Influence of loudness of noise events on perceived sound quality in urban context

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ABSTRACT

One of the aims of Cart_ASUR project is to propose an indicator of urban sound quality based on perceptive and acoustic data. The originality of this project consists in using mobile phone technology to collect data. 60 persons had to assess about 20 locations in Paris at four or five homogenous periods (days, evening, night, summer, winter) with a specific questionnaire through mobiles. In the questionnaire, the first questions are related to global sound environment characterization with semantic scales. The next questions concern the perceived loudness assessment of some emergent sources (light vehicles, trucks, bus and mopeds). Finally, the last questions deals with the presence time ratio assessment of sources that do not emerge from the background (birds, voices, steps, etc). Before each assessment, sound pressure level is recorded each second from the mobile phone's microphone during a 10-minute period. In this paper, the link between global sound quality and loudness assessment of emergent sources is developed. A particular attention is devoted to the situation classification. Depending on the type of location, some identified sources have an influence on the sound quality of the environment.

Keywords: Soundscape, Urban sound quality I-INCE Classification of Subjects Number(s): 56.3, 68.2

1. INTRODUCTION

Since 2002 and the European Directive 2002/49/EC, cities with more than 100.000 inhabitants must publish noise maps [1]. These maps show the L_{DEN} indicator and must be used to communicate with citizens about noise. But L_{DEN} indicator based on the density of traffic is not always representative of people's perception on noise. Indeed, L_{DEN} is a weighted average indicator which represents noise only when traffic is continuous. But what happens when it is not continuous? When places are far away from roads or protected? For these cases, the L_{DEN} indicator seems to be less relevant. That is why, in order to be more representative of people's perception in the urban context, the Cart_ASUR project aims at building a sound pleasantness indicator which could integrate more information than just the sound level due to traffic. Emerging sources such as motorbikes or horns, or sources such as birds or voices seem to be also important for sound quality.

Previous work showed that a good prediction of the sound pleasantness could be obtained from twelve independent perceived variables [2]. But this work was based on about 300 interviews. By increasing the number of perceptive data and by recording simultaneously the evolution of the sound level, the Cart_ASUR project tries to improve the indicator of urban sound quality. To collect a lot of information, the Cart_ASUR project uses the mobile phone technology to record perceptive and acoustic data. The mobile application and the questionnaire are presented in the second section of this paper. The perceptive data is then analyzed to build a model in order to predict sound quality. According to the kinds of locations, models can be different. Indeed, some urban characteristics may have an influence on the choice of variables used in the model (§ 3 and 4). Finally, the discussion

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focuses on specific variables such as global loudness, emergence of sources and envelopment (§ 5).

2. ACOUSTIC AND PERCEPTIVE DATA COLLECTION

A specific mobile phone application was developed by the BrusSense Team of Vrije Universiteit Brussel (VUB). The application and calibration are based on the NoiseTube developments [3].

2.1 Mobile calibration

After some tests on mobiles' microphone, the mobile phone "HTC one X" is chosen to conduct this project. The mobiles were calibrated during a campaign in anechoic room conducted by the VUB team. The figure 1 shows the results of measurements obtained after calibration for three phones.

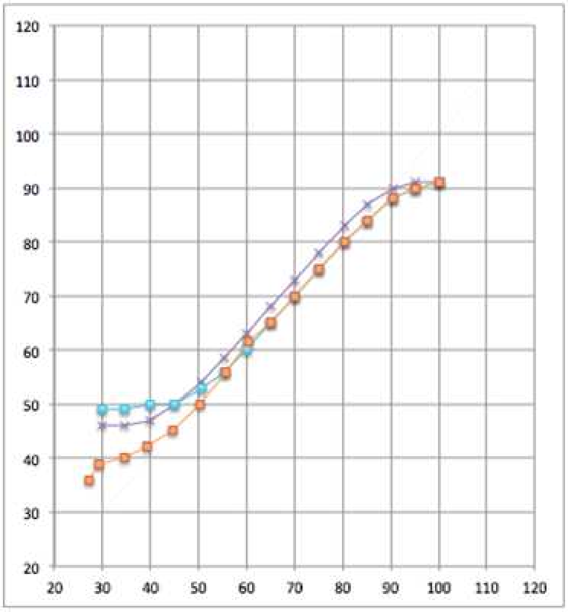

Figure 1 – Mobile measurements in dB(A) in function of the real value in dB(A)). It shows the measurement of phones after a first set of calibration (blue and purple). The orange curve corresponds to an improved set of calibration for low levels.

Between 50 dB(A) and 90 dB(A), the lines are very close to the diagonal, which represents perfect accuracy. As expected, below 50 dB(A) and above 90 dB(A), accuracy decreases greatly. That is why the calibration of mobile phones has been slightly adjusted for low levels to obtain the orange curve. But the poor accuracy below 50 dB(A) and above 90 dB(A) is not an issue for Cart_ASUR since measurements take place in urban areas, where sound levels are set inside this range.

As part of the study, a comparison between the *in situ* acoustic measurements delivered by calibrated mobile phones and the measurements made by Bruitparif measuring stations commonly used for overall documentation of environmental noise is expected.

2.2 Cart_ASUR application

To help participants carrying out the experiment, a mobile application was developed. It makes possible the management of all measured locations, named "objectives". An objective defines a specific location and a specific time of measurement. For each objective, the application allows a 10-minute recording of sound pressure levels (stored each second) followed by a perceptive questionnaire. This questionnaire is composed of three parts (Figure 2). The first part is related to global sound environment. Global loudness, animation, envelopment, sound pleasantness, visual amenity and familiarity are assessed with semantic scales. The second part concerns the emergent sound sources. The perceived loudness of mopeds, cars, trucks or buses, sky trains, horns and urban activities are assessed with scales from "low" to "high". The last part deals with the time presence of sound sources which don’t emerge from the background noise such as traffic, voices, footsteps, birds, water and wind. A scale from “rarely present” to “continuously present” is used for these sources.

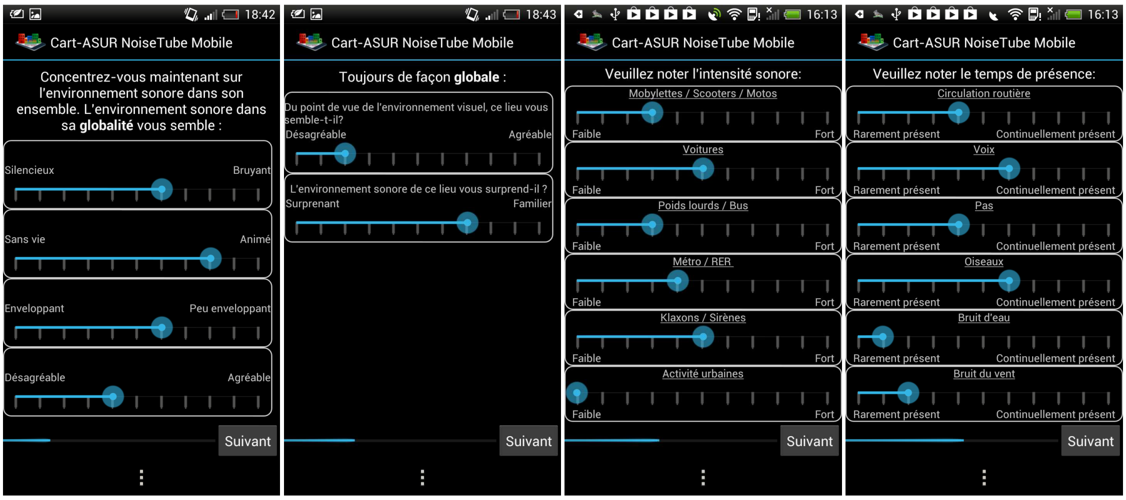

Figure 2 – Screenshots of Cart_ASUR questionnaire

In the questionnaire, a particularity can be observed for the traffic noise. Indeed, this kind of noise can be considered as an emergent noise assessed with specific sources or, depending on the flow of vehicles, assessed as a whole.

At the end of the experiment (in September 2014), we expect a total of 4000 measurements. For now, 1934 measures have been carried out between October 2013 and March 2014. It represents about 100 objectives, and each objective is assessed by about 20 persons. The analyses presented in the paper were conducted on these measurements.

3. CLUSTERING OF LOCATIONS

In order to adapt the model to the different kinds of locations, a classification on places was conducted. It was based on the perceptive characterization of these locations. The classification was conducted on the medians and inter-quartile differences. The inter-quartile difference makes it possible to take into account the dispersion of answers in the assessment of emergent sound sources. Indeed the distribution of these variables is not Gaussian.

3.1 Method

Clustering is performed on the Kohonen’s Self-Organizing Maps (SOM), followed by a Ward classification. In the seventies, Teuvo Kohonen has developed an artificial neural network algorithm that makes it possible to classify inputs [4]. This method is an unsupervised classification. Namely classification is only driven by the input as opposed to supervised classification. Only one neuron is modified at each learning step. At the end of the classification, the data are distributed between different neurons mapping the same topology as the data space.

After this first classification, it is possible to gather neurons in different classes by using a Ward classification. These two classifications are used one after the other for two reasons:

- Reducing the number of input data, in our case: 1934 measures which sometimes make the Ward classification unreadable and difficult to interpret.
- Highlighting perceptual variables that explain the clustering of values in different classes

3.2 Results

A double classification is conducted on the 1934 measurements. The number of classes is chosen after considering the dendrogram and the semi-partial R-Square index (SPRSQ) (Figure 3).

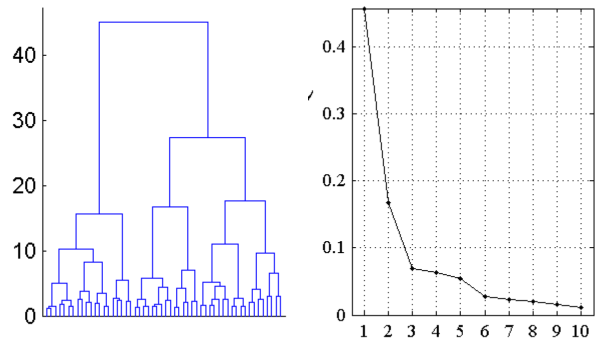

Figure 3 – Number of classes to consider. At left, dendrogram representation with dissimilarity index in ordinate. At right, SPRSQ index with the ratio of inter-class inertia on the total inertia in ordinate and the number of classes in x-axis

The two slope breaks in the SPRSQ index show that 3 or 6 classes can be considered. This is also observed in the dendrogram representation. In this article, we decided to work on six classes because the distinction between the classes was easy to interpret.

The Kohonen map is composed of 54 neurons grouped together in 6 classes (Figure 4). The objects of the map correspond to the 100 objectives and each one is coded as follow: the first letter corresponds to the kind of location, the three next correspond to the three first letters of the place name and the last letters to the period (for example A_ITA_SJ means Avenue ITAlie, measured on a week day (“Semaine” in French) and on a day period (“Jour” in French).

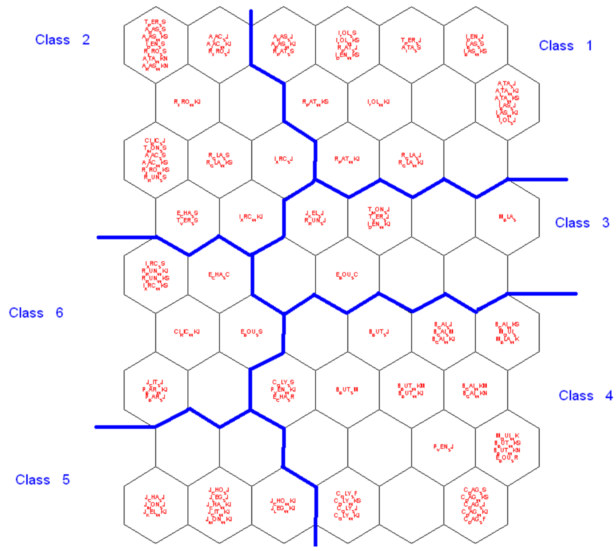

Figure 4 – Clustering of locations in six classes

With the SOM, it is possible to analyze the influence of perceptive variables on classification. Different variables are shown in Figure 5 (for median values) and Figure 6 (for quartile values). For each class, the kind of places and the characteristics are given:

- Class 1 is composed mainly of measurements performed in streets, boulevards or crossroads during day. These locations are rather loud with a lot of traffic.
- Class 2 is composed mainly of measurements performed in streets, boulevards or crossroads during evening and night. It is worth noticing that the inter-quartile variables on heavy vehicles and on motorcycles are high (Figure 6). These locations are without life and rather not enveloping with medium noise levels. The place with sky train is also in this class.
- Class 3 is composed of various locations: small streets, crossroads in evening, schools during class, etc. All variables are medium in this group, showing that all kind of sources are present.
- Class 4 is composed mainly of measurements performed in market streets, restaurants and pubs streets. Footsteps and voices are present in these places.

- Class 5 is composed only of measurements performed in parks. These places are very pleasant with noise of birds and water.
- Class 6 is composed of various places: parks, markets, streets, mixed areas, etc. These locations are characterized by the absence of animation and silence. It leads to an “unfamiliar” feeling.

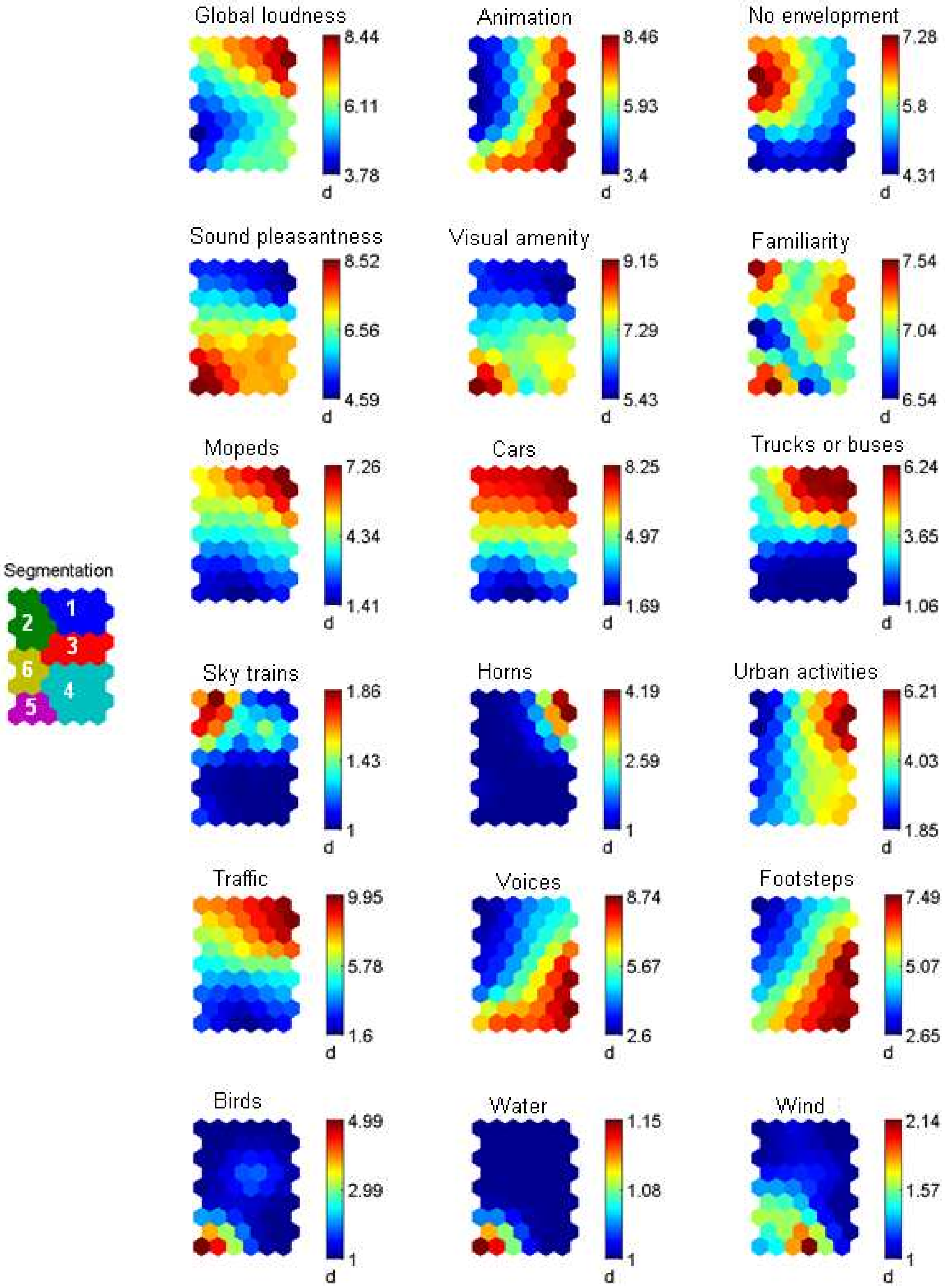

Figure 5 – Distribution of median values of each perceptual variable on the SOM - At left, segmentation shows the distribution of different classes of SOM

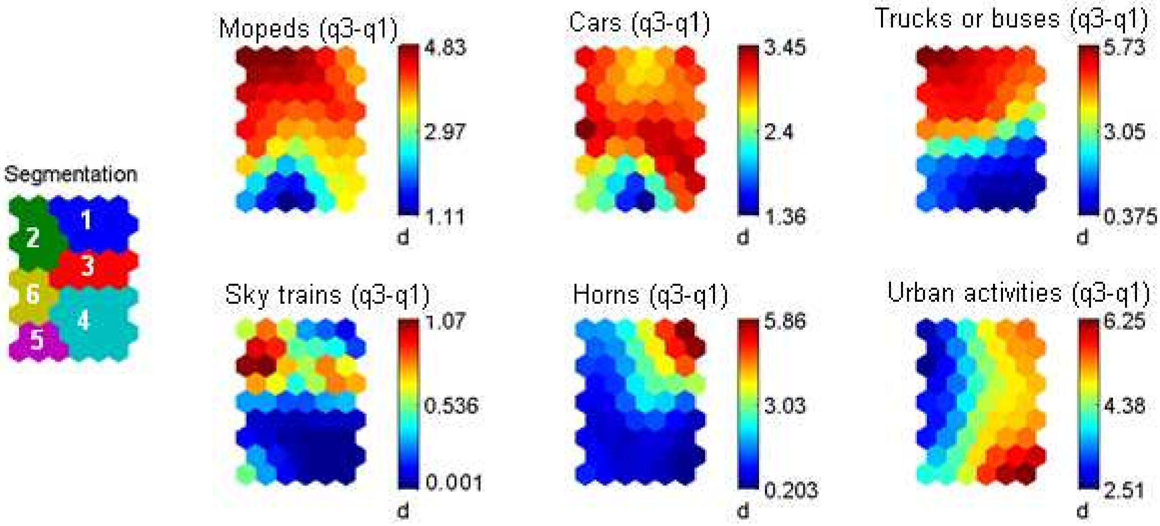

Figure 6 – Distribution of inter quartile values for emergent sound sources on the SOM. At left, segmentation shows the distribution of different classes of SOM

4. CONSTRUCTION OF PREDICTIVE MODELS OF SOUND QUALITY

4.1 Method

A predictive model is calculated for each class on the individual evaluations through various steps. The first step consists in verifying the independence between each variable with the correlation coefficients. When two or more variables are found correlated, only one is chosen and kept for the prediction models. Each class includes a large number of data. So, the significance of the correlations is always very high ($p<0.001$), even for a poor correlation. It has been decided to consider that two variables are correlated when the correlation coefficient is greater than 0.5. Variables that do not vary are also removed from the analysis.

The second step consists in choosing the best model from linear regressions calculated with Statgraphic software. The best model has the highest value of adjusted R^2. The adjusted R^2 is a coefficient based on coefficient R^2 which measures the quality of the fit of estimated linear regression equation. When the best model is found, the correlation coefficient between the model prediction and the evaluated perceived sound quality is calculated.

4.2 Results

4.2.1 Correlations between sound quality and visual amenity

When calculating the various models, we observed that visual amenity was the most correlated variable with the sound quality (Table 1). It can be also observed on the variable maps in Figure 5 that sound agreement map and visual agreement map are similar. This means that if a place is considered as “beautiful”, the sound environment is also considered as “pleasant”. Previous studies have already highlighted the relation between audition and vision [5]. But the importance of the visual setting is more an artifact in this study where the sound environment in many existing places is correlated with the visual situation.

Table 1 – Correlations between sound quality and visual amenity

Class	class 1	class 2	class 3	class 4	class 5	class 6
Correlation	0,51** (433)	0,54** (444)	0,55** (137)	0,57** (525)	0,66** (199)	0,54** (184)

In order to select a model which would be able to predict the sound quality only from acoustic variables (perceived or calculated), it has been decided to remove the visual agreement variable from the models. For our urban corpus, this variable tends to mask the importance of the acoustic variables.

4.2.2 Models

Models are calculated for each class without the visual amenity variable, the sound pleasantness as the dependent variable and the other perceptive variables as the explanatory variables. They are presented in Table 2.

Table 2 – Models of different classes

Class	Equation of model	Corr.
Class 1	Sound pleasantness = 7,26 - 0,28 * Global loudness - 0,07 * Loudness of trucks or bus - 0,09 * Time ratio of traffic + 0,12* Time ratio of footsteps	0.28** (433)
Class 2	Sound pleasantness= 6,19 - 0,44 * Global loudness + 0,19 * Animation + 0,15 * No envelopment + 0,07 * Familiarity	0.43** (444)
Class 3	Sound pleasantness = 9,17 - 0,52 * Global loudness + 0,16 * No envelopment - 0,13 * Familiarity + 0,09 * Time ratio of footsteps	0.59** (137)
Class 4	Sound pleasantness = 5,94 - 0,16 * Global loudness + 0,19 * No envelopment - 0,06 Familiarity - 0,14 * Loudness of trucks or bus + 0,16 * Time ratio of footsteps	0.35** (525)
Class 5	Sound pleasantness = 7,62 - 0,17 * Global loudness + 0,22 * No envelopment - 0,28 * Loudness of cars + 0,14 * Time ratio of birds	0.45** (199)
Class 6	Sound pleasantness = 8,29 - 0,47 * Global loudness + 0,15 * No envelopment - 0,08 * Familiarity + 0,13 * Time ratio of birds	0.45** (184)

Except for class 3, the models are less good to predict sound quality without visual amenity. The most important decrease is observed for the class 1 where coefficient changes from 0.51 to 0.28.

In all models, we observe the presence of the “Global loudness” variable (quiet/loud) with an important coefficient which is always negative, that is to say, the louder the sound, the less pleasant the sound quality. The global loudness is the most important variable for all models, except for the class 5 which gathers the parks. For this group, loudness of cars has the most important coefficient. The positive impact of the “No envelopment” variable is difficult to interpret. A dedicated questionnaire has been sent to participants in order to better understand how they answered this specific question on “Envelopment” (see section 5.2)

The variables involved in models are different according to the locations or periods of measurements. Only the models of class 3 and 6 are relatively close in term of variables and coefficients. Actually, the difference lies only on the type of sources (footsteps for one and birds for the other). This result is not surprising given that the class 3 and the class 6 are not typical urban location where class 3 is animated (with human presence) whereas class 6 is not.

Finally, among the different variables, only the coefficient of familiarity is sometimes negative and sometimes positive. It can be noticed that this variable does not vary so much (between 6.5 and 7.5 on the 11 point-scale)

5. Discussion

5.1 Global loudness

During the construction of models, the global loudness has often been correlated with other variables (“animation”, “loudness of cars”, “time ratio of traffic” and “time ratio of voices”). But, as the correlation coefficient between loudness and sound quality is the highest compared to its correlated variables, the global loudness was kept instead of the other variables. However, the variables correlated with this global loudness are not the same for the different classes (Table 3).

Table 3 – Correlation between global loudness and other perceptive variables

(In red, the variables assessed correlated for the model, coefficient is upper to 0.5)

Class	Animation	Loudness of cars	Time ratio of traffic	Time ratio of voices
Class 1	0.52**	0.55**	0.39**	0.20**
Class 2	0.40**	0.60**	0.54**	0.15**
Class 3	0.43**	0.43**	0.28**	0.37**
Class 4	0.53**	0.14*	0.24**	0.52**
Class 5	0.56**	0.08	0.07	0.51**
Class 6	0.45**	0.58**	0.57**	0.25**

Correlations observed in table 3 correspond to various kinds of locations of each class. So, when analyzing models, global loudness will not always have the same meaning. For a street, boulevard or place, global loudness is related to loudness of light vehicles (class 1, 2 and 6). For parks, shopping areas, etc., where human presence is important, the sound intensity is related to animation and voices (class 4 and 5). In the class 3, where all variables are medium, loudness is not correlated with any particular source variable. So a particular attention should be brought to the loudness variable when the results are crossed with perceptual data.

Table 4 presents the correlation between $L_{Aeq,\ 10\ min}$ and perceptive variables.

Table 4 – Correlations between $L_{Aeq,\ 10\ min}$ and variables

Variable	class 1	class 2	class 3	class 4	class 5	class 6
Perceived global loudness	0.43** (433)	0.37** (444)	0.41** (137)	0.31** (525)	0.32** (199)	0.31** (184)
Sound quality	-0.21** (433)	-0.30 ** (444)	-0.33** (137)	-0.17** (525)	-0.25** (199)	-0.18** (184)

We note that all correlations are significant statistically but the correlation coefficients are under our threshold of 0.5. For the perceived global loudness, this means that the equivalent level is not a very good indicator for this feeling. This has been already revealed especially for no continuous sounds. L_{A10} or L_{A5} should be further taken into account [6-8]

5.2 No envelopment

Except for the class 1, the “No envelopment” variable is in all models. In each case, the “no envelopment” coefficient is positive which means that less envelopment in the environment induces greater sound quality. This result is in contradiction with the results found by Brocolini where an environment more enveloping induced a greater sound quality [2].

To try to understand this observation, participants were asked to precise their understanding of this specific envelopment question. By observing the participants answers, it seems that a sound environment is enveloping when the background noise is louder, for example:

- “I am enveloped when I cannot distinguish different sounds separately and assign an origin and / or distance” (“Je suis enveloppé lorsque je ne peux pas distinguer divers bruits de manière distincte et leur attribuer une origine et/ou une distance”).

- " I considered the constant and dull background noise as enveloping" (“J'ai considéré un bruit de fond constant et sourd comme enveloppant”).

Envelopment seems to be linked to the background noise. When the background noise is important, the noise environment is assessed as less pleasant. In the continuation of this study, the enveloping variable could be correlated with an acoustic indicator which could make it possible to assess the background noise level such as the L_{A90} for example.

5.3 Emergent sound sources

Emergent sound sources are involved in models of classes 1, 4 and 5. In all these models, coefficients of emergent sound sources are negative. So the more emergent the noise is, the less pleasant the sound quality is.

By observing results, class 5 is very interesting because for this group, the coefficient of car loudness is the most important in the linear regression model. This class gathers individual evaluations conducted in different parks. Only two parks are not part of this group when measurements are performed during a week day: “Kellerman” and “Cité universitaire” parks. These two Parisian parks are both located along the ring road. They are correctly clustered in the class 5 for measurements carried out during the weekend when there is less traffic and more people in these parks.

So the emergence of cars seems to have an important impact on assessment of noise environment quality in parks where the streets are relatively far. Conversely in class 1 (thoroughfare, crossroad, etc.), time ratio of traffic is more important for assessments of sound quality. So these two classes are different for traffic noise. People pay attention to time ratio in class 1 locations because the noise due to the traffic is continuous and people pay attention to emergent sound of cars in class 5 locations because noise due to the traffic is perceived as events. This same observation can be conducted on classes 1 and 4, where the trucks or buses are not continuously present and where these sources are more perceived as events instead of being perceived as a continuous noise.

When continuous, the time ratio of traffic is easy to predict by using calculation of L_{DEN} [9] but what could be used to predict sound events due to cars, trucks or buses? Perhaps indictors such as the number of events over a specific threshold NNEL or the duration when sound levels exceed a certain threshold MIL could be used as noise event indicators, and could be correlated to the source emergence [10-12].

CONCLUSIONS

Through the analysis of 1934 perceptive assessments and the corresponding acoustic measurements, this work made it possible to better understand the influence of variables involved in noise quality. By classifying locations according to their perceptual features, models could be adapted to each kind of places. For streets, boulevards and crossroads two models are required: one for day periods (class 1) and one for evening or night (class 2). In both cases, the sound quality is influenced by traffic noise but during the day it is so important that it is taken into account through the global loudness (correlated to the loudness of cars) and through the time ratio of vehicle presence. In the evening or at night these two variables are correlated, so only one variable is taken into account in the models.

In the parks the traffic noise, more distant or less continuous, is taken into account with the emergence of car sounds. The presence of trucks or buses which is not continuous is involved also in class 1 and 4 models.

The models highlighted in this study show that for some locations, where the sound source is not continuous, the emergence of sound sources is important for assessing sound quality. The representation of sound in noise maps should take into account these events in order to be closer to people's perception.

Now, this study must continue in order to find an acoustic indicator which will make it possible to predict the sound quality with acoustic parameters.

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