Measurement network for urban noise assessment: comparison of mobile measurements and spatial interpolation approaches

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Abstract

This paper investigates the relevance of different interpolation techniques to improve the spatial resolution of urban noise maps, in complement to measurements achieved at fixed stations. Interpolation techniques based on mobile measurements are compared to usual spatial interpolations techniques, namely Inverse Distance Weighting and Kriging. The analyses rely on a measurement campaign, which consisted of nearly 8 hours of geo-referenced mobile noise measurements performed at random moments of the day, conducted simultaneously with continuous measurements collected at five fixed stations located on the inner city of Gent, Belgium.

Firstly, a procedure is proposed to build a noise map with a high spatial resolution (one point every 5m). The procedure relies on both mobile and fixed measurements: the mobile

measurements are used to capture spatial variations on the network, and the measurements at fixed stations are used to capture the temporal variations. The map produced is then used as reference to compare the interpolation techniques based on a significantly more sparse measurement set.

The spatial interpolation techniques tested fail in predicting accurately the noise level variations within streets. The explanation given is that they do not offer a sufficient covering of the network, and assume spatial variations which are not coherent with traffic dynamics or street configurations. Inversely, mobile measurements cover the entire network. As a result, they allow a more accurate prediction of noise levels even if very short samples are used, provided that the procedure used to estimate noise levels includes a spatial aggregation, which aims at smoothing the high spatial variations inevitable with short samples. Moreover, mobile measurements can advantageously be used to optimize, through a genetic algorithm, the locations where to install fixed stations, promising an efficient noise monitoring at reduced operational costs.

1. Introduction

The strong recent urbanization and the increasing demand of city dwellers for a better quality of life have led to the development of policies towards sustainable cities. A consequence in regards to noise is the enactment of the European Noise Directive, which made mandatory strategic noise maps for cities with more than 100 000 habitants [1]. Those maps play an important informative role, pointing black points and quiet zones; this information has for example a significant impact on the property market [2]. They can also be a powerful tool for comparing the impact of different noise reduction strategies [3][4], provided that a special care is given during the traffic modelling step [5][6][7].

Although the Directive leaves some liberty concerning the methods to produce noise maps, modelling based on traffic data collection and sound propagation calculation is the most widespread technique [8]. Noise contour maps with grid spacing of less than 10 m are then recommended in urban areas [8]. Spatial interpolation techniques can be used to determine noise levels with a greater resolution than the initial grid of results [9][10]. It has been shown however that this step can yield uncertainties, especially if maps are built based on wide initial grids [11].

Beyond their known advantages, modelling based on traffic data collection and sound propagation calculation has the disadvantage of needing some prior data collection and network acquisition steps that are long and costly. Moreover the estimation of noise levels within shielded streets requires time consuming sound propagation calculations [12][13]. Finally, some discrepancies can be observed between modelled maps, which mainly focus on road traffic noise, and measurements, which capture all kinds of noise sources [14].

Measurement is thus necessary to complement these models and calibrate noise maps [15][16][17]. Then measurement durations can be reduced by combining different sampling spans, either made of long-term (complete days [18][19]) or short-term (few minutes [20][21]) measurements. Spatial interpolations can afterwards be performed to assess noise levels between sensors; this last step also influences the accuracy of the noise maps obtained [22][23]. Another possibility offered by noise monitoring networks is their integration into wider heterogeneous monitoring networks, using their expected correlation with other traffic or pollutant parameters to reduce monitoring costs [24][25][26].

More advanced, the recent technological improvements, such as low-cost noise sensors [27] or mobile phones equipped with Global Positioning Systems (GPS) [28][29], open the possibility for dynamic noise monitoring relying directly on measurements. Measurements given by mobile phones can be accurate enough to fulfil the noise mapping requirements through participatory sensing [30]. Interestingly, the maps obtained could also help city dwellers to act directly on their exposure during soft mode displacements, by choosing low-exposure route options [31].

However, beyond the technological issues, some related statistical questions are arising, to guaranty a sufficient accuracy to those maps and optimise their spatial resolution-to-cost ratio. First elements of response can be found in [32][33], which showed how mobile measurements should be operated and processed, and in [34], which showed how temporary and fixed noise stations can be combined to estimate daily noise patterns.

The contribution of this paper is to test the benefits of combining measurements at fixed stations and interpolation techniques to estimate noise maps with a high spatial resolution. Interpolation techniques based on mobile measurements are compared to classical spatial interpolation techniques. Mobile data have been collected on a bicycle equipped with a GPS, in an area of Gent (Belgium). The 1-s evolution of sound pressure levels was measured. In addition, 5 monitoring fixed stations continuously measuring noise levels were placed at building facades. Interpolation techniques have been compared on their ability to estimate a selected set of noise indicators, the reference being the noise map built with the totality of the collected data.

Section 2 describes the experiment and the procedure followed to build the reference noise map. In section 3, the potential of spatial interpolation techniques, namely the Inverse Distance Weighting (IDW) and the Kriging techniques, for improving the spatial resolution of noise maps, is evaluated. Results are compared in section 4 with the estimations obtained with short term mobile measurements corrected with measurements collected at fixed stations. In section 5, the possibility to rely on mobile measurements to optimise the location of fixed stations, thanks to a Genetic Algorithm, is evaluated. Finally, the conclusion lists some recommendations and the further investigations needed to improve measurement-based noise mapping.

2. Methodology

2.1. Site description and instrumentation

The experimentation consisted of a mobile measurements campaign, combined with simultaneous measurements at 5 fixed stations. The objective of this combination is to benefit from both measuring approaches: the mobile measurements can potentially capture the spatial noise variations along the network, while measurements at fixed stations can capture the temporal variations and determine overall noise levels. The procedure proposed is described in section 2.2.

Measurements were conducted between 04/04/2011 and 18/05/2011, in a few neighbouring streets, covering 0.2 km² of the inner city of Gent, Belgium. Each mobile measurement consisted of a bicycle ride of approximately 20 minutes in the zone considered, performed at a random time of the day. The operator was equipped with a GPS and a microphone synchronized, collecting the 1s-evolution of positions and the 1s A-weighted sound pressure levels $L_{\mathrm{Aeq,1s}}$, respectively. The Noise Level Meter used was a Type 1 Svantek 959®, protected by a waterproof windscreen, and calibrated on regular intervals using a Svantek SV 30 A acoustic calibrator. The Noise Level Meter was in a backpack, carried by the operator while cycling, and installed so that it was pointing upward, at the back of the bicyclist's head, less than 30 cm from the bicyclist's ears (see Figure 1a). The bicycle speed was on average lower than 5m/s as it was constrained by urban traffic. This guarantees that wind-induced noise did not perturb measurements, as environmental noise measurements are valid without any adjustment until this speed in the range of the noise levels measured according to standards [36]. Moreover, the bicycle was maintained with care, to limit the parasite noise generated by the bicycle itself, as recommended in [33]. Note that spectral evaluations could improve further operational use of mobile noise measurements as shown recently in [32], but this was out the scope of this paper.

A total amount of 7 h 51 min of data have been collected, resulting in a set of 28260 elements of $\{t, x(t), y(t), L_{\mathrm{Aeq,1s}}(t)\}$ values. Note that the zone was unevenly covered by the experiment, as the rides followed random paths; the influence of this is discussed further in the paper.

Additionally, 5 microphones were placed at the facades of some buildings of the network, at heights between 3 and 5 m, measuring continuously the $L_{\mathrm{Aeq,1s}}$ evolution during the whole mobile measurements period. A detailed description of the noise measurement set up can be found in [27]. Two microphones were closely located near a crossing of the Doornzelestraat and the Sleepstraat, and one microphone was located in the middle of Sleepstraat; see their exact location in Figure 2. Doornzelestraat and Sleepstraat are two busy 2-lane streets, with traffic flow rates that amount for light vehicles to about 4200 and 5800 Average Annual Daily Traffic for week days including holidays, respectively. Doornzelestraat is characterized by many bus passages and Sleepstraat is characterized by many tram passages in both directions. Two microphones were placed in calmer streets; one in the Bomastraat, where the traffic intensity is much lower, and one in Nieuwland, which is a one-way street mainly carrying local traffic and is the calmest street of the zone.

a) b)

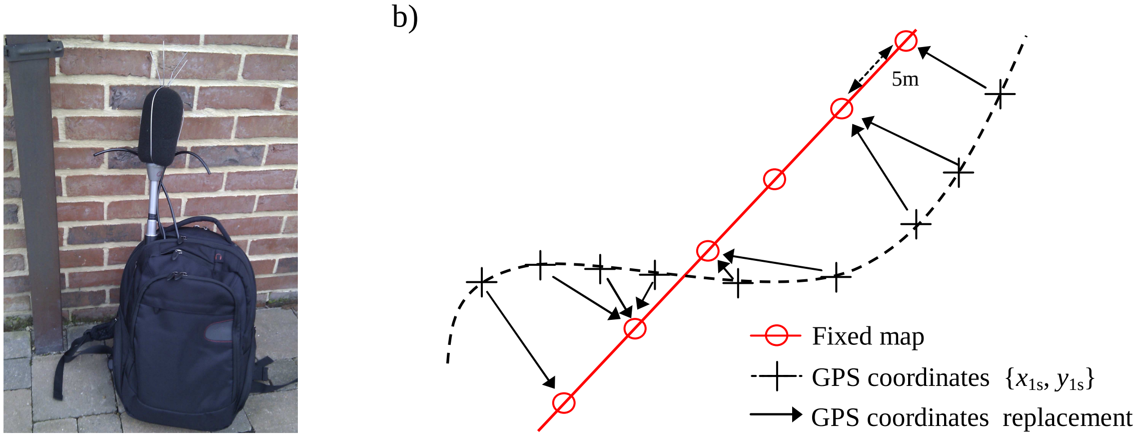

Figure 1. a) Operational set-up; b) Mapping into a fixed grid

2.2. Reference noise map

A high spatial-resolution noise map has been built with the complete set of mobile data, combined with the data collected at the 5 fixed stations. It will be used as reference for testing the interpolation techniques. The procedure to build the reference map, validated in [31], is described below and contains three steps.

a) Mapping into a fixed grid

Positions given by the GPS are mapped into a fixed map of 662 points $p = \{x_p, y_p\}$, with p={1…662}, following the road network with a 5m-resolution; see Figure 1b. In practice, each of the 28260 coordinates $\{x(t), y(t)\}$ collected on the bicycle is replaced by the coordinates of the closest point of the fixed map. Then, the 28260 elements of $\{t, x(t), y(t), L_{Aeq,1s}(t)\}$ values are subdivided into 662 samples s_p. Each sample s_p gathers the moments when the bicycle passed by p, that is the elements such as $\{x(t), y(t)\} = \{x_p, y_p\}$. It covers several pass-bys, each of a few seconds duration. For example, if the bicycle was constantly evolving at the speed of 5m/s, each pass-by through one given point p would last 1s, since points are separated by 5 meters. On average 28260/662=43 elements of $\{t, L_{\mathrm{Aeq,1s}}(t)\}$ values are collected for each of the 662 points p of the fixed map.

b) Reduction of spatial variations

The set of mobile data collected offers potentially rich spatial information. However, the short term sampling inherent to mobile measurements results in a strong variability in the data collected. The average of the 662 standard deviations $\sigma(s_p)$ of the $L_{\mathrm{Aeq,1s}}$ values collected for each sample s_p amounts to 4.5dB(A). This variability has three causes: (i) the small duration of each passing by at a given point (only a few seconds) that makes samples sensitive to the dynamics of traffic (one vehicle in the vicinity of the bicycle or not), (ii) the small amount of passing-bys (43s of sampling on average per point p in this study), (iii) the heterogeneity in the sampling instants, that may fall during noisy or less noisy moments of the day. To reduce this variability, each of the 28260 $L_{\mathrm{Aeq,1s}}(\mathrm{t})$ value collected is replaced by an acoustical average of the noise levels collected in the vicinity during the same minute. It is expected that, since the speed on the bicycle differs from the speed of motorized vehicles, this consideration of the local sound environment will reduce the influence of the distance between the bicycle and the closest motorized vehicles. The filter works in two steps: (i) the data collected during the same minute and at less than 50 m are selected (averaging only data from the same minute and at less than 50 m guarantees that the noise environment is homogeneous, (ii) an acoustical average of the selected data is achieved with a spatial Gaussian filter that has a standard deviation of σ=20m: thus data collected at a distance of 0 m and 50 m have a weight of 1 and 0.05 in the average, respectively (this gives a greater weight to data collected at a closer distance). This process smooths the short-distance spatial variations, which are sample-related. Meanwhile the influence of the road network layout on noise levels is captured (increase of noise levels in busy streets, noise variations around intersections, etc.).

c) Correction with fixed stations

However, the map produced after application of the Gaussian spatial filter is still affected by the heterogeneity within sampling instants (cause (iii)). Thus measurements at the fixed stations are used to reduce this variability, as their continuous measurements allow capturing the temporal variations of global noise levels on the network. For each point *p*, the acoustical average $L_{\mathrm{5m,p}}^{s_{\mathrm{p}}}$ of the $L_{\mathrm{Aeq,1s}}$ values collected at *p* during s_p, is calculated. Similarly, for each period s_p the average over the time interval of $L_{\mathrm{FS}}^{s_{\mathrm{p}}}$ at each of the five fixed stations are calculated. The possibility to rely on the relationship between $L_{\mathrm{5m,p}}^{s_{\mathrm{p}}}$ and the $L_{\mathrm{FS}}^{s_{\mathrm{p}}}$ value at the fixed station closest to *p* to account for temporal variations has been tested, but the pass-bys were then too short to extract relevant relationships between $L_{\mathrm{5m,p}}^{s_{\mathrm{p}}}$ and $L_{\mathrm{FS}}^{s_{\mathrm{p}}}$. Instead, it has been chosen to average for each s_p the 5 $L_{\mathrm{FS}}^{s_{\mathrm{p}}}$ values to give $L_{\overline{\mathrm{FS}}}^{s_{\mathrm{p}}}$. This choice is supported by a recent study which showed that spatial correlations between noise levels collected over the zone are high [34]. $L_{\overline{\mathrm{FS}}}^{s_{\mathrm{p}}}$ values vary within a range of 5 dB(A), depending on whether s_p falls during a noisy or less noisy moment of the day. Hence the difference $d_{\mathrm{5m,p}}^{s_{\mathrm{p}}} = L_{\mathrm{5m,p}}^{s_{\mathrm{p}}} - L_{\overline{\mathrm{FS}}}^{s_{\mathrm{p}}}$ is calculated. It highlights whether *p* is a noisy location or not, independently of the sampling period. Moreover it highlights the fact that noise levels are generally more important on the road than on the facades. $d_{\mathrm{5m,p}}^{s_{\mathrm{p}}}$ varies from -12.1 to 12.1 dB(A) on the network. Finally, as one is interested here in noise levels along the road, the noise level $L_{\mathrm{5m,p}}^{S}$ at *p* during the whole period S of the experiment ($S = \bigcup_{p=1:662} s_p$) is determined with: $L_{\mathrm{5m,p}}^{S} = d_{\mathrm{5m,p}}^{s_p} + L_{\overline{\mathrm{FS}}}^{S}$. Note that L_{den} values or daily average noise patterns could be estimated with the same procedure, as the 5 fixed stations collect continuous measurements.

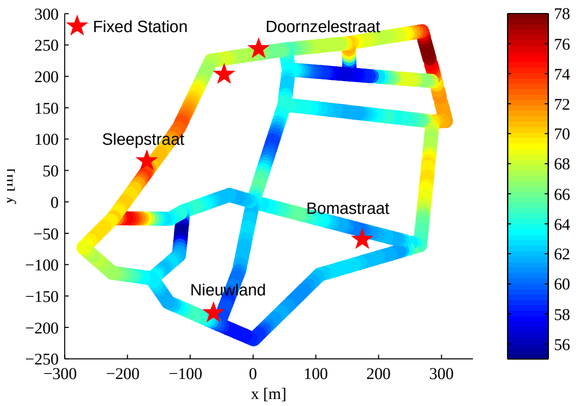

Figure 2. **Reference noise map, obtained with the totality of measurements**

The reference noise map thus obtained highlights the difference in noise levels between busy streets and inner roads. The map underlines noise variations within streets as well, which are due to the street configuration and the distance to intersections. This is proved by calculating the standard deviation of noise levels estimated for a sample of points located in the vicinity (distance smaller than 20 m) of each point of the network. As expected, the average of those standard deviations amounted to 2.2 dB(A) without spatial aggregation, while it is only 0.9 dB(A) after aggregation.

However this procedure cannot be extended to a whole city, as it would require an extensive measurement set up that would be prohibitively expensive. For example, for a city of about 7.5km² like Gent, nearly 200 fixed stations and 330 hours of mobile measurements would be required to cover the whole city with the same resolution. Different techniques, implementable to alleviate the quantity of measurements required, will be compared in sections 3 and 4.

3. Limits of spatial interpolation techniques

3.1. Definitions

This section compares two spatial interpolation (SI) techniques, namely the Inverse Distance Weighted (IDW) and the Kriging (K), and determines their limitations for implementation into urban noise measurement networks. SI techniques aim at estimating continuous surfaces based on irregularly distributed data; an overview of those techniques can be found in [37]. Such techniques are adapted to the environmental monitoring context, as they permit the estimation of quantities with a high spatial resolution, unachievable through modelling or measurements. They are moreover suitable for mapping [38][39]. In the noise context, they are sometimes applied with Geographical Information Systems (GIS) [35] to determine noise map isolines [11] and refine the spatial resolution of noise maps [9][40], or be directly integrated into sound propagation calculations [41]. They have also been used to interpolate a sound quality map in [42], to estimate the exposure of citizens to noise in [43], or finally to refine a noise map extrapolated directly from a coarse measurement grid in [44]. However, it is shown in [11] that such techniques applied on an initial map too wide (100m*100m in their example) can yield to strong uncertainties, because of the high spatial noise variability.

Instead of applying SI techniques on regular grids as in the listed references, in this section Kriging and IDW interpolations are compared for different locations and numbers of fixed sensors deployed, without sound propagation calculation. The aim is to determine their advantages and limitations for implementation into measurement networks.

$M \leq 5$ fixed stations (FS) are placed randomly on the network. As the noise maps calculated depend on this random choice, the procedure is repeated over several replications r, and the quality of the maps produced is evaluated over the whole set of replications (see section 3.2). Each station $m_{i,r}$, with $1 \leq i \leq M$, is picked as one of the 662 points of the reference map. Noise levels are supposed to be known at $m_{i,r}$ and equal the noise level of the reference map at this point. Two strategies are compared for locating fixed stations:

- In the “random strategy” mentioned further as SI_{rd}, with SI={IDW,K}, the fixed stations are placed randomly on the network, but with at least 100 m between them;
- In the “smart strategy”, mentioned further as SI_{sm}, a prior knowledge on the network is assumed and some constraints are added to cover more smartly the network. The 1st FS is necessarily placed on Sleepstraat, which is the noisiest street. Moreover, there is at least 200 m between the three first FS, and at least 100 m between the other FS, to cover more homogeneously the network.

SI techniques are used to estimate noise levels at the 662 points *p* of the map, based on the noise levels known at the *M* sensors and the distance $D_{m,p}$ between *p* and each sensor *m*. Two definitions of $D_{m,p}$ are tested:

- The “Euclidian distance” $de_{m,p}$ is defined as: $de_{m,p} = \sqrt{(x_m - x_p)^2 + (y_m - y_p)^2}$,
- The “road network distance” $dr_{m,p}$ is the length of the shortest path, following the road network, that links *m* to *p*. This distance is introduced to avoid that a noisy street influences too much noise levels in a parallel street close but separated by buildings (this configuration gives a low $de_{m,p}$, but a high $dr_{m,p}$). The distances $dr_{m,p}$ are determined thanks to the Dijkstra’s algorithm [45]. Interpolations with $de_{m,p}$ and $dr_{m,p}$ will be further mentioned as SI_e and SI_r, respectively.

3.1.1. Inverse Distance Weighted (IDW) interpolation

IDW interpolations estimate the noise level L_p at each point *p*, as an average of the noise levels collected at the *M* fixed samples, with weights inversely proportional to the distance. Three different weighting are compared: the squared weighting IDW_{sq}, the linear weighting

IDW$_{lin}$, and the logarithmic weighting IDW$_{log}$, leading to $L_{p,IDW_{sq}} = \sum_m \frac{L_m}{D_{m,p}{}^2} \Big/ \sum_m \frac{1}{D_{m,p}{}^2}$,

$L_{p,IDW_{lin}} = \sum_m \frac{L_m}{D_{m,p}} \Big/ \sum_m \frac{1}{D_{m,p}}$ and $L_{p,IDW_{\log}} = 10\log_{10}\left(\sum_m \frac{1}{D_{m,p}} 10^{\frac{L_m}{10}} \Big/ \sum_m \frac{1}{D_{m,p}}\right)$, respectively.

3.1.2. Kriging interpolation

The spatial interpolation with Kriging aims at minimizing the variance of interpolates on the network. Details about Kriging theory can be found in [37]. The parameters used in this study are the ones commonly encountered: a spherical variogram is used, with three values of ranges tested: 100m, 250m and 500m.

3.2. Performance evaluation

The spatial interpolation techniques are compared on their ability to estimate a set of noise indicators, comparatively to the reference procedure described in section 2.2. As the techniques involve some stochastic choices in the potential locations for the fixed stations, R=25 replications are achieved over which the indicators of quality selected are averaged. These indicators are:

- RMSE$_{mean,L20m}$: For each replication *r* and each point *p* on the network, the estimated $L_{est,20m,p,r}$ and the reference $L_{ref,20m,p,r}$ are calculated by making the acoustical average of the $L_{est,5m,p,r}$ and the $L_{ref,5m,p,r}$ values of points located at less than 20 m of *p*. Then the Root Mean Square Error RMSE$_{L20m,r}$, between $L_{est,20m,p,r}$ and $L_{ref,20m,p,r}$ values, is calculated for each replication *r*. Finally the RMSE$_{L20m,r}$ values are averaged to give the $RMSE_{mean,L20m}$. It is chosen to present statistics on L_{20m} values instead of L_{5m} values, because the standard deviation of points located at less than 20 m, averaged over the reference map, is 0.9 dB(A) (see section 2.2), thus shorter spatial variations seem difficult to estimate. Moreover a spatial resolution of 20 m is considered as sufficient to characterize the sound environment. Analyses with the L_{5m} were carried out but are not presented here: they lead to higher errors but similar conclusions.

- $e_{50mean,L20m}$: For each replication *r* and each point *p* on the network, the error $e_{L20m,p,r} = |L_{est,20m,p,r} - L_{ref,20m,p,r}|$ is calculated. $e_{50,L20m,r}$ is the median of the $e_{L20m,p,r}$ values for a given replication *r*. Finally, the $e_{50,L20m,r}$ values are averaged to give $e_{50mean,L20m}$. This indicator is less impacted by local strong errors than the $RMSE_{mean,L20m}$ is.

3.3. Results

The results of the estimations are shown in Figure 3, for the indicators $RMSE_{mean,L20m}$ and $e_{50mean,L20m}$. It firstly reveals that none of the SI techniques tested allows an accurate estimation of the L_{20m} values. Indeed, even when 5 fixed stations are placed on the network, the $RMSE_{mean,L20m}$ values range between 3.6 and 4.4 dB(A), and the $e_{50mean,L20m}$ values range between 2.2 and 3.6 dB(A). Hence SI techniques prove useful to estimate how noisy the neighbourhood is, but not to estimate precisely noise levels within streets. This is coherent since spatial interpolations use as only input the noise levels collected at fixed stations. This phenomenon is visible on Figure 4 which shows the noise maps obtained for one given replication: (i) the noise estimation is very accurate in the vicinity of the fixed sensors, (ii) the spatial noise variations are much lower than the real ones, (iii) the method fails in predicting the low noise levels within the inner calm street if no sensor is deployed here.

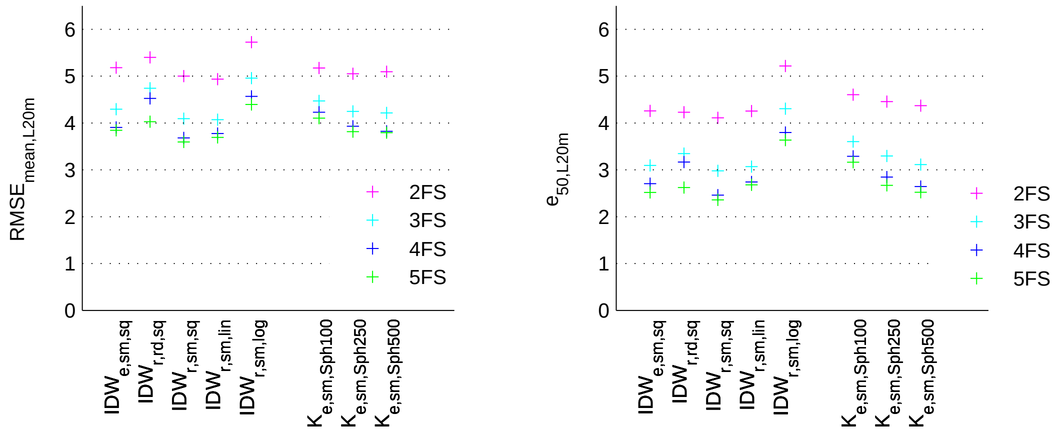

Figure 3. **Quality of the noise map produced with different spatial interpolation techniques**

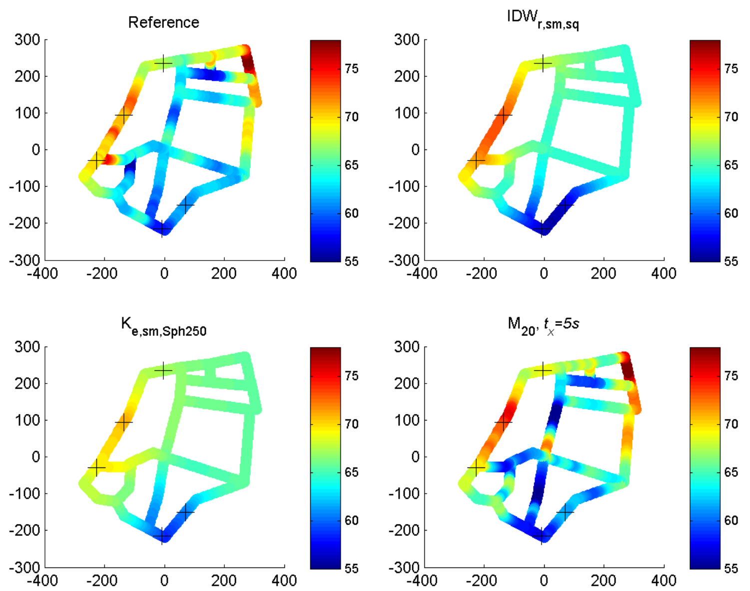

Figure 4. **$L_{Aeq,5m}$ estimation following the different spatial interpolation techniques; example of the 4th replication. The locations of the fixed sensors are indicated by crosses.**

As could be expected, the noise characterization gets more accurate when the number of fixed stations installed increases, as it corresponds to a better covering of the network. Note that this improvement is significant from m=2 to m=3 (decrease of the RMSE$_{mean,L20m}$ averaged over the 7 SI techniques tested of 0.8dB(A)), but less pronounced for a higher number of FS (0.3 dB(A) from m=3 to m=4 and 0.1 dB(A) from m=4 to m=5).

Although the differences between the SI techniques tested are not very pronounced, some conclusions can be drawn. Firstly, the "smart strategy" for locating sensors slightly improves estimation, as it offers a better covering of the network; the decrease of $RMSE_{mean,L20m}$ from $IDW_{r,rd,sq}$ to $IDW_{r,sm,sq}$ is nearly 1 dB(A). This confirms that the choice in locations for noise monitoring networks is important; this point will be detailed in section 5. Secondly, the "road distance" definition slightly improves interpolations, by about 0.5 dB(A) compared to the Euclidian distance definition; compare results between $IDW_{e,sm,sq}$ and $IDW_{r,sm,sq}$. Finally, the best weighting method seems to be the squared weighting IDW_{sq}. Surprisingly, the log weighting gives less good estimations, although theoretically it is more in accordance with sound propagation than the others.

The Kriging method gives estimations comparable to IDW interpolations, with range values of 250m or 500m. In fact, Kriging suffers from the same issue than IDW that is the poorness of representativeness in the covering of the network. This has to be confronted to the spatial variations on the network, which can be illustrated by the standard deviation for the reference map of couples of points (x,y) distant of h (which is an adaptation of the variogram used for Kriging): $\sigma(h)=\sqrt{\frac{1}{n(h)}\sum_{h-\delta h<dr_{x,y}<h+\delta h}\left(L_{\mathrm{Aeq,20m}}(x)-L_{\mathrm{Aeq,20m}}(y)\right)^2}$, where h varies from 5m to 500m by step of dh=5m, $\delta h=dh/2$, $n(h)$ is the number of couples (x,y) whose distance falls between h- δh and $h+\delta h$. $\sigma(h)$ takes the following values: σ(h=20m) = 1.5 dB(A), σ(h=50m) = 3.1 dB(A), and σ(h=100m) = 4.3 dB(A). In comparison, each point on the network is on average at a distance of 101m from the closest fixed station when there are 5 fixed stations on the network. Consequently it is not realistic to expect a good accuracy in $L_{\mathrm{Aeq,20m}}$ estimations with SI techniques due to these high spatial variations, unless they are combined with additional information on the network (road classification, description of the layout, information on traffic, etc.). Further research will be required to investigate this point.

4. Possibilities offered by mobile measurements

4.1. Definitions

Interpolations based on mobile measurements are applied following the same procedure as in section 2.2, but with shortened samples. The objective is to determine if a limited number of pass-bys, compatible with operational use, may still allow a precise estimation of noise levels. A sub-sample $s'_{p,r}$ of s_p of t_x seconds is selected for each point p of the network and each replication r, taken randomly from the initial database that was used to build the reference map. As in the previous section, replications are required as the formation of the sub-samples is partly random. Durations t_x of 3s, 5s, 10s and 15s are tested, to determine which procedures are statistically relevant. Note that for a bicycle speed of 5m/s, t_x equals the number of pass-bys. Practically, since the network of this study is made of about 0.2 km² and 662 points, the sample durations tested would lead to a total duration of measurements of about 20h, 34.5h, 69h and 103.5h, respectively, for a city of 7.5 km² with the same density. These durations are much lower than the data collection and simulation durations required for obtaining a similar noise map following classical modelling; thus operational costs can potentially be dramatically reduced.

The following procedure is used to select the shortened samples $s'_{p,r}$. For each replication r, a random ordination of the l bicycle rides of the initial database is done, defining l samples $s''_{i,r}$ where i={1…l} is the number of ordination. For each point p, $s'_{p,r}$ is a sub-selection of $s''_{1,p,r}$ of size t_x. If $s''_{1,p,r}$ is smaller than t_x (for example if the ride l does not pass by p), $s'_{p,r}$ is completed with data from $s''_{2,p,r}$, and so on till a sample of the size t_x is formed. This avoids that samples from different rides are used to build a sub-sample of a few seconds, what would be unrealistic as practically samples are collected per rides, and would dope artificially the representativeness of the shortened samples.

Once the L_{5m} values are obtained following the procedure described in section 2.2, a spatial filter that corrects each L_{5m} value with the neighbouring noise levels can be applied to diminish the spatial variations that are high for such very short samples. Gaussian filters with standard deviations of σ = 8m, σ = 20m and σ = 40m are tested, referred further as M_8, M_{20} and M_{40}, respectively. Finally, the fixed stations can be combined to mobile measurements to reduce the errors in their vicinity, as they give at their location the real noise value. Hence, each fixed station m gives the correction c_m to apply, defined as the difference at $p = m$ between noise levels measured with the fixed station and estimated with mobile measurements. This correction is right at $p = m$, but it loses reliability at increased distance from m. Therefore a Gaussian correction envelope is applied in the vicinity of m, that takes the value c_m at m and decreases with $dr_{m,p}$, with a standard deviation σ =40m.

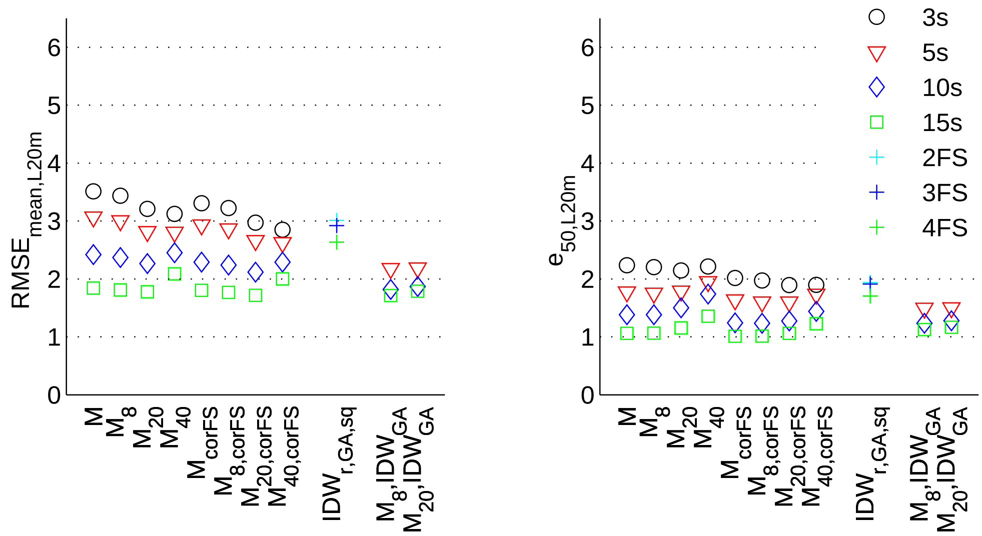

Figure 5. **Quality of estimations, spatial interpolations based on mobile measurements**

4.2. Results

The results are reported in Figure 5. Mobile measurements, even with very short samples of t_x=3s, outperform SI techniques. Actually, as they cover every point of the network, they contain more relevant spatial information, capturing the lower noise levels in inner roads and the spatial variations due to traffic flow (intersections, bus stops, tramway pass-bys, etc.), as well as non-traffic punctual noise sources. As expected, the samples durations play an important role in estimates: the $RMSE_{mean,L20}$ averaged over the 8 models reported decreases from 3.3 dB(A) to 1.9 dB(A) as the samples durations increase from t_x=3s to t_x=15s. As a result, $RMSE_{mean,20m}$ of about 2dB(A) can be obtained with samples of t_x=10s or more (that is for about 10 pass-bys at every point).

The effect of the spatial filter is balanced. When samples are very short, smoothing data with neighbouring noise estimates improves estimates (compare for example the $RMSE_{mean,20m}$ values for model M with M_{20} and M_{40} for t_x=3s). Indeed, this increases artificially the length of the samples and thus reduces the local strong spatial variations inherent with very short samples. Inversely, when samples are already long enough to be statistically relevant, as this is the case for $t_p \geq 10$s, the spatial filter erases the refinements that were shown, and consequently it deteriorates the results.

Finally, the corrections with the fixed stations have no significant impact on estimations, as show the quality indicators for M and M_{corFS} estimations. This can be explained by the high spatial variations shown in section 3.3, which make corrections with measurements at fixed stations useful only in the very close vicinity of the station. As a conclusion, it appears that the fixed stations on the network are necessary to account for the period when mobiles measurements are collected (noisy period of the day or not), but are useless to correct the local errors that can result from too short sampling.

5. Optimization of the measurement network

Optimizing the design of measurement networks schemes is a major issue of urban pollutant monitoring [47][48], but it is are rarely addressed in the noise context. However, the poor results obtained with SI techniques in section 3 could be the consequence of the random positioning of the FS, and could hide the fact that some sets of FS offer a higher spatial representativeness and perform well. The possibility to rely on short term mobile measurements to determine the optimal position for the FS within a monitoring network is tested.

Sub-samples $s'_{p,r}$ are constructed as in section 4.1, with t_x = 5s, to generate short term mobile measurements. A Genetic Algorithm (GA) is used to select the optimized locations, converging from generation to generation towards an optimal solution. To initialize the algorithm, the first generation consists of 5 elements, each element being a random choice of M fixed stations ($M \leq 5$) among the 662 possible ones. Then each new generation is created with the following procedure:

- Select the 5 best elements of the previous generation. To do so, the $RMSE_{L20m}$ value is calculated, for each element of the generation, between the map built with the sub-samples of t_x = 5s (this is crucial at this step to evaluate the noise map on the sub-samples of t_x = 5s, which are the only data supposed to be available), and the map built with the $IDW_{r,sq}$, applied with the set of FS of each element. Then the elements that give the lowest $RMSE_{L20m}$ value are selected ;
- Cross over these 5 elements to create 5 new elements, by applying the following procedure for each new element: a) select the $n<M$ first FS of one random element of the 5 original ones, b) add to it the M-n last elements of another random element of the 5 original ones;
- Mutate 2 of the 10 obtained elements, by replacing, for each of the two, one of the M FS by a new one chosen randomly among the 662 possible choices;

- Add 10 new random elements;
- Add the 2 best elements of the previous generation, if they have been modified by the cross over or the mutation operations;

The algorithm converges in less than 50 generations. Due to the high spatial resolution of the network, many sets of FS can offer similar results, so the set of FS finally selected is not a unique solution. Once the set of FS selected by the algorithm, the final noise map is estimated with the $IDW_{r,sq}$ technique. The noise map obtained is compared as for the other interpolation techniques to the reference noise map, that is the one built in section 2.2 with the whole set of data. The algorithm is tested on 25 replications as for the other techniques, since the initial choice in the sample selection involves random choices.

The results are reported in Figure 5, and are referred as $IDW_{r,GA,sq}$. Optimizing the location for FS is really efficient, even with the short samples duration used to make this optimization (t_x = 5s). For example, $RMSE_{mean,20m}$ of 3dB(A), 2.9 dB(A) and 2.6 dB(A) are obtained with $IDW_{r,GA,sq}$ with 3, 4 and 5 FS, respectively, compared to $RMSE_{mean,20m}$ of 4.1dB(A), 3.7 dB(A) and 3.6 dB(A) obtained with $IDW_{r,sm,sq}$. The improvement is even more significant if one looks at the errors exceeded for 10% of the replications, with a $RMSE_{10,20m}$ of 3.6 dB(A) and 5.6 dB(A) for $IDW_{r,GA,sq}$ and $IDW_{r,sm,sq}$ with 5 FS, respectively. The more homogeneous results over replications with $IDW_{r,GA,sq}$ are explained by the fact that it avoids deploying FS at non relevant locations. As a practical conclusion, SI techniques can prove useful, once the locations for FS are optimized by means of additional short term measurements and an optimization algorithm.

Further, the short term measurements used to optimize the FS locations can serve as well to improve the noise map produced. Indeed, even once the FS locations optimized, SI techniques are not sufficient to fully capture the spatial noise variations on the network, what mobile measurements are aimed to do. The simplest possible combination is done, which consists of averaging the L_{20m} values estimated with the $IDW_{r,GA,sq}$ technique and the L_{20m} values estimated with mobile measurements M_8 or M_{20}. Although very simple, this procedure improves the results significantly, with $RMSE_{mean,20m}$ of about 2dB(A), with t_x=5s, 10s or 15s. The improvement is nearly null for t_x=15s since this sample duration was already long enough to be statistically representative. Interestingly, errors are highly reduced for t_x=5s. Indeed, the local errors due to too short samples are corrected thanks to the optimized location for FS, contrarily to model $M_{8,corFS}$ for which corrections with measurements at FS were not efficient, because FS were not placed at relevant locations. Consequently, by using short term samples (t_x=5s corresponds to 5 pass-bys for a speed bicycle of 5m/s) to define the best locations for FS and capture the spatial variations on the network, an accurate noise map with a high spatial resolution can be built.

6. Conclusion

This paper relies on an extensive noise measurement campaign to test the relevance of different interpolation techniques to improve the spatial resolution of urban noise maps, in complement to measurements achieved at fixed stations. Interpolation techniques based on mobile measurements are compared to usual spatial interpolations techniques, namely Inverse Distance Weighting and Kriging. Nearly 8 hours of geo-referenced noise measurements were collected with a bicycle on a 0.2 km² network in Gent (Belgium), jointly with continuous measurements at 5 fixed stations. Techniques are compared on their ability to estimate the noise levels L_{20m} on the network, in comparison with a reference map built with the whole set of data. The procedure proposed to construct this reference map uses jointly mobile measurements to capture the spatial variations, corrected with measurements at the fixed stations, to account for the heterogeneity within the sampling periods.

None of the spatial interpolation techniques tested enables an accurate estimation of the L_{20m} values. This is explained by the low spatial representativeness of fixed stations. A blind use of these techniques can yield important errors in urban areas if a high spatial resolution is aimed. It is shown that if the distances used for the interpolation are refined by following the road network, estimates are slightly improved, as this implicitly accounts for the noise screen of buildings. This could be furthermore significantly improved by taking the geometric layout into account (height of buildings, etc.), or by introducing sound propagation calculation or external data information (road classification, information on traffic, etc.).

Mobile measurements clearly outperform the spatial interpolation techniques tested, even when very short samples are used: taking 5s of measurements every 5m on the network is sufficient (that is 5 pass-bys with a bicycle evolving at 5m/s). However the processing of mobile data still requires some reference fixed stations to correct for the bias due to the heterogeneity in the sampling periods. The question of the density in the fixed stations installed required to do this correction cannot be answered in the framework of this study, whose network was too small to carry such analysis. The procedure will indeed gain in efficiency if stations located further can be used to capture temporal noise variations over the network; this can be expected since urban noise levels are highly correlated [34]. Further research will investigate this point.

Finally, it is proved that mobile measurements can also be used to optimize the locations where to deploy fixed stations in a monitoring network, by mean of a genetic algorithm. The algorithm selects where installing fixed stations minimizes the errors when noise levels are estimated afterwards with spatial interpolation techniques. It is proved that the selection made on a small quantity of mobile measurements stays optimal when compared to the reference map. The model could be operationally enriched with information on the availability of the candidate locations for fixed stations, as this can be a limitation in practice. Once validated over wider networks, this optimization tool for designing noise monitoring networks will prove practically very useful.

7. References

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