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Acoustic mapping based on measurements: space and time interpolation

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ABSTRACT

Noise maps based on measurements gained interest during the last decade. Network monitoring systems are deployed in various cities over the world and mobile applications allowing participatory sensing are now very common. Nevertheless, the sparseness of the collected measurements, either in space or in time, complicates the production of such noise maps. A large measurement campaign has been conducted in the XIII[th] district of Paris in order to test different temporal and spatial interpolating strategies. 23 fixed monitoring stations have been deployed during eight months. In parallel, mobile measurements with backpacked stations have been collected walking in every street of the district between 1 and 15 times. The data analysis of the 23 fixed monitoring stations allowed constructing a temporal interpolation model, while the mobile measurements served to construct a spatial Kriging model. The combination of both models is explored in this paper, which enables to produce a fine cartography, both spatially and temporally, of sound levels within the district.

Keywords: Interpolation, Measurements, Noise mapping I-INCE Classification of Subjects Number(s): 76

1. INTRODUCTION

The development and harmonization of noise prediction models following the implementation of the Directive 2002/CE/49 has led to a better characterization of the sound environment of European cities (1). Noise maps are usually produced with numerical engineering methods, which offer a good compromise between accuracy and computation times (2). Nevertheless, their limitation to classical sound sources (usually road traffic, railways, aircraft and industries) neglects the diversity of urban soundscapes. As a response, noise maps based on measurements recently gained interest.

The recent development of small and autonomous acoustic sensors contributes to this movement, and network monitoring systems are now deployed in an increasing number of cities over the world, based on either high-quality or low-cost sensors (3,4). Also, smartphone applications, allowing participatory sensing, are now very common, which multiplies the amount of available data to potentially map the sound environment of a city based on measurements (5–7).

However, the time sparseness of the measurements collected through mobile monitoring networks, and the space sparseness of the measurements collected through fixed monitoring networks, complicate the production of such noise maps. Therefore, it is fundamental to know the time and space representativeness of such measurements, and it is fundamental to rely on this knowledge to propose relevant interpolation methods for elaborating sound maps over the whole time and space of the studied domain.

The strong temporal structure of urban sound levels (highly correlated day or week patterns, seasonal trends) can be used to diminish the number of sampled days (8), or to rely on measurements performed at selected periods of the day (9), in order to estimate L_{den} values or Daily Average Noise Patterns. A method under development, on which this paper relies, aims to project short term measurements performed at random periods of the day, on a targeted period (10).

The space representativeness and the spatial interpolation of the measurements is also a matter of investigation. The approach to adopt may differ from other disciplines such as air pollution where the problem is largely studied, because the space scale of variation of sound environments is very small. Maps interpolated from fixed station measurement networks have however recently been produced (11–13). These works state that they are useful to estimate how noisy the neighborhood is or for a global overview of the city sound levels. But the distance between the measurements did not permit to map finely noise levels at the street level, such as maps based on numerical methods can offer.

This paper aims to present a statistical analysis of spatial and temporal dynamics of urban sound levels, in order to highlight which of their characteristics should be included in interpolated maps. A large measurement campaign has been conducted in the XIIIth district of Paris in order to test different temporal and spatial interpolating strategies. Mobile measurements have been performed, with backpacked stations, walking in every street of the district between 1 and 15 times. Also, 23 fixed monitoring stations have been deployed during eight months. The temporal and spatial analyses are discussed and a resulting interpolation method, which combines the results from both analyses, is presented. Finally, we will present an example of an application of the method on a simulated participatory measurement campaign.

2. DATA COLLECTION

2.1 Study area

Figure 1 presents the study area, which corresponds to the XIIIth District of Paris. This district includes a large variety of urban sound environments: large avenues with high traffic density, lively streets with bars and restaurants, schools, small and large parks, quiet streets. The size of the study area is approximately 2.8 km² with a maximum extent of 2 km west to east and a maximum extent of 1.7 km north to south.

2.2 Measurement set-up

2.2.1 Apparatus

The measurements were carried out using a dedicated sound monitoring station developed by ASAsense. Instantaneous 1/3-octave band levels were recorded with a 125-ms temporal resolution, simultaneously with GPS synchronized 1-s position data. To fully capture the sound environment characteristics, a very large set of indicators has been calculated including the basic sound level indicator used in this study, the global $L_{Aeq,1s}$ in dB(A).

2.2.2 Mobile stations

The devices were mounted in a backpack for mobile measurements. Mobile measurements were performed between October 22th 2014 and May 26th 2015. Five operators participated in the measurements that were carried out on weekdays, from Monday to Friday. In order to measure homogeneous sound environments, the measurements were done only from 10 a.m. to 12 a.m. and from 2 p.m. to 4 p.m. According to the variability of the sound environment, a different number of walks has been done in each street. For example, the sound environment of a calm street is more sensitive to particular events than a large boulevard, and will require several passages to record a representative sound level. After each day of measurements, the variance of the sound level was computed, and then provided feedback on which streets more measurements would be advantageous to get a stable estimate. Between 1 and 15 passages were done in each street.

A GPS track was recorded along with the measurements. Nevertheless, the resolution of the GPS depends on many factors such as the quality of the GPS receiver, the position of the GPS satellites at the time the data was recorded, the characteristics of the surroundings or the weather. In this study, the median standard deviation associated to our GPS localizations was about 10 meters. All the GPS signals are snapped to the center of the closest street under the condition that the operator walked at 5 km/h maximum and that the map-matched point conserves the direction of displacement (with a tolerance degree of 60°) within the original signal. As a consequence, all the measurement points were finally located on the roads network. This approximation is justified because mobile measurements were only performed on sidewalks. The road network is provided by OpenStreetMap (14).

To realize a spatial interpolation between measurements, the first necessary step is to aggregate all measurements witin a radius *r* onto road segments (represented by a their middle point), thus associating a representative sound level value to each road segment. The resulting median sound level in dB(A) ($\hat{L}_{A50}$) has been chosen as the aggregated indicator in this study. This indicator, well correlated to the perceived loudness of the urban sound environment, also presents the advantage to be less sensitive than the standard L_{Aeq} to peak values associated with sound events that are exceptionally generated by the operators (15).

The variation within each road segment due to the limited number of measurements shall be significantly smaller than the global variation between the levels associated with all road segments within the study area. Using a bootstrap method, it was estimated that if we consider an acceptable standard deviation inferior to 1 dB(A), this requires a minimum aggregation radius of 25 meters and a sample composed by a minimum of 180 1-s measurements. These thresholds still guarantee to have enough data to realize the spatial analysis (4360 road segments). In this study, we assume that the variance due to the metrology and due to the variability of the sound level is not included.

Figure 1 presents the resulting reference map of the sound levels ($\hat{L}_{A50,[10\text{-}12h,14\text{-}16h]}$). The average length of each road segment is about 9.5 meters.

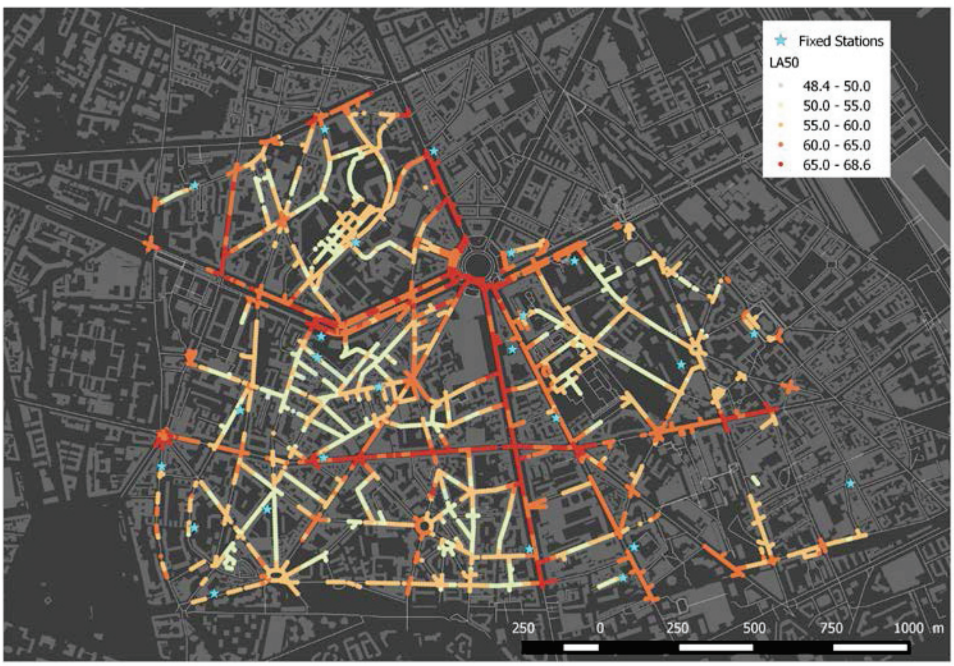


Figure 1 – Reference sound map of the $\hat{L}_{A50,[10\text{-}12h,14\text{-}16h]}$ and location of the 23 fixed stations (stars).

2.2.3 Fixed stations

Noise data collection was performed using 23 long-term monitoring stations, during 8 months lasting approximately from July 2014 to February 2015. The stations cover different road traffic and morphologic configurations, with low to high traffic volumes, pedestrian streets, and points near parks. Figure 1 presents the location of the 23 stations. The $L_{Aeq,1s}$ time series obtained enables the calculation of a wide range of derived indicators. The selected base indicator for this study is the $L_{A50,1h}$ evolution.

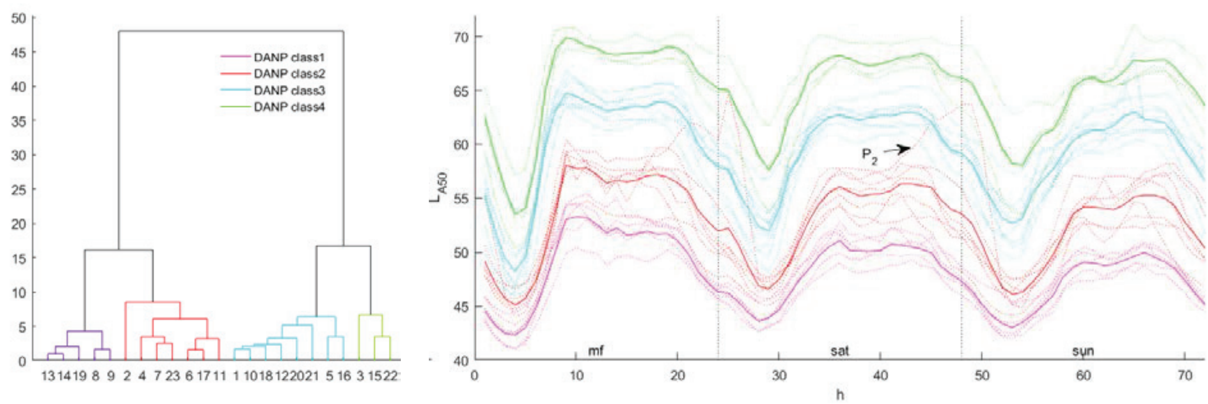
3. TEMPORAL INTERPOLATION

3.1 Statistical analysis

The objective of the temporal interpolation is to deduce from the short-term measurements an estimate of long-term noise indicators. Based on previous works (10,16), we focus on the day-to-day repeatability of sound levels. A Daily Average Noise Pattern $\mathrm{DANP}_{i,s}$ is calculated at each fixed station s, where i stands for the day-of-the-week, $i=\{mf;\ sat;\ sun\}$. Three typical days-of-the-week are considered: “Monday-to-Friday” (*mf*), “Saturday” (*sat*) and “Sunday” (*sun*), which are known to show different temporal trends in the sound level. The $\hat{L}_{50,\mathrm{day}}$, is calculated in addition as the indicator to estimate and represent: it is derived from the estimated DANP and simply corresponds to the arithmetical average of the $\hat{L}_{\mathrm{A50}}$ values that form the DANP, for period [6-18h]. These are the targeted indicators that one aims to estimate locally and then interpolate spatially.

The presented temporal analysis focuses on $\hat{L}_{A50,[1h]}$values. It aims to deduce from measurements performed at a given period an estimate of L_{A50} values at any other period of interest. This section highlights the temporal characteristics of sound levels. More specifically, a statistical analysis of the 8 months of collected data at the 23 stations is performed, with the aim to underline the specificities of the urban sound environments that must be taken into account for temporal sound level interpolation.

Figure 2 (a) represents the DANP at the 23 stations, highlighting the large range of sound levels in the area, which have 20 dB(A) range between the noisiest point and the quietest one. This shows the large variety of the encountered urban sound environments even at a small spatial scale. Despite this large range in sound levels, the DANP are highly correlated, suggesting the possibility to dissociate the temporal and the spatial interpolations in the modelling. From our data set, classes of stations seem to emerge. An agglomerative hierarchical cluster tree that uses the Ward method is thus performed. The hierarchical clustering forms the classes illustrated by the dendrogram in Figure 2 (b). The stations within each of the 4 classes share both similar sound level values and similar temporal dynamics. The use of these classes is for now restrained to this case study, but the classes and patterns could easily be generalized through measurements in other cities and urban contexts. Note finally the specific sound level evolution at the point P_2, which is classified within the class 2 but is poorly correlated to the other sound level patterns of the class. This poor correlation, which explains why the station P_2 constitutes its own subclass in the dendrogram, is caused by the high evening sound levels at this location, which is in “La Butte aux Cailles”, a street with pubs and restaurants.



(a) (b)

Figure 2 – (a) Dendrogram of the 23 stations: the classification distinguishes 4 classes. (b) DANP of the 4 classes of the 23 stations (in dots).

3.2 Interpolation

The repeatability of the DANP at each monitoring station suggests the possibility to estimate the $\mathrm{DANP}_{i,s}$ based on samplings of a few $L_{\mathrm{A50,[h1\text{-}h2]}}$ values at s, assuming that a measurement achieved for instance during the period [11-12h] informs about the sound levels that can be expected during the period [16-17h]. Therefore, 9 matrices $\delta_{i1,i2}$ are determined for each of the 4 classes, with i_1 and $i_2=\{mf,sat,sun\}$, and each of its elements $\delta_{i1,i2}(h_1,h_2)$ containing the estimated delta value $\delta_{i1,i2}\,(h_1,h_2) = L_{\mathrm{A50},h1,i1}\text{-}L_{\mathrm{A50},h2,i2},$ with h_i an elementary period. In addition, these delta matrices are associated with a given uncertainty, expecting that a L_{A50} value collected for instance on a Monday-to-Friday during the period [10-11h] tells more about the sound levels on a Monday-to-Friday day at [9-10h] than on a Sunday during the period [15-16h].

To account for this uncertainty, each of the nine matrices $\delta_{i1,i2}$ is associated with a matrix $\sigma_{i1,i2}$ that encodes the standard deviation associated to the δ values. In this study, the δ and σ matrices correspond respectively to the differences and standard deviations of the differences in the $\hat{L}_{50,1h}$ values $\hat{L}_{50,h1,i1} - \hat{L}_{50,h2,i2}$, calculated among the 8 months of data, for the samples of couples $\{i_1, h_1\}$ and $\{i_2, h_2\}$.

Since this study is limited to measurements obtained during the periods [10-12h ; 14-16h] from Monday-to-Friday, where sound levels are rather stable, the delta values are limited to *i={mf},* and only one time period [10-12h;14-16h] is considered. The δ and standard deviation σ matrices that result for the 4 classes are illustrated in Figure 3. The figure shows that δ values are negative for almost all periods, since the period [10-12h;14-16h] corresponds to noisy hours of the day. Moreover, the δ values vary from one class to another, both in global values and amplitudes. For example, night to day noise levels amplitude is lower for the noisiest noise stations.

The standard deviation matrices express the confidence in the data interpolated temporally, which will serve to determine the global confidence in the produced sound level maps. The standard deviations averaged over the pattern evolve between 1.2 to 1.5 dB for classes 1, 3 and 4 (see Figure 3). Standard deviations are higher for class 2, mainly because of the high evening sound levels at station P_2. Finally, standard deviations rise for night periods: as expected, measurements achieved during the [10-12h;14-16h] inform with a lower confidence about night noise levels than about day noise levels. These low standard deviations originate from the high correlations between noise patterns within each class.

Then, the δ matrices can then be used on the mobile measurement campaigns, as described in Section 2, for estimating the DANPs at any location, although not all time periods are covered by measurements. We focus in this study on the δ matrixes for the [10h-12h;14h-16h] period, but the same interpolations could be proposed for measurements performed at various times of the day.

In practice, the temporal interpolation follows the following steps. First, the class to which the point belongs to is defined based on the mobile measurements. The distance to each class is calculated as the difference in L_{A50} between the measurements and the DANP at the same period. The smaller distance defines the class. For instance, L_{A50} values of about 70 dB(A) measured in the period [10-11h] will classify the point within class 4 (in green in Figure 3). Then, the δ matrix of the corresponding class is used to define the DANP at the point, associated to the standard deviation $\sigma_{temporal}$ (the green ones in Figure 3 the given example). Finally, a global indicator as the $L_{50,day}$ with its associated uncertainty can be calculated.

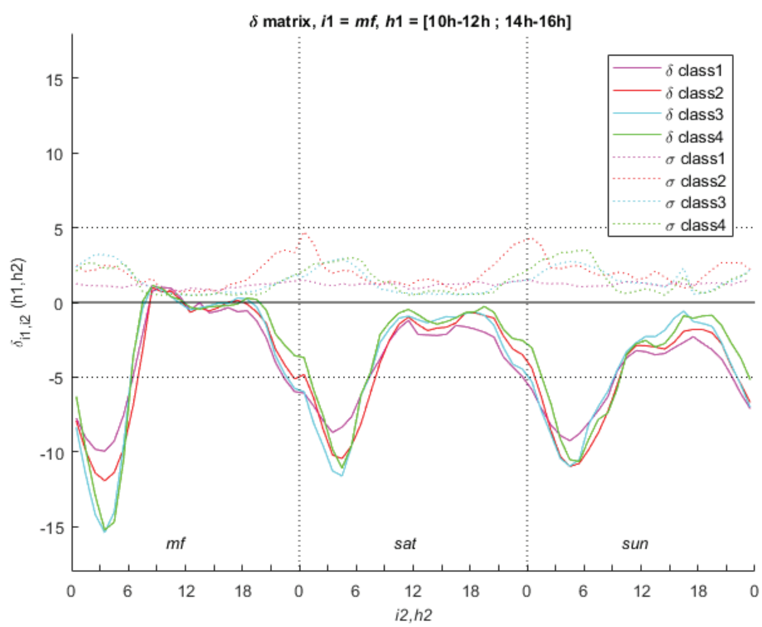


Figure 3 – Example of δi1,i2 (h1, h2) values with h1=[10-12h,14-16h] and h2 corresponds to the 72-hour periods.

4. SPATIAL INTERPOLATION

4.1 Statistical analysis

A spatial statistical analysis is performed on the data collected by the mobile stations. The objective is to investigate the potential of a spatial interpolation of acoustics measurements, and its parameters.

The variogram and Kriging algorithms presented in this study are computed using the functions variog (computation of the variogram), variofit (best fit of the variogram) and krige.conv (Kriging function) of the package GeoR (17). The variogram is computed over a distance of 1000 meters with a modulus estimator. The Matérn model is used to compute the best fit for the variogram.

Two Kriging methods are compared: ordinary Kriging (OK) and universal Kriging (UK). Universal Kriging is a variant of the Ordinary Kriging operation that includes a local trend. In this study, a linear trend is defined from four variables. The four variables is defined as the distance between the targeted road segment and the closest road that belongs to one of the four categories. The road categories have been defined from the OpenStreetMap attributes as shown on Figure 4.

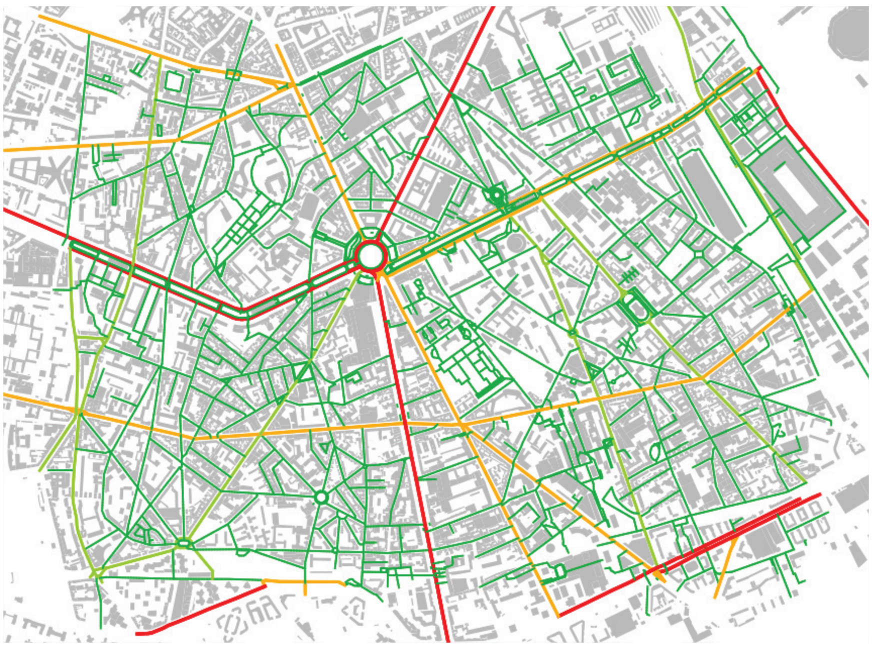


Figure 4 –Road categories (4 colors) based on OpenStreetMap data.

The spatial dependence of the data is highlighted through the calculation of variograms, which express the semi-variance between $\hat{L}_{A50}$ values for a couple of locations according to their distance. On Figure 5, two fitted variograms from the reference sound map are presented, which correspond to (a) an Ordinary variogram (OK), (b) a Universal variogram that accounts for the trend (UK).

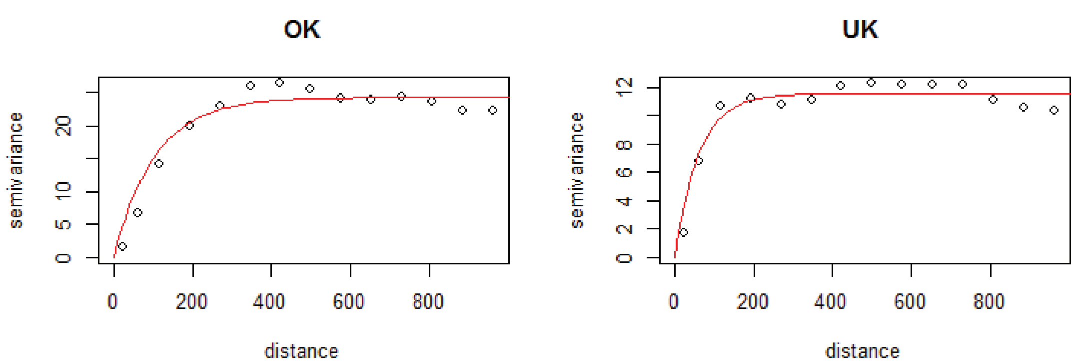


Figure 5 – Empirical variograms (dots) and best fitted parametrical models (red line) computed using the Ordinary Kriging (OK) or Universal Kriging (UK) methods (distance in meters, and semivariance in dB(A).

The parameters of the best fitted covariance models are presented in Table 1. The practical ranges of the variograms, defined as the value for which the correlation function decays to 5% of its value at 0, are (a) 312 m for OK (b) 182 m for UK. Also, no information is given by an observation to an estimated value located at a distance superior to approximatively 250 m, except by the trend for the UK method. The semi variance at 1000 meters is approximately 25 dB for OK method, and approximately 10 dB for UK. Thus, adding the trend, defined in Section 2, permits to reduce significantly the semi variance of the variograms and illustrates the strong correlation between the urban sound levels and the proximity to different type of roads. To conclude, the Universal Kriging should be the preferred method to interpolate the L_{A50} values.

Table 1 – Parameters of the Kriging methods

Kriging method	Covariance model	τ	σ	φ
OK	Matérn with fixed κ = 0.5	0.0	24.3	104.2
UK	Matérn with fixed κ = 0.5	0.0	11.57	60.9

4.2 Interpolation

The optimized Kriging parameters (see Table 1) can be used to interpolate the $\hat{L}_{A50,[10\text{-}12h,14\text{-}16h]}$ measurements over the domain. The associated variance $\sigma_{spatial}$ computed by the Kriging algorithm informs about the uncertainty associated to the estimated values.

5. APPLICATION TO A PARTICIPATIVE CAMPAIGN

5.1 Method

A participative campaign is simulated from the dataset. Twelve small areas have been selected as if only for these areas, $\hat{L}_{A50,[10\text{-}12,14\text{-}16h]}$ values were available from mobile measurements. Figure 6 presents the step-by-step method to interpolate in space and time the observations. The method can be divided in 5 steps from the $L_{eq,1s}$ measurements to the representation of the $\hat{L}_{A50,day}$ over the map. For the spatial interpolation, Universal Kriging method with the parameters extracted from Section 4 is used. The $\hat{L}_{A50,day}$ computation is carried out on the basis of the δ matrices calculated from the statistical analysis. Interestingly, the global method presented in this paper gives insight about the variance associated to each interpolation step. Also, the variance due to the spatial interpolation can be combined with the variance due to the temporal interpolation to have information about the level of confidence of the final estimated value as presented, for example, in Table 2.

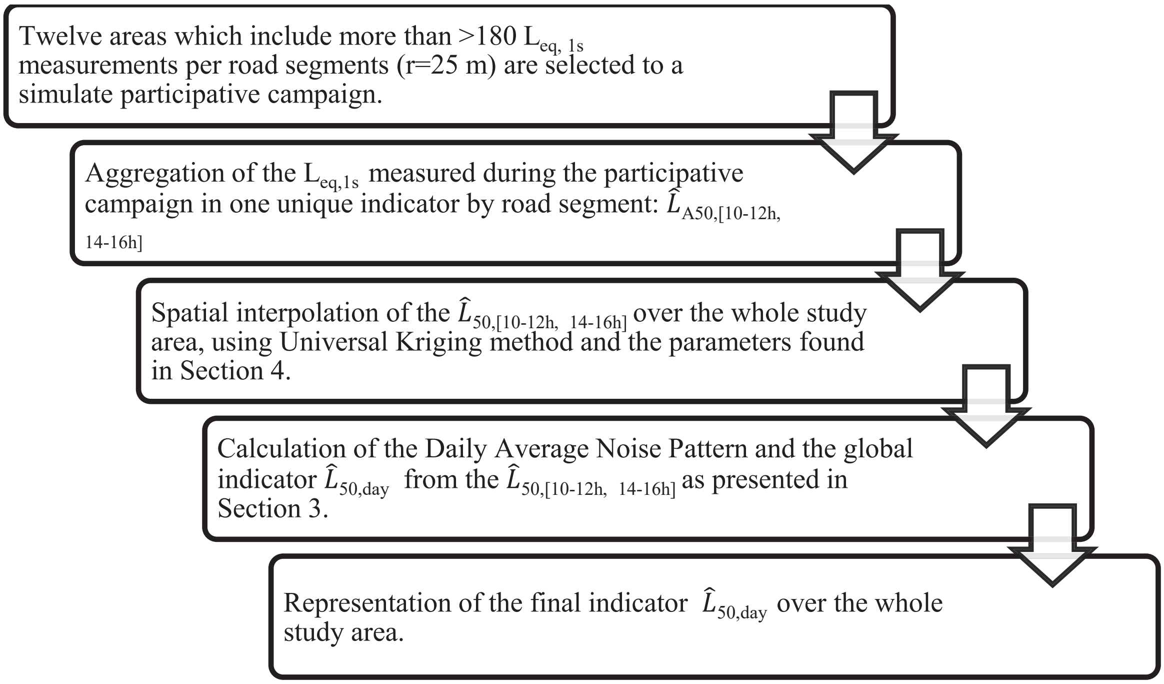


Figure 6 – Step-by-step method to compute the final sound level map from the $L_{Aeq,1s}$ measurements.

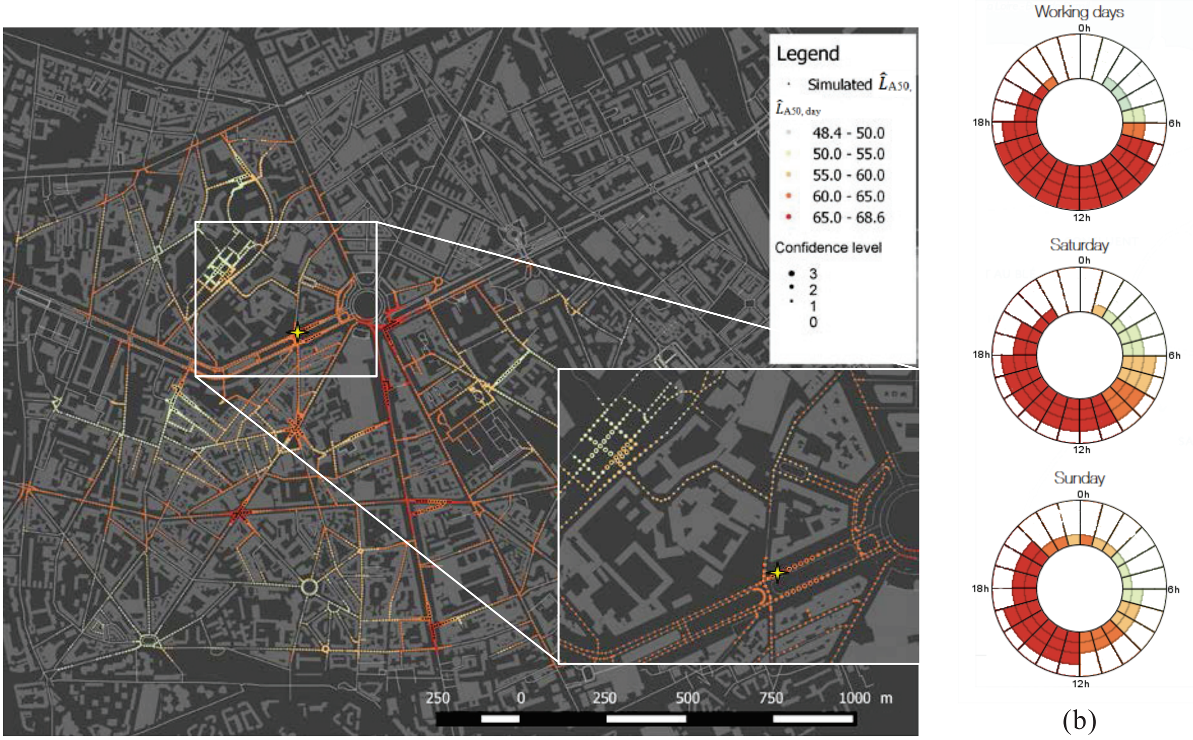
5.2 Visual representation

Figure 7 shows a representation of the results. The black dots represent the selected road segments for which observations were available. On the map, the sound level values are associated to a color as it is usually done in standard noise maps. The size of the dots represents the confidence over the measurements and is associated to their estimated variance. The level of confidence is defined as presented in Table 2. Finally, the right part of the figure represents the variation of the sound level of the Daily Average Noise Pattern statistically estimated. The level of confidence is represented by the size of the colored circles. The combination of both models explored in this paper enables producing cartography, both spatially and temporally, of sound levels within the district. The representation of the uncertainty gives information about the quality of the values shown, which can be useful, for example, to determine those areas that should be measured in priority.

Table 2 – Definition and representation of the confidence level from variance information

Confidence level	$\sqrt{(\sigma^2_{spatial} + \sigma^2_{temporal})}$	Dots size
0/3	> 6 dB	0 mm
1/3	3 dB	0.5 mm
2/3	1.5 dB	1 mm
3/3	< 0.5 dB	1.5 mm

Note that the visualized uncertainty is the one due to the interpolation method. It does not consider the uncertainty due to the sound level variations, or the metrological errors, which can be important. If known, these uncertainties could be added afterwards, or integrated through another data fusion method.



(b)

(a)

Figure 7 – (a) Interpolated $\hat{L}_{A50,\,day}$ sound levels map. The dots size represents the confidence level and the small black dots represent the location of the $\hat{L}_{A50,\,[10\text{-}12h,\ 14\text{-}16h]}$ available from simulated mobile measurements. (b) Daily Average Noise Pattern statistically estimated at the location symbolized by the yellow star, and the associated level of confidence.

6. DISCUSSION

One limitation of the temporal analysis consists of the limited set of 23 observed sound environments using the fixed monitoring stations. The domain of validity of the proposed models is restrained to the variety of the observed sound environments. However, the similarities between the temporal trends in the sound level are probably high between cities, making it a priori possible to use the dataset for other cities. Comparisons between measurement campaigns in various cities are nevertheless required to test this hypothesis. In addition, the constituted database is meant to be enriched in the future with any new long-term measurement associated with the proposed statistical analysis, including measurements collected in other cities. One expects that monitoring stations at locations with similar morphologies or traffic situations but from different cities will prove useful to apply the proposed methodology at new locations.

Also, the temporal analysis disregards the metrological errors and the errors linked to the shortness of the samples. Results from the literature show that a period of 10-15 min of measurements is sufficient to represent a homogeneous period for describing sound environments (18). However further analyses are required to extend these results to several amounts of 1 to 3 min periods, as provided by our experimental set-up. In addition, to this uncertainty must be added the variability due to the $L_{50,[x]}$ from one day to the other. For instance, in our dataset, the $\hat{L}_{A50,[10-11h]}$ is the average of the $L_{A50,[10\text{-}11h]}$ values with a standard deviation of 3 dB(A).

Furthermore, the measure of similarity included in the model to classify our data, which simply relies on a calculation of global distance between L_{A50} observations and classified DANP, could be based on similarity evaluations that call for both relevance and redundancy metrics. Specific outlier detection algorithms could be designed, to exclude abnormal measured L_{A50} values. The difficulty then stands in the need to exclude default measures but still capturing the specificities in noise level evolution (periods with atypical sound levels). Also, the classification of the observation locations could be done thanks to prior noise maps of the study area.

One limitation of the spatial method is that the Kriging method used does not associate an error vector to the observations. For example, different uncertainties should be associated to L_{A50} values based on 10 minutes $L_{Aeq,1s}$ instead of L_{A50} values based on 3 minutes $L_{Aeq,1s}$. In the same way, the metrological errors are neglected in this study but should be integrated.

Universal Kriging shows a much better approach than Ordinary Kriging, given that preliminary information about the network has a very strong impact on the results, dividing the resulting variance by a factor of 2. The use of prior noise simulation results to assimilate with the measurements is probably a good method to have strongly correlated sound level maps with the in situ observations. Assimilation methods as used in meteorology (e.g. 3D-Var) permit to do so and also to take into account the observational errors. Finally, as proposed in (19), a model-based approach could be used, where source powers and propagation attenuations are hereby corrected through a small adjusted offset.

Finally, space and time variations are considered fully uncorrelated in this paper, which is probably not always the case. For example, the fitted parameters of the variogram could potentially be different between day and night time. A much larger measurement campaign, integrating night and day mobile measurements, or a much more dense fixed station network, are needed to investigate this hypothesis.

7. CONCLUSIONS

This study presents a method to interpolate, both in space and in time, sparse sound level measurements and its application to a simulated participative campaign. It also shows the interest of the method for visual representation of the sound levels of an urban sound environment. Based on a statistical analysis of the data from a large measurement campaign using mobile sound level meters, it is shown that the practical range of a spatial interpolation using Kriging method is not over 300 meters, and that the variance could be significantly reduced using an a priori based on a road network classification. A temporal interpolation is also proposed based on a statistical analysis of 23 fixed stations during 8 months. The study confirms the strong temporal repeatability over the week already observed in previous studies and proposes a method to use the observations obtained during one specific period to deduce the sound level of the Daily Average Noise Pattern.

In the future, the focus of research should be oriented toward other data fusion methods which permit to combine measurements and noise simulations taking into account the uncertainties linked to the observations.

Finally, the methodology presented in this paper could be applied to other sound indicators bringing complementary information to the sound level as sound variation indicators, or sound sources indicators (15).

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