Proceedings of Meetings on Acoustics

AUGUST 22 2023

Predicting vehicle category using psychoacoustic indicators from road traffic pass-by noise FREE

Ablenya Barros ; Michiel Geluykens; Frederico Pereira; Luc Goubert; Elisabete Freitas; Cedric Vuye

Proc. Mtgs. Acoust. 51, 040001 (2023)
https://doi.org/10.1121/2.0001775

POMA Proceedings of Meetings on Acoustics

Volume 51 http://acousticalsociety.org/

184th Meeting of the Acoustical Society of America

Chicago, Illinois

8-12 May 2023

Noise: Paper 2aNS2

Predicting vehicle category using psychoacoustic indicators from road traffic pass-by noise

Ablenya Barros
Faculty of Applied Engineering, University of Antwerp, Antwerp, 2020, BELGIUM; ablenya.barros@uantwerpen.be

Michiel Geluykens
University of Antwerp, Antwerp, BELGIUM; michiel.geluykens@weit.co.at

Frederico Pereira
University of Minho, Guimarães, Minho, PORTUGAL; frederico.pereira@ccg.pt

Luc Goubert
Belgian Road Research Centre, Brussels, BELGIUM; l.goubert@brrc.be

Elisabete Freitas
University of Minho, Guimarães, Minho, PORTUGAL; efreitas@civil.uminho.pt

Cedric Vuye
University of Antwerp, Antwerp, BELGIUM; cedric.vuye@uantwerpen.be

A set of road traffic pass-by noises containing more than 2000 vehicles was recorded following the Statistical Pass-By (SPB) methodology. Besides the acoustic descriptors, psychoacoustic indicators (loudness, sharpness, roughness, fluctuation strength) were retrieved for each pass-by of three vehicle categories defined in the standard (passenger cars, dual-axles and multi-axles heavy vehicles). A fourth vehicle category, comprised of delivery vans, was also investigated. All psychoacoustic indicators significantly differed among vehicle categories, meaning that not only intensity descriptors but also temporal and spectral features of pass-by noise distinguish those classes. With enough instances and a balanced dataset across groups, a machine-learning classification algorithm was trained with 70% of the dataset to predict vehicle categories using the psychoacoustic indicators. Classification accuracy on the test set reached 72%. Accuracy losses were primarily caused by 25% of the actual passenger cars being misclassified as vans and vice-versa. These results show the potential of using noise features other than uniquely the maximum noise level to classify vehicles in terms of noise perception. In this way, limiting classifications based on visual aspects of vehicle categories may be overcome, increasing the practicality and accuracy of measurements such as the SPB, as vehicle fleets worldwide are more consistently represented.

Published by the Acoustical Society of America

 https://doi.org/10.1121/2.0001775

1. INTRODUCTION

Psychoacoustics strives to establish functional relationships between acoustic properties and the auditory perception phenomena. In this sense, psychoacoustic indicators aim to objectively quantify how acoustic information is perceived[1]. Given the increased interest in environmental acoustics research to switch from an approach based on physical noise exposure towards one more focused on the human experience, psychoacoustic indicators create a valuable bridge between the complex characteristic of noise and the practicality of using single-value indicators.

Road traffic noise is considered the second most prevailing environmental risk factor to human health, especially in densely populated European cities[2]. To date, strategies concerning road traffic noise reduction account mainly for exposure levels, even though it is known that noise levels decrease solely does not necessarily reduce the annoyance and other health outcomes trigged by it.

Among the already limited number of studies exploring psychoacoustic indicators from road traffic noise, tyre/road noise samples are often the subject of study[3,4,5]. In this way, differences in road surface characteristics are assessed, but the actual traffic flow, as perceived by the receiver, is not accounted for. Studies where roadside noise measurements were carried out typically retrieve the psychoacoustic indicators from the noise of a traffic assemblage[6]. However, understanding the acoustic signature of individual vehicles is appealing, given that large-scale urban traffic noise maps are developed from characteristics of the traffic flow microstructure, such as vehicle type and driving speed. Finally, studies that assessed psychoacoustic indicators of individual pass-by vehicles have used only a few instances to mainly evaluate noise-induced annoyance[7,8].

In this work, the authors leveraged the Statistical Pass-By (SPB) method (ISO 11819-1:2023[9]) to collect a large number of noise samples on individual pass-by vehicles. The strict requirements of ISO 11819-1:2023 for free-field conditions, low background noise, and pass-by vehicles driving at a constant speed while maintaining sufficient distance from other vehicles ensure that recordings from these measurements result in clean audio samples of individual vehicles. The pass-bys were categorized into the three vehicle classes according to ISO 11819-1 (passenger cars, dual and multiple-axle heavy vehicles), besides an extra category composed of delivery vans. With a dataset of 2199 vehicle audio samples, the psychoacoustic indicators differences across vehicle categories could be investigated.

Besides gaining insights on the sensitivity of psychoacoustic indicators to vehicle category, this work aimed at tackling an issue brought by ISO 11819-1:2023. This standard prescribes a visual-based vehicle classification method performed on-site by the operator based on the number of seats, vehicle size (related to gross vehicle mass), and number of axles. However, vehicle fleets worldwide can have very different aspects, and the application of this visual classification becomes limited.

Noise levels may not provide enough information to differentiate among vehicle categories, but psychoacoustic indicators bring information on more complex noise characteristics. Therefore, we checked the feasibility of using the indicators as features to train a classification algorithm to predict vehicle category and, in this way, reduce the visual dependency of the current vehicle classification system.

2. MATERIALS AND METHODS

Figure 1 displays a flowchart of the research methodology. The data collection via the SPB method is detailed in Section 2A, the segmentation of the audio samples and calculations of the (psycho)acoustic indicators is given in Section 2B, and the logistic-regression statistical and machine-learning models are described in Section 2C.

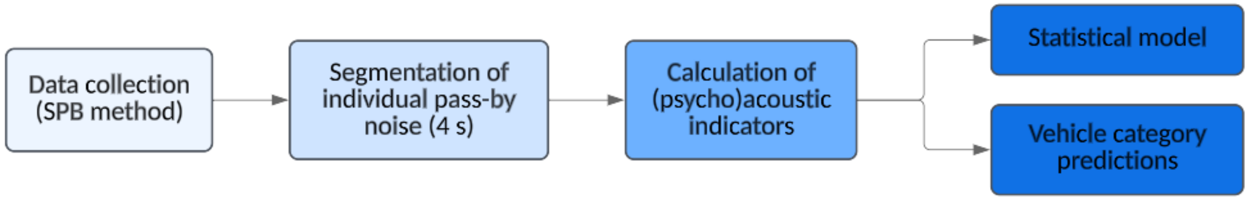

Figure 1. Research methodology steps.

A. STATISTICAL PASS-BY MEASUREMENT CAMPAIGN

SPB measurements were conducted in three locations in Belgium, over two months. A sonometer model NTi XL2 and speed radar KR-10 SP were used. The road surfaces of these locations were in hot mix asphalt, with maximum aggregate sizes of 10 mm. By visual inspection, they were determined to be in good conservation condition.

The operators registered each vehicle pass-by according to the three categories defined in ISO 11819-1: passenger cars, dual-axle heavy vehicles (HD) and multiple-axle heavy vehicles (HM). Many delivery vans were observed as part of the vehicle fleet on the measurement sites, thus the operators decided to record them as a separate group.

B. RECORDINGS AND CALCULATIONS

Continuous audio files were recorded and the moment the pass-bys' midpoint passed in front of the microphone was registered. This moment results in the peak in maximum A-weighted sound level ($L_{A,max}$) caused by a vehicle passage. To capture enough information on the vehicle approaching and driving away from the microphone to comprise a noise sample for each vehicle passage, a time window of 4 s was chosen around that moment for cropping the long audio files. The audio files and timestamps recorded in this measurement campaign can be retrieved from an open-source online data repository[10].

Using the 4-s audio excerpts, the following psychoacoustic indicators were calculated from a MATLAB-based environment using algorithms from PsySound3[11]: Loudness (N), Sharpness (S), Roughness (R), and fluctuation strength (FS). The percentile 50 from the calculations was chosen to represent each indicator. Besides these, the average maximum A-weighted sound level ($L_{A,max}$) was retrieved, along with ΔL, which means the subtraction between the $L_{A,max}$ at 2 seconds in the signal (peak) and the $L_{A,max}$ from the beginning of each signal.

A dataset with 2199 observations was retrieved in total, with 823 passenger cars, 188 vans, 85 HD, and 1103 HM.

C. LOGISTIC REGRESSION

Logistic regression (LR) is a classification algorithm used to predict a binary categorical outcome. LR models the relationship between the input variables and the probability of the outcome being in a certain class. Multinomial logistic regression (MLR) is an extension of LR for more than two classes.

In LR, the dependent variable is treated as an event. The odds of an event are the probability of its occurrence (π) divided by the likelihood of the non-occurrence (1-π). Using a linear function to fit a probability would lead to predicted values outside the range of 0 to 1. A sigmoid curve, such as the logistic function, is, instead, the natural choice for modelling a probability. For that, a logit transformation is applied to the term π/(1-π) so that it can be modelled as a linear function of the n predictors (Equation 1):

$$Log\left(\frac{\pi}{1-\pi}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n \tag{1}$$

Where: $X_{1,}\ X_{2,} \ldots, X_n$: n predictors; $\beta_0, \beta_{1,} \ldots, \beta_n$: regression coefficients

In the case of multinomial logistic regression, one of the response categories is set as a baseline, and the log odds for all other categories are described in relation to this reference. To implement an MLR model and to study the impact of the explanatory variables on vehicle classification, the MNLogit function from the Statsmodels library in Python was used.

While classic statistics emphasizes inference, machine learning aims to optimize predictive accuracy. Therefore, besides explaining and describing the contribution of each explanatory variable, the capability of predicting vehicle categories from the available dataset was explored. 70% and 30% of the dataset were employed to respectively train and test the model using the LogisticRegression function from the Scikitlearn library in Python. The training algorithm used the cross-entropy loss given that the 'multi_class' option was set to 'multinomial', the 'lbfgs' solver, and L2 regulatization.

The imbalanced sample size across classes in the dataset needed to be fixed to avoid injecting bias into the model's predictive tasks. For that, the goal was to achieve 500 observations per class. Vehicle categories containing more than 500 instances (passenger cars and HM) were reduced using random undersampling. To create new synthetic instances for HD and vans, Synthetic Minority Oversampling Technique (SMOTE) was applied[12]. Therefore, the final dataset contained 2000 observations.

The features chosen to train the model were $L_{A,max}$, ΔL, N_{50}, S_{50}, R_{50}, and F_{50}. However, after a preliminary study, $L_{A,max}$ and N_{50} presented strong multicollinearity, as expected, given that both are measures of noise intensity. A model with N_{50} led to higher prediction accuracy, so $L_{A,max}$ was removed to the final model.

Lastly, the features were standardized to a mean of 0 and a standard deviation of 1 (Z-scored). This procedure is beneficial for the logistic regression model as it helps to prevent features with larger scales from dominating the model's learning process and ensures that the coefficients accurately represent the relative importance of the predictors.

3. RESULTS AND DISCUSSION

A. AVERAGE ACOUSTIC AND PSYCHOACOUSTIC INDICATORS

In far-field noise measurements like the SPB, driving and environmental conditions, such as the air temperature and speed, impact vehicle noise levels and spectra and, therefore, are expected to affect the psychoacoustic indicators. Before grouping the observations and comparing them across vehicle categories, the indicators were normalized to a reference temperature of 20 °C and 50 km/h speed. These corrections were performed via the slope of linear regressions for those indicators that presented a statistically significant linear correlation with temperature and speed.

Table 1 presents the average results and the standard deviations for the acoustic and psychoacoustic indicators after normalization.

Table 1. : Acoustic and psychoacoustic indicators averages and standard deviations

	Passenger cars	Vans	HD	HM
$L_{A,max}$ (dB)	75.2 ± 2.0	75.9 ± 2.0	79.7 ± 2.1	81.7 ± 2.6
ΔL (dB)	10.1 ± 4.1	10.1 ± 4.1	13.5 ± 4.2	14.4 ± 4.1
N_{50} (sone)	23.07 ± 2.37	24.54 ± 2.45	31.94 ± 3.07	37.21 ± 4.67
S_{50} (acum)	1.254 ± 0.060	1.293 ± 0.065	1.263 ± 0.055	1.302 ± 0.058
R_{50} (asper)	0.059 ± 0.009	0.062 ± 0.009	0.065 ± 0.009	0.072 ± 0.011
FS_{50} (vacil)	0.502 ± 0.061	0.489 ± 0.049	0.468 ± 0.051	0.494 ± 0.075

Considering the two extreme ends (Passenger and HM), the noise level difference of 6.5 dB results in HM being perceived as twice as loud as passenger cars. Although the $L_{A,max}$ of passenger cars and vans almost overlap, ANOVA at a 5% significance level with Tukey's post hoc tests showed that their means still differ significantly. HD and HM are 2 dB apart. This difference is smaller but similar to the 2.7 dB prescribed in ISO 11819-1 (2023) to be added in the $L_{A,max}$ of HD to create a single group pooled with HM.

ΔL gives information on the noise level increase rate caused by the approaching vehicle. Table 1 shows that these rates are sharper for heavier vehicles. According to Tukey's test results, no statistically significant differences were observed between passenger cars and vans (p-value = 0.900) or between HD and HM (p-value = 0.222).

Regarding loudness (N_{50}), vans exhibit a 1.5 sone increase compared to passenger cars, whereas the difference expands to 8.9 sones for HD and 14.1 sones for HM. ANOVA with post hoc Tukey tests have confirmed the statistical significance of the average differences in N_{50} across all categories.

The sensation of sharpness depends on the noise spectral envelope rather than the spectrum's fine structure. Sharpness is a noise high-frequency content descriptor since narrow-band noises increase sharply at high center frequencies. For a noise signal with a loudness level of 60 phon, the sharpness produced by a narrow-band noise centred at 200 Hz, corresponding to 2 Bark, is about 0.25 acum. From frequencies near 200 Hz to high frequencies around 10 kHz, sharpness increases by approximately 50 times[13]. Therefore, a large high-frequency content variation is necessary to increase the magnitude of sharpness. Considering the S_{50} values displayed in Table 1 range from 1.25 to 1.30 acum, the differences in high-frequency noise content among the vehicle categories are probably not extensive enough to result in a large variation in sharpness. Furthermore, there is no evident relation between vehicle characteristics and sharpness. The ANOVA with post hoc Tukey test results indicate no statistically significant differences between passenger cars and HD (p-value = 0.491), nor between vans and HM (p-value = 0.172). Studies such as Morel et al.[14], Fu and Murphy[15], and Paviotti and Vogiatzis[16] also did not find trends for sharpness with vehicle type.

Roughness and fluctuation strength are both measures of temporal modulations of noise signals. While the first captures quickly modulated noise indistinguishable by the human ear, the latter accounts for slowlier modulation, which patterns are more perceptible. Table 1 shows that roughness, represented by R_{50}, tends to increase from light to heavy vehicles. One possible explanation for this result is a share of engine noise present in the heavy vehicles' noise samples. ANOVA with post hoc test results indicate that all differences in mean across each pair of vehicle categories are statistically significant.

Lastly, fluctuation strength (F_{50}) is the largest for passenger cars and the lowest for HD. ANOVA with Tukey's post hoc test showed that the differences in mean for vans to passenger cars and HD to HM were not statistically significant. Unlike most of the other psychoacoustic indicators, F_{50} does not exhibit a clear pattern; thus, it is challenging to relate this result to any characteristic of the vehicle categories.

B. STATISTICAL MODEL

The model fitting information allowed us to conclude that there is a statistically significant difference between the model without independent variables and the model with independent variables [$\chi 2(15) = 2907.370$, $p<.001$], which suggests a relationship between the independent variables and the dependent variable.

Table 2 presents the parameter estimates with passenger cars as the baseline category. The p-values coloured in red are the indicators that did not present statistically significant differences between the baseline and the compared categories. It is observed that ΔL and FS_{50} do not contribute to differentiating passenger cars and vans; the differences between passenger cars and HD are not pronounced for S_{50} and FS_{50}; and FS_{50} is the only parameter that does not aid the model in telling apart passenger cars to HM.

A positive β value or an $Exp(\beta) \geq 1$ means that, with an increase in the indicator, the vehicle noise sample is more likely to belong to the comparative category than the base category. Additionally, the odds ratio ($exp(\beta)$) indicates that for every one unit increase in an indicator, while holding all other variables in the model constant, the odds of a vehicle belonging to the comparative category rather than the base category increases by a factor equal to the odds ratio.

Table 2. Parameter estimates of logistic regression model

Category		β	Std. error	Wald	df	Sig.	Exp (β)	95% Confidence Interval for Exp(B)	
								Lower bound	Upper bound
Vans	Intercept	1.252	0.186	45.452	1	<0.001			
	N_{50}	1.242	0.200	38.470	1	<0.001	3.464	2.339	5.130
	ΔL	-0.059	0.081	0.533	1	0.465	0.942	0.803	1.105
	S_{50}	0.710	0.079	81.236	1	<0.001	2.033	1.743	2.373
	R_{50}	0.463	0.090	26.379	1	<0.001	1.589	1.332	1.896
	FS_{50}	-0.013	0.083	0.026	1	0.872	0.987	0.838	1.162
HD	Intercept	2.315	0.199	134.720	1	<0.001			
	N_{50}	5.774	0.330	306.380	1	<0.001	321.893	168.622	614.485
	ΔL	0.834	0.145	33.238	1	<0.001	2.301	1.734	3.055
	S_{50}	-0.184	0.130	1.995	1	0.158	0.832	0.644	1.074
	R_{50}	0.467	0.160	8.488	1	0.004	1.595	1.165	2.183
	FS_{50}	-0.198	0.148	1.802	1	0.180	0.820	0.614	1.096
HM	Intercept	0.305	0.250	1.491	1	0.222			
	N_{50}	7.960	0.380	438.270	1	<0.001	2865.19	1359.843	6036.970
	ΔL	1.048	0.170	38.020	1	<0.001	2.852	2.044	3.980
	S_{50}	0.359	0.161	4.959	1	0.026	1.432	1.044	1.963
	R_{50}	1.029	0.187	30.397	1	<0.001	2.797	1.940	4.032
	FS_{50}	0.312	0.167	3.514	1	0.061	1.367	0.986	1.895

The B values for all statistically significant indicators are positive. Therefore, with an increase in these indicators, the odds increase for a vehicle noise sample to belong to vans/HD/HM rather than passenger cars.

Looking at the exp(β) values for each pair individually, for passenger cars and vans, the impact of N_{50} in the model means that for every 1-sone increase in a vehicle noise sample, the chances that it is a van rather than a passenger car is 3.464 times greater. S_{50} and R_{50} also have considerable significance in differentiating between the two classes. The importance of N_{50} in aiding the model telling apart a vehicle from passenger cars increases for HD and HM (exp(β) equal to 322 and 2865, respectively). In these cases, ΔL is the second most important indicator to differentiate these classes, followed by R_{50}.

C. PREDICTION TASK

Figure 2 displays the confusion matrix for the machine-learning model using ΔL, N_{50}, S_{50}, R_{50}, and F_{50} as features. The values in each cell represent the count of predictions falling into each category, from 150 instances per class in the test set.

The overall accuracy of the model reached 71.5%. Notably, accuracy decreases are primarily caused by a 27% misclassification between passenger cars and vans, and vice-versa. Additionally, 17% of the actual HD were mistakenly identified as HM, while 19% of the HM were incorrectly labelled as HD. There were hardly any misclassifications between passenger cars and vans as HM, but a small portion (8%) of passenger cars and vans were classified as HD.

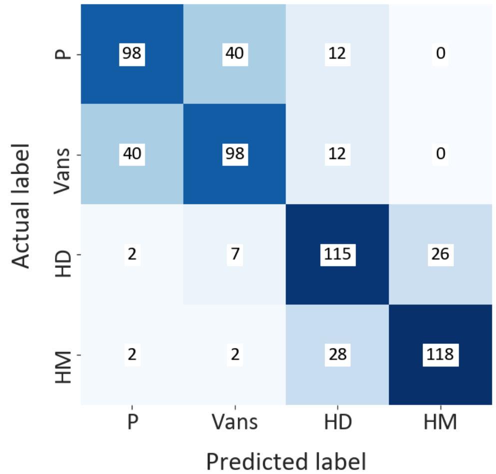

Figure 2. Confusion matrix from predictions on the test set.

The high misclassification between passenger cars and vans is expected, given the similarities in the averages of psychoacoustic indicators observed in Section 3A and the relatively small exp(B) values observed in the statistical model. This performance demonstrates that vans are considerably similar to passenger cars regarding the auditory sensation of their passage. One way to leverage having a "vans" group in an SPB measurement would be to combine them with the passenger cars. This practice could enhance the practicality of SPB measurements as vehicles that would be excluded in the current vehicle classification could instead increase the number of samples collected.

However, if the goal is to develop an auditory-based classification system that captures the nuances of traffic flow microstructure to estimate factors like noise-induced annoyance, it may be more advantageous to have a greater number of detailed classes, even if it leads to a decrease in prediction accuracy.

4. CONCLUSIONS

This study showed the feasibility of calculating the acoustic and psychoacoustic indicators of pass-by road traffic noise obtained from SPB measurements.

The averages of the indicators related to noise intensity, namely $L_{A,max}$, ΔL, and loudness, increased as the vehicle type became heavier, larger and with more axles. Similarly, roughness also grew for heavier vehicles, a behavior attributed to a large share of engine noise. On the other hand, no clear patterns were identified for sharpness and fluctuation strength through the vehicle categories.

Given the large number of instances in the dataset plus the considerable differences in psychoacoustic indicators observed across vehicle categories, a prediction model for vehicle categories could be developed using the following features: ΔL, N_{50}, S_{50}, R_{50}, and FS_{50}.

With a statistical multinomial logistic regression model, the regression coefficients allowed for making inferences on the contribution of each indicator to differentiate among vehicle categories. N_{50}, S_{50} and R_{50} shared almost the same importance in helping the model tell apart passenger cars to vans. On the other hand, N_{50} became the primary indicator for distinguishing between passenger cars to HD and HM, with ΔL and R_{50} following behind.

Lastly, using machine learning to train an algorithm with the same features led to a prediction accuracy of 71.5% in the test set. This relatively good accuracy indicates that the psychoacoustic indicators have allowed the algorithm to derive patterns that matched the visual vehicle classification.

For the SPB method, this result demonstrates the potential to facilitate a vehicle classification task less reliant on visual cues and operator subjectivity. Instead, the classification could be accomplished using features extracted from the audio signal. In this way, the problem of inconsistent vehicle classification systems outlined in ISO 11819-1 for the vehicle fleet worldwide may be tackled. Additionally, pass-by vehicles that do not match the category defined in ISO 11819-1:2023 could be included within the existing classes based on their acoustic similarity, as demonstrated by vans and passenger cars in this study.

In the context of environmental noise control, where the focus is more and more on minimizing noise exposure based on the human perception of noise, a vehicle classification system that considers the auditory sensation instead of factors like vehicle size, gross vehicle mass, or number of axles, can be used to reshape the vehicle classes. Such an approach can be further implemented to create noise maps and better assess noise-induced annoyance.

ACKNOWLEDGMENTS

The authors thank the Research Foundation – Flanders (FWO) for the travel grant allocated to Ablenya Barros (file ID K149723N).

REFERENCES

[1] M. Engel., A. Fiebig, C. Pfaffenbach, J. A. Fels, "Review of the Use of Psychoacoustic Indicators on Soundscape Studies", Current Pollution Reports **7**, 359–378 (2021).

[2] O. Hänninen, A. B. Knol, M. Jantunen, T.-A. Lim, A. Conrad, M. Rappolder, P. Carrer, A.-C. Fanetti, R. Kim, J. Buekers, et al., "Environmental Burden of Disease in Europe: Assessing Nine Risk Factors in Six Countries", Environmental Health Perspectives, **122**, 439–446 (2014).

[3] F. Soares, E. Freitas, C. Cunha, C. Silva, J. Lamas, S. Mouta, J. A. Santos, "Traffic noise: Annoyance assessment of real and virtual sounds based on close proximity measurements". Transportation Research Part D: Transport and Environment, **52**, 399-407 (2017).

[4] Z. Guo, J. Yi, S. Xie, J. Chu, D. Feng, "Study on the Influential Factors of Noise Characteristics in Dense-Graded Asphalt Mixtures and Field Asphalt Pavements". Shock and Vibration, **5742412** (2018).

[5] E. Freitas, F. Martins, A. Oliveira, I. Rocha Segundo, H. Torres, "Traffic noise and pavement distresses: Modelling and assessment of input parameters influence through data mining techniques". Applied Acoustics, **138**, 147-155 (2018).

[6] F. Lo Castro, G. Brambilla, S. Iarossi, L. Fredianelli, "The LIFE NEREiDE project: psychoacoustic parameters and annoyance of road traffic noise in an urban area". Euronoise 27-31 May 2018, Heraklion, Crete (2018).

[7] J. Morel, C. Marquis-Favre, L. A. Gille, "Noise annoyance assessment of various urban road vehicle pass-by noises in isolation and combined with industrial noise". Applied Acoustics, **101**, 47–57 (2016).

[8] M. E. Altinsoy, "The Evaluation of Conventional, Electric and Hybrid Electric Passenger Car Pass-By Noise Annoyance Using Psychoacoustical Properties". Applied Sciences, 12(10), 5146 (2022).

[9] EN ISO 11819-1; EN ISO. Acoustics—Measurement of the Influence of Road Surfaces on Traffic Noise—Part 1: Statistical Pass-By Method. The International Organization for Standardization: Geneva, Switzerland (2023).

[10] A. Grangeiro de Barros, C. Vuye, "Psychoacoustic indicators of pass-by road traffic noise" [Dataset]. Zenodo (2023). https://doi.org/10.5281/zenodo.7904680

[11] D. Cabrera, D. Jimenez, W. Martens, "Audio and Acoustical Response Analysis Environment (AARAE): a tool to support education and research in acoustics". Internoise 16-19 November 2014, Melbourne, Australia (2014).

[12] N. V. Chawla, K. W. Bowyer, L. O. Hall, W. P. Kegelmeyer, "SMOTE: Synthetic Minority Over-sampling Technique". Journal of Artificial Intelligence Research 16, 321–357, (2002).

[13] H. Fastl, E. Zwicker, "Psycho-acoustics: facts and models". 3rd edition. Springer, Berlin, Germany (2007)

[14] J. Morel, C. Marquis-Favre, D. Dubois, M. Pierrette, “Road Traffic in Urban Areas: A Perceptual and Cognitive Typology of Pass-By Noises”. Acta Acustica United With Acustica **98**, 166-178 (2012).

[15] Y. Fu, D. Murphy, "Spectral Modelling Synthesis of Vehicle Pass-by Noise". Internoise 27-30 August 2017, Hong Kong (2018).

[16] M. Paviotti, K. Vogiatzis, "On the outdoor annoyance from scooter and motorbike noise in the urban environment". Science of the Total Environment **430**, 223–230 (2012).