

### Evaluation of short-term road traffic noise exposure using physiological measurements and auralized sound samples? a preliminary panel study

Julien Maillard, Fabrice De Oliveira, Gwénaëlle Haese

### ▶ To cite this version:

Julien Maillard, Fabrice De Oliveira, Gwénaëlle Haese. Evaluation of short-term road traffic noise exposure using physiological measurements and auralized sound samples? a preliminary panel study. Forum Acusticum, Dec 2020, Lyon, France. pp.1699-1705, 10.48465/fa.2020.0862. hal-03233758

### HAL Id: hal-03233758 https://hal.science/hal-03233758

Submitted on 26 May 2021

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers. L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

### Evaluation of short-term road traffic noise exposure using physiological measurements and auralized sound samples a preliminary panel study.

J. MAILLARD<sup>1</sup> F. DE OLIVEIRA<sup>2</sup> G. HAESE<sup>2</sup>

<sup>1</sup> Centre Scientifique et Technique du Bâtiment (CSTB), 24 rue Joseph Fourier, 38400 Saint Martin D'Hères, France

<sup>2</sup> Pioneering hUman Lab for Sensory Evaluation (PULSE), Centre Scientifique et Technique du Bâtiment (CSTB), 11 rue Henri Picherit, BP 82341, 44323 Nantes Cedex 3, France

Picherit, BP 82341, 44323 Nantes Cedex

julien.maillard@cstb.fr

#### ABSTRACT

Road traffic noise remains a major source of noise pollution in urban areas where long-term exposure has been shown to cause a wide range of health-related problems, including serious illnesses such cardiovascular disease. The health-related effects of traffic noise exposure are well correlated to the long-term averaged sound pressure levels. Traffic noise also results in noise annoyance. Noise annoyance, in this case, is influenced by several acoustical as well as non-acoustical factors, in addition to long-term averaged levels. Its direct evaluation usually relies either on field questionnaires or on listening tests in controlled environments. Predictive models may then be derived by correlating perceived annovance with acoustical and psychoacoustical indices. To improve the direct evaluation of noise annoyance, this paper presents preliminary work on the correlation of perceived annoyance, acoustical indices and physiological using autonomic nervous measurements system monitoring based on heart rate, respiration rate, skin electrodermal response, and skin blood flow. To this purpose, measurements were carried out in a laboratory on several subjects exposed to different simulated road noise soundscapes. The reproduced soundscapes are based on auralized sound samples which model road traffic noise scenarios comparing different abatement solutions. The auralization approach ensures replicable traffic flow conditions with and without the abatement solution. Results show the correlation between physical and physiological parameters and perceived sound quality, as well as the potential for new ways of analyzing auralized sound samples from physiological parameters.

#### **1. INTRODUCTION**

Transportation noise remains today the main source of noise pollution in urban areas and long-term exposure has been shown to cause serious health-related problems [1], [2]. Another measured effect of traffic noise is the perceived noise annoyance which is a result of several acoustical as well as non-acoustical factors, in addition to long-term exposure. Different methods exist for the direct evaluation of noise annoyance using questionnaires in-situ or in controlled laboratory environments [3], [4]. Work is also carried out to estimate noise annoyance from

acoustical and/or psychoacoustical indices, thus avoiding the need to rely on panel studies [5]. To improve the direct evaluation of noise annoyance, it is of interest to also consider physiological measurements. Preliminary work on the subject was recently published, combining perceived annoyance rating with acoustical properties and biometric data [6]. The present paper shows new results based on a laboratory experiment where several subjects were exposed to different simulated road noise environments. The reproduced soundscapes are created using auralized sound samples of road traffic scenarios, different abatement comparing solutions (noise barriers) [7], [8]. The choice of auralized sound samples was made in order to obtain the same flow of vehicles for each abatement solution under study. The physiological measurements monitor the autonomic nervous system (ANS) based on heart rate, electrodermal response (EDR), respiration rate and skin blood flow (µCirc). This type of measurements was previously applied in the context of different sensory stimuli, such as tastes and flavor, to objectively assess induced physiological stress without declarative questionnaires [9]. The relationships between the activity of the autonomic nervous system and emotions have been studied extensively in the past [10]. One important result of this work is that ANS activity can be used to identify recurrent behaviors or patterns, based on different physiological indicators (such as respiration, mental sweating, cardiovascular responses). Particularly, emotions with a negative valence induce an ANS response whose intensity is correlated to the intensity of physiological stress. In that case, the ANS response activates the sympathetic nervous system (SNS). In a related study [11], psychophysiological measurements including variability of the heart rate, electromyography, and respiratory rate, were also applied to study the effect of noise on mental load.

#### 2. EXPERIMENTAL SETUP

The experimental setup includes two main systems: the physiological data logger and the auralized sound samples reproduction. The associated equipment is shown in Figure 1.



Figure 1. Experimental setup: (A) test room visual feedback, (B) data collection laptop PC with Labchart software and (C) Audient ID14 audio interface for the reproduction of auralized sound samples.

#### 2.1 Physiological monitoring system

The physiological monitoring system is composed of a Powerlab 8 channel datalogger connected to ADInstruments Labchart software (see Figure 2). The recorded physiological data includes heart rate, using IIIlead and ADInstruments FE232 dual bioamp, breathing rate, using ADInstruments thoracic conductance belt, skin blood flow, using PeriFlux 5000 Perimed laser Doppler, and the electrodermal conductance response, using ADInstruments galvanic skin response amplifier, FE116 GSR Amp.



Figure 2. Labchart acquistion software with physiological signals during measurements: Red signal: ECG; Blue signal: EDRc, electrodermal conductance; Dark green signal: µcirc, skin blood flow; Pink signal: Respiration, breathing pattern; Purple signal: HRV, heart rate variability (BPM : beat per minute); Light green signal: breating rate (BPM: breath per minute).

#### 2.2 Sound reproduction system

The auralization system uses binaural reproduction over headphones. Sound samples are played back on a laptop PC connected to an Audient ID14 audio interface. All sound samples are 24 bit/44100 Hz non-compressed audio files. Beyerdynamic DT770 PRO 80 Ohm headphones are used. Figure 3 shows a subject during measurements.

#### 2.3 Experiment sequence

The measurement session was carried out on 5 healthy volunteering subjects (2 men and 3 women) ranging in age from 21 to 60 (mean age 39). Their hearing ability was not measured, but none of them reported any hearing impairment. The set of audio samples for each subject is the same and follows a predefined order. Three scenes are

selected from a set of previously auralized scenes. Each scene includes two 20 second samples associated with two configurations of the abatement solution: "with" and "without". The playback order is as follows: "scene 6 without", "scene 6 with", "scene 7 without", "scene 7 with", "scene 14 without", and "scene 14 with" (the reader is referred to Section 3 for a description of each scene). A pause is inserted between each sound sample playback such as to ensure the subject returns to a stable physiological state. Note however, that the effects of sound onset on the measured parameters were not addressed in this preliminary study. During all measurement sessions, the subjects closed their eyes and were comfortably seated on an inclined chair.



Figure 3. A subject in the test room, equipped with physiological sensors and headphones.

#### 2.4 Data processing

Each physiological signal is windowed over the 20 second duration of audio samples and post-processed in Matlab 2018<sup>®</sup>. Post-processing includes the computation of mean and standard deviation values. In addition, for the breathing rate, the heart rate and the digital skin blood flow signals, three basic nonlinear features are extracted as described below. They are indexed as "r", "hr" and "c", respectively, in the remaining of this paper.

First, the "Poincaré plot" features [13] are determined, based on the analysis of the scatterplot of several physiological indices (breathing rate, heart rate and digital skin blood flow signals). The derived indices SD1 and SD2 are perpendicular standard deviations, as illustrated in Figure 4. For example, the "Poincaré plot" indices associated with the ECG R-R index and the derived heart rate time period, RRI (ms), are defined as: =

$$SD1_{hr}$$

$$\sqrt{\frac{1}{N}\sum_{n=1}^{N} (RRI(n) - R1)^2 - (RRI(n+1) - R2)^2}$$
(1)  
SD2<sub>hr</sub> =

$$\sqrt{\frac{1}{N}\sum_{n=1}^{N} (RRI(n) - R1)^2 + (RRI(n+1) - R2)^2}$$
(2) with



Figure 4. Poincaré plot of a RR time series with  $SD1_{hr}$  and  $SD2_{hr}$  features (reproduced from [13]).

The SD1  $(SD1_r, SD1_{hr} \text{ and } SD1_c)$  and SD2  $(SD2_r, SD2_{hr} \text{ and } SD2_c)$  indexes are measures of the short-term and long-term components, respectively, of the physiological signals.

The second non-linear feature extracted from the physiological signals is obtained with a PUCK Analysis. The PUCK Analysis [14] is a method which was introduced to assess the non-linear dynamic properties of time series. For example, it has been used for analyzing the R-R intervals based on a scatterplot, as illustrated in Figure 5. The potential force can be estimated by comparing (or by using a correlation analysis on) the R-R interval difference in successive times RR(i + 1) - RR(i) and from the long-term trend  $RR(i) - RR_{mi}$  where  $RR_{mi}$ represents a moving average (see Figure 5). This method suggests that the slope and the slope standard deviation, SSD1 and SSD2, parameters, are indicators of sympathetic and parasympathetic modulation, respectively [15]. The calculation of SSD1 and SSD2 is similar to the standard deviation calculations of the SD1 and SD2 indexes carried out in the "Poincaré plot" analysis.



**Figure 5.** Time and trend difference scatter plot. The slope represents the linear least-squares function (red line). SSD1 (yellow line) is the standard deviation of the data perpendicular to the slope, while SSD2 (blue line) is the standard deviation of the data parallel to the slope (reproduced from [15]).

The third non-linear feature, extracted from the physiological signals, is the approximate entropy (ApEn) index. ApEn is a statistical variable quantifying regularity and complexity of time series [16]. This index is computed here for heart rate, breathing rate and skin blood flow.

To reduce the inter-individual variability of physiological signals between subjects, all parameters introduced above are normalized with the mean-centered and normalized standard deviation.

Statistical analysis of the above parameters is then carried out both with principal component analysis (PCA) and partial least squares (PLS) based on optimal multicollinear subspace, and according to the best physiological features to explain the descriptive physical components of the acoustic stimuli (see Figure 9). Last, multidimensional Fisher tests, with a minimal significance level set to p<0.05, are used to identify the classification abilities of the subspaces according to the sound samples characteristics.

The above statistical analysis gives a first approach to assess objectively the effect of noise on human physiological stress (neuro-vegetative and mental stress).

#### 3. DESCRIPTION OF THE STIMULI

The stimuli used in the experiments correspond to sound samples of road traffic and tramway noise for a fixed pedestrian in three different urban environments. The sound samples were obtained during previous work on low-height noise barriers for urban environments [7]. In this work, several scenes were modeled, representing typical scenarios where low-height barriers can significantly reduce traffic noise exposure. Each scenario was evaluated with and without noise barrier for several receiver positions. All sound samples were generated with the outdoor noise auralization engine of MithraSound<sup>®</sup> [8]. The reader is referred to previously published work for a detailed description of the traffic noise auralization technique implemented in MithraSound<sup>®</sup>. In this study, the auralized samples use the 3D binaural output suited for headphones reproduction. For each scene, the samples "with" (B) and "without" (NB) noise barriers contain the same traffic and ambient noise sources, which enables a direct comparison of the two configurations. Among all available scenes and receiver positions from this previous work, three scenes were selected to conduct the present experiment. "Scene 6" (Figure 6) is a small half-circle plaza bordered by a main 2x1 road and a 2x1 tramway line as well as a circle one-lane road with less traffic. The receiver is located near the main axis on the right side of the plaza and looking up across the 2x1 road. "Scene 7" (Figure 7) is a rectangular square crossed by a one-way 2x1 road and a 2x1 tramway line with smaller one-lane roads on each side. The receiver is positioned near the main axis in the center and looking down across the main traffic lanes. "Scene 14" (Figure 8) represents a 2x1 tramway line with one-lane roads on each side and no close-by buildings. The receiver is 30 m away from the main axis, looking left towards the traffic.



Figure 6. Auralized "scene 6" (scale in meters).



Figure 7. Auralized "scene 7" (scale in meters).



Figure 8. Auralized "scene 14" (scale in meters).

All sound samples have a 20 second duration. Figure 9 presents the averaged equivalent sound pressure level, Leq, per octave band for each scenario along with the A-weighted total level,  $LA_{eq}$ , and the A-weighted L10 statistical index. The Leq levels in each octave band are written as Leq63, Leq125, etc. in the remaining of this paper.



Figure 9. Auralized sound samples averaged SPL per octave frequeny bands, .

Figure 10 shows the instantaneous sound pressure level, LA<sub>eq,125ms</sub>, versus time.

![](_page_4_Figure_11.jpeg)

**Figure 10.** Auralized sound samples fast instantaneous Leq,125 ms in dB(A) versus time.

#### 4. RESULTS

# 4.1 Correlation between acoustical indices and physiological features

Five physiological samples were collected for each scene (without and with barrier). The cross-correlation of this 30 samples matrix showed interrelation between noise level components (physical parameters) and physiological features. The next figure presents the PCA first two components explaining 50.77% of the inertia of the physiological data only.

![](_page_5_Figure_3.jpeg)

**Figure 11.** PCA correlation circle for the first two components (F1, F2). Red dots: explicative physiological variables; blue dots: illustrative acoustic variables.

In Figure 11, the F1 component (30.68%) corresponds to the cardio-vascular pathway of physiological stress (non-linear parameters of skin blood flow and heart rate). The F2 component (20.09%) corresponds to the electrodermal (mean and standard deviation over the 20 second sound samples) and breathing signals. The physical components of the acoustic scenes are more correlated to the F2 (20.09%), F4 (9.6%) and F5 (5.62%) components (see Figure 12). The 35.31% inertia of the physiological parameters explains the physiological stress induced by the physical properties of the sound samples. According to this relation between physiological and physical parameters, preliminary studies can be carried out in order to discriminate between sound samples and/or predict their physical characteristics. The physical parameter that best explains the physiological response is the total A-weighted sound pressure level, LAeq. The ones that least explain the physiological response are the octave band sound pressure levels, Leq, in the 63Hz, 250Hz and 500Hz bands.

![](_page_5_Figure_6.jpeg)

**Figure 12.** PCA correlation circle for the third and fourth components (F4, F5). Red dots: explicative physiological variables; blue dots: illustrative acoustic variables.

## 4.2 Physiological features explaining physiological stress induced by noise exposure

According to the results in Section 4.1, part of the data inertia can be used to identify and classify important variables which explain the physiological stress induced by noise exposure.

A partial least square regression was carried out in an attempt to construct a model of physical noise level. The Partial Least Square (PLS) method [17] finds the best subspace to explain all considered noise level indices (LAeq, L10, Leq63, Leq125, Leq250, Leq500, Leq1000, Leq2000, Leq4000 and Leq8000). Figure 13 shows the Variable Importance in Projection (VIP) of the PLS first sub-component.

![](_page_5_Figure_11.jpeg)

Figure 13. Variable Importance in Projection of the PLS first sub-component.

The most important variables (VIP>1) identified from the PLS analysis, according to the noise level indices of the acoustic stimuli, are:

- the mean and the standard deviation of electrodermal conductance (tonic component variation induced by the 20s acoustic stimuli);
- the  $SD1_{hr}$ ,  $SSD2_{hr}$  and slope for heart rate.

Variables with a VIP lower than 0.8 are non-important and are not considered in the analysis.

As an example, according to the optimal physiological subspace calculated from the PLS regression, the LAeq prediction model has a  $R^2$  coefficient of 0.674.

# 4.3 Sound samples classification ability of physiological stress features

Another way to use optimal physical parameters (the first three PLS components) is the classification of sound samples according to the induced physiological stress. In this preliminary study, there are too few data collections for implementing a discriminating factor analysis due to the risk of over-learning. Instead, a Mahalanobis distance and discriminant Fisher test is carried out. Table 1 shows the intra and inter class Mahalanobis distances between all sound samples (6 NB, 6 B, 7 NB, etc.).

Scene	6 NB	6 B	7 NB	7 B	14 NB	14 B
6 NB	0.0	8.1	6.9	25.1	22.9	44.0
6 B	8.1	0.0	0.2	6.1	4.8	16.8
7 NB	6.9	0.2	0.0	6.4	5.5	17.2
7 B	25.1	6.1	6.4	0.0	0.4	2.7
14 NB	22.9	4.8	5.5	0.4	0.0	4.4
14 B	44.0	16.8	17.2	2.7	4.4	0.0

 Table 1. Mahalanobis distances between sound samples

 with (B) and without (NB) barrier.

Wilks' Lambda test is also carried out. This statistical test is used to decide whether several groups of multivariate observations have significantly different means. This test is significant (p < 1e-4) which indicates that sound sample means are different.

This result is confirmed by the Fisher discrimination test. Table 2 gives the significance of the Mahalanobis distance given in Table 1. This significance shows the ability of the optimal subspace of physiological variables to discriminate sound samples. All samples are different from each other except for scenes 6B vs 7NB and scenes 7B vs 14B.

Scene	6 NB	6 B	7 NB	7 B	14 NB	14 B
6 NB	1	< 5e-3	< 0.01	<1e-4	<1e-4	< 1e-4
6 B	< 5e-3	1	NS	< 5e-2	< 5e-2	<1e-4
7 NB	< 1e-2	NS	1	< 5e-2	< 5e-2	<1e-4
7 B	<1e-4	< 5e-2	< 5e-2	1	NS	0.130
14 NB	<1e-4	< 5e-2	< 5e-2	NS	1	< 5e-2
14 B	<1e-4	<1e-4	<1e-4	0.130	< 5e-2	1

**Table 2.** Discriminant Fisher test between sound sampleswith (B) and without (NB) barrier.

#### 5. CONCLUSIONS

This paper presents a preliminary panel study for the evaluation of short-term road traffic noise exposure using physiological measurements and auralized sound samples.

The first result is that correlations exist between the physical noise level indices of the sound samples and the physiological parameters extracted from electrodermal response and heart rate. Potentially, these correlations can be used to analyze objectively the effect of noise exposure on human physiological stress with, e.g., PLS regression.

The second result is that there is a possibility to use an optimal subspace of physiological parameters to classify or construct categories of sound samples.

Further research is needed to validate and extend these results using more subjects and more samples. This should include samples with lower noise levels in order to assess the sensitivity of physiological measurements. In addition, the methodology for reproducing the set of sound samples must be refined to reduce the effects of sound onset transients on the physiological response. Also, randomization of the samples is necessary to improve the robustness of the results.

#### 6. REFERENCES

- [1] L. Fritschi *et al.*: "Burden of disease from environmental noise: Quantification of healthy life years lost in Europe", *World Health Organization Regional Office for Europe*, 2011.
- [2] I.C. Eze *et al.*: "Transportation noise exposure, noise annoyance and respiratory health in adults: A repeated-measures study", *Environment International*, 121, pp. 741-750, 2018.
- [3] D. Schreckenberg, C. Belke and J. Spilski: "The development of a multiple-item annoyance scale (MIAS) for transportation noise annoyance", *International Journal of Environmental Research and Public Health*, 15 (5), art. no. 971, 2018.
- [4] A. Trollé *et al.*: "Impact of urban road traffic on sound unpleasantness: A comparison of traffic scenarios at crossroads", *Applied Acoustics*, 94:46 – 52, 2015.
- [5] L.-A Gille, and C. Marquis-Favre: "Estimation of field psychoacoustic indices and predictive annoyance models for road traffic noise combined with aircraft noise", *Journal of the Acoustical Society* of America, 145 (4), pp. 2294-2304, 2014.
- [6] D.A.H. Williams, *et al.*: "Towards biophysiological and acoustic markers for perceived annoyance in response to reproduced environmental soundscapes", *INTER-NOISE (2019)*.
- [7] J. Defrance *et al.*: "Outil d'aide à la décision pour la réalisation de mobiliers urbains acoustiques", *Congrès Français d'Acoustique*, 2018.
- [8] J. Maillard and A. Kacem, "Auralization Applied to the Evaluation of Pedestrian and Bike Paths in Urban Environments", *INTER-NOISE*, 2016.

- [9] G. Haese, P. Humeau, F. De Oliveira, P. Le Callet and P. Le Cloirec, "Tastes and odors of water -Quantifying objective analyses: a review", *Critical Reviews in Environmental Science and Technology*, *Taylor & Francis*, Vol. 44, I. 22, pp. 2455-2501, 2014.
- [10] S.D Kreibig ., "Autonomic Nervous System Activity in Emotion: A Review", *Biological psychology*, 84, pp. 394-421, 2010.
- [11] Kristiansen J., Mathiesen L., Kofoed Nielsen P., Hansen A.M., Shibuya H., Petersen H.M., Lund S.P., Skotte J., Jørgensen M.B. and Søgaard K., "Stress reactions to cognitively demanding tasks and openplan office noise", *Int Arch Occup Environ Health*, vol 82, pp.631–641, 2009.
- [12] Mikuckas, A., Mikuckiene, I., Venckauskas, A., Kazanavicius, E., Lukas, R., and Plauska, I., "Emotion Recognition in Human Computer Interaction Systems", *Electronika Ir Elektrotechnica*, 20(10), pp. 51-56, (2014).
- [13] B. Sohrab, A. Akhshani, H. Mahmodi, and H. Hobbenagi C, "On the Calculation of Chaotic Features for Nonlinear Time Series", *Chinese Journal* of *Physics*, vol. 46(4), Aug. 2007.
- [14] M. Takayasu, T. Mizuno, H. Takayasu, "Potentials of unbalanced complex kinetics observed in market time series", 2005, E-print http://arxiv.org/abs/physics/0509020
- [15] T. Igasaki, T. Morie, M. Utsunomiya, I. A. Akbar, & A. Mourits Rumagit, "Can Potentials of Unbalanced Complex Kinetics of Heart Rate Variability Estimate Drowsiness?", *The 2017 Biomedical Engineering International Conference*, 2017.
- [16] S.M. Pincus, "Approximate entropy as a measure of system complexity", *Proc Natl Acad Sci U S A. Mar* 15; 88(6): pp. 2297–2301, 1991.
- [17] R. Rosipal and N. Krämer, "Overview and Recent Advances in Partial Least Squares", *International Statistical and Optimization Perspectives Workshop: Subspace, Latent Structure and Feature Selection*, pp. 34-51, 2005.