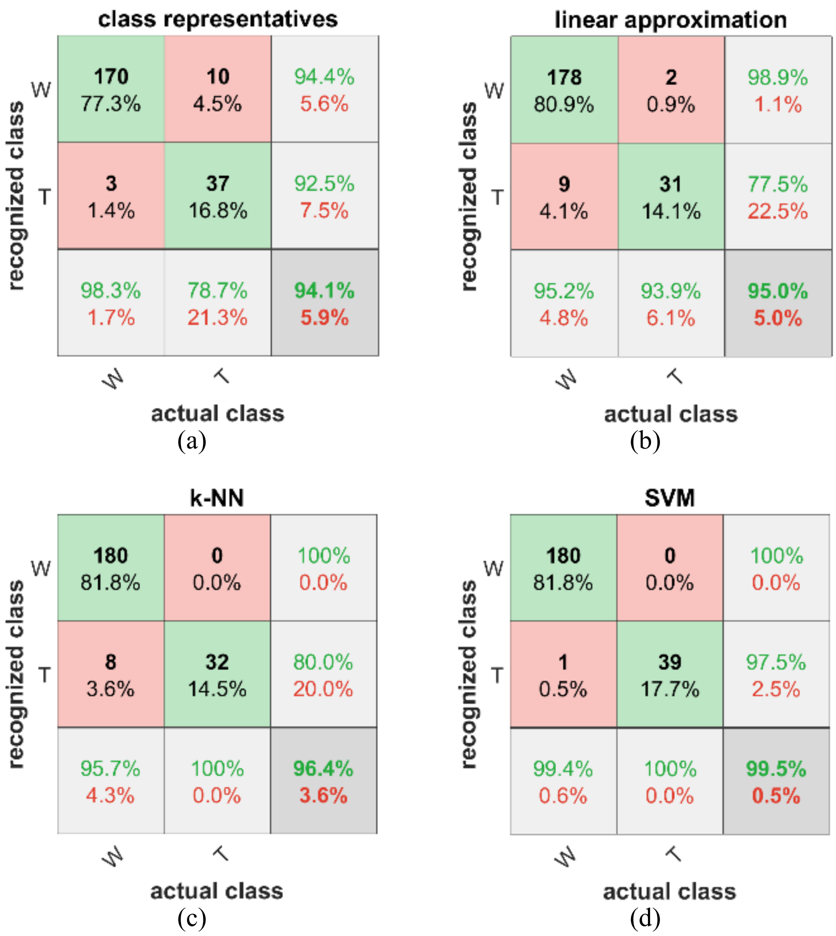


Figure 11. Confusion matrices calculated for the methods of classification when all nine features were used (W and T denote wheeled and tracked vehicles respectively).

As can be seen, obtaining the desired result of recognition based on the set of the nine features is possible with acceptable error but only with the use of SVM procedure, which outperformed the non-iterative methods. Also, the nearest neighbours approach yielded better results – its overall accuracy of 96.4% was greater than accuracies in the class representatives and linear approximation methods.

Against this background, the question arises as to if the set of features is optimal for used classifiers, especially for the non-iterative ones. The features were selected individually in an effective way but by the method that ignores the mutual relationship among them. To take the advantage of the possible synergy of features with respect to the classifiers, the algorithm of feature subset selection based on sequential search strategy was additionally applied [26,27]. In the strategy, the candidate subsets of features are evaluated by an objective function that uses the misclassification rate given by a classifier. Thanks to that, specific interactions between the classifier and the dataset can be exploited. Subsets of features selected by this method for each of the classifiers are presented in Table 3.

Table 3. Features selected to use with the analysed classifiers.

Classifier	Class representatives	Linear approximation	k-NN	SVM
Features	2, 3, 4, 5, 7, 8, 9	1, 3, 5, 9	4,7	1, 3, 4 ,6, 7, 9

Results of recognition obtained with the combination of vectors of selected features and the corresponding classifiers are depicted in Figure 12. As compared to results presented in Figure 11, all the methods give improved results; however, the simplest method based on class representatives still generates misclassifications. Fortunately, this time the data could be correctly assigned to classes by the second non-iterative method which is based on linear approximation.

Figure 12. Confusion matrices calculated for the methods of classification after sequential feature selection.

CONCLUSION

Presented material shows the ability to automatically identify the vehicle types based on the characteristic features of the sound signals generated by them in motion. In the analysis, real-world data was used. Correct discrimination between wheeled and tracked vehicles was proved to be possible with relatively simple methods of pre-processing and methods of classification. Spectral analysis, as well as analysis based on linear prediction coding, was used to determine the features (parameters), which after selection, provided proper recognition of the vehicle type with the use of a hyperplane that can be determined by non-iterative algebraic equations based on linear approximation. Achieved results turned out to be no worse than they were in the case of standard, but less computationally efficient methods of classification, just like SVM or k-NN. The developed methods, because of their simplicity, can be easily applied in intelligent sensors supported with single board computers for embedded applications.

However, it is necessary to be aware that the presented results apply to the analysis of signals acquired in a specific environment and will require further studies to take into account different testing conditions (different surface types and a wider range of speed). It would also be beneficial to find a feature vector which would allow identification of light and heavy vehicles.

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