UNIVERSITAT POLITÈCNICA
DE CATALUNYA
BARCELONATECH

UPCommons

Portal del coneixement obert de la UPC

<http://upcommons.upc.edu/e-prints>

Aquesta és una còpia de la versió *author's final draft* d'un article publicat a la revista *Applied acoustics*.

URL d'aquest document a UPCommons E-prints:

<http://hdl.handle.net/2117/171691>

Article publicat / *Published paper:*

G. Quintero, P. Aumond, A. Can, A. Balastegui, J. Romeu. (2019) Statistical requirements for noise mapping based on mobile measurements using bikes. *Applied acoustics*, vol. 156, p. 271-278. Doi: 10.1016/j.apacoust.2019.07.020

Statistical requirements for noise mapping based on mobile measurements using bikes

G. Quintero^{1*}, P. Aumond², A. Can², A. Balastegui¹, J. Romeu¹

¹ *LEAM, Polytechnic University of Catalonia, Colom 11, 08222 Terrassa, Spain*

² *IFSTTAR, CEREMA, UMRAE, F-44344 Bouguenais, France*

Abstract

This research presents a modeling framework that allows checking the statistical requirements for building noise maps based on mobile measurements. First, a sound field of reference is created based on a micro-simulation traffic modeling coupled with acoustic modeling, which outputs sound levels each second on a grid of receivers. The aggregated indicators (L_{Aeq}) calculated from this sound field serve then as reference. Mobile targets performing measurements evolve within the simulation, aiming to estimate these indicators. The difference between the reference noise map and the one generated by the moving receivers, characterized by the Root Mean Square Error (RMSE), is computed for different aggregation radius of mobile receivers, and as a function of the number of passes-by and to the distance to its nearest cross street. It is observed that the mobile sampling is actually possible and the RMSE can be reduced by setting an optimal aggregation radius and a minimum number of passes-by. With the optimal parameters, 95% of the mobile samples fall within an estimation error interval of $[-3, 2.2]$ dBA from the reference. It is

*Corresponding author.

E-mail address: guillermo.quintero@upc.edu

also shown that the distance to the nearest cross street affects the estimation error depending on the traffic flow.

Keywords: Noise mapping, Mobile sampling, Dynamic noise modeling, Exposure assessment

1. Introduction

To evaluate the noise exposure of the population, the European Noise Directive (European Commission, 2002) requires that the Member States develop noise maps and actions plans for noise reduction every 5 years, for agglomerations higher than 100,000 inhabitants. The parameters suggested to be plot in the noise maps are, at least, L_{night} and L_{den} for the equivalent time of 1 year.

For the production of a noise map, the noise levels are mainly based on on-site measurements or calculated based on computational models. Both approaches share the need of huge amount of input data, whether they are large sampling campaigns for noise maps based on measurements or detailed traffic information for noise maps based on simulations.

For noise maps based on simulations, there is a wide variety of traffic noise models (Steele, 2001), which are meant to predict the sound pressure level of a single vehicle in the road. Anyway, since they are usually developed at a local scale, mainly for action plans on noise reduction, they do not allow a direct comparison of the presented data between different models (Kluijver et al., 2003; Licitra and Ascari, 2014), even with commercial software (King and Rice, 2009). For instance, as indicated in (European Commission, 2002), the CNOSSOS framework emerges as a solution to standardize noise

21 modeling, which would allow results from different countries to be compared
22 (Kephalopoulos et al., 2012; Morley et al., 2015).

23 A common way to represent the vehicles as the noise source in the com-
24 putational models, which also reduces the required computations, is using
25 long-term average values such as speed or traffic flow rates. Since it dis-
26 regards the vehicle dynamics along the roads, a correction factor for each
27 segment of the road can be used (De Coensel et al., 2007). Furthermore, the
28 dynamic traffic representation is shown to improve the noise level estima-
29 tions (Chevallier et al., 2009; Can et al., 2010). As the different situations
30 that can be observed on real scenarios such as traffic jams, free flow, accel-
31 erations, decelerations, roundabouts, among others, are considered (usually
32 1 s), it would bring noise estimations closer to reality, but with an increase
33 in the computational complexity since the amount of input data would con-
34 siderably increase. Moreover, different paradigms have been investigated to
35 represent the noise from multiple sources (Aletta and Kang, 2015; Aumond
36 et al., 2018b) to emulate on-site sampling, where sources that exists in urban
37 environments are measured (Chew and Wu, 2016).

38 For the case of noise maps based on measurements, it is necessary to
39 perform spatio-temporal sampling. Thus, to improve the temporal sampling
40 process, several techniques have been proposed to estimate long-term noise
41 levels from short-term measurements (Safeer et al., 1972; Gaja et al., 2003;
42 Ng and Tang, 2008; Romeu et al., 2011; Brocolini et al., 2013; Prieto and
43 Barrigón, 2015; Prieto et al., 2016; Quintero et al., 2018). For the spatial
44 sampling, many ways reduce the amount of sampling points through street
45 classifications have also been proposed (Barrigón Morillas et al., 2005; Romeu

et al., 2006; Zambon et al., 2016; Jiménez et al., 2008; Quintero et al., 2019).

In addition, the tasks that were traditionally executed by experts using certified equipment (Hakala et al., 2010), are being replaced by other sampling approaches such as sensor networks, that are usually developed with low-cost hardware to cover large areas (Sevillano et al., 2016; Wessels and Basten, 2016; Alsina-Pagès et al., 2017; Segura-Garcia et al., 2015; Rawat et al., 2014; Mydlarz et al., 2017). Another sampling scheme that has gained interest recently is the participatory sensing, which enables to any person to take measurements either with a specific measurement equipment or through their mobile phones with enough accuracy as the standard noise maps (Kanhare, 2011; D’Hondt et al., 2013; Kardous and Shaw, 2014). A comparison between traditional mapping methods and participatory noise mapping is presented in (D’Hondt et al., 2013). The study states that, when measurements are performed following specific requirements such as calibrated handsets, spatio-temporal density, proper measurement protocols and trained citizens, participatory sensing could be another approach to address the Noise Directive guidelines. Some past and current projects regarding participatory sensing are shown in (Smartcitizen, 2011; NoiseTube, 2008; CITI-SENSE, 2012; Kanjo, 2010; Rana et al., 2010).

A common practice, which mixes both noise mapping schemes, is to take on-site measurements to calibrate the noise map based on computational models or to use them to dynamically update noise maps based on interpolation methods (King and Rice, 2009; Wei et al., 2016; Aumond et al., 2018a).

Finally, an approach that has not been widely studied, is the mobile sam-

71 pling. One of the advantages of mobile sampling is that it would increase the
72 temporal and spatial resolution, even with short length samples (Can et al.,
73 2014), in a more controlled environment than participatory sensing, since the
74 measurement is carried out by professionals or trained people. Furthermore,
75 combining the mobile sampling with the static one could enhance the advan-
76 tages of making noise maps based on measurements (Guillaume et al., 2019).
77 Nevertheless many drawbacks should be addressed for the case of mounting
78 the measuring device on any vehicle such as the noise contribution of the
79 vehicle itself, the air flow and the position of the microphone among others
80 (Bennett et al., 2010; Alsina-Pagès et al., 2017; Guillaume et al., 2019). Be-
81 yond these metrological issues, the temporal variations of noise due to the
82 traffic dynamics (vehicle passes-by, vehicle platoons due to traffic lights, het-
83 erogeneity between vehicle noise emissions, etc.) define the feasibility and
84 statistical requirements for noise mapping based on mobile measurements.

85 Therefore, through a controlled simulated framework that reproduces the
86 actual spatial and temporal noise variations, which is based on road traffic
87 dynamic modeling, the present paper evaluates the statistical requirements
88 for making a noise map based on mobile measurements, where the noise meter
89 is simulated as mounted on a moving vehicle, ideally a bicycle to diminish the
90 mentioned drawbacks. The aim of this research is to obtain the number of
91 bikes passes-by required for different traffic flow rates and different distances
92 to intersections. Furthermore, in order to reduce the estimation error, a
93 spatial aggregation of mobile samples is also evaluated.

2. Methodology

2.1. Study area

The place under study is an area of almost 4.5 km² located at the north-east of the city of Lyon, France (Figure 1). The total length of the traffic network, which also includes Tram and Bus trajectories, is about 51.4 km. The micro-simulation software SYMUVIA (SYMUVIA, 2005) was used to provide the traffic input data for the dynamically modeled noise maps and also to simulate the mobile receivers (bikes). SYMUVIA is a software able to reproduce all the dynamics that would occur in the studied area, such as bus stops, traffic lights, lane changing and queues, giving as output the position $x_i(t)$, speed $v_i(t)$ and acceleration/deceleration $a_i(t)$ of each i vehicle within the studied road network for each time-step ($\Delta t = 1$ s).

Two independent traffic simulations, but performed for the same time period, were executed. The first one for the vehicles, that would be the input for the noise emission (sources), and the second one, that corresponds to the mobile receivers (bikes). This means that interactions between bicycles and vehicles are neglected when considering the position of bicycles on the network. However, their difference in kinematics is taken into account as detailed later in the investigation.

The vehicles demand, for the case of the sources simulation, was set to match the actual behavior of the traffic in the zone during 1 hour, from 8:00 to 9:00 hrs. Furthermore, the traffic lights, Bus and Tram stops, trajectories and speed limits are also set to match the real scenario.

For the case of the mobile receivers, the bikes were simulated as a regular car but their speed was limited to a maximum of 5 m/s. Additionally, to

Figure 1: Area under study located in the northeast of Lyon, France.

119 have a constant demand and a similar distribution of bikes through most of
 120 the studied streets, some input parameters related to the route calculation
 121 algorithm were also adjusted. A video of the whole simulation of the mobile
 122 noise sampling can be found in ¹.

123 2.2. *Dynamic noise modeling*

124 The dynamic simulation methodology is based on (Chevallier et al., 2009;
 125 Can et al., 2010; Aumond et al., 2018b), where the vehicles are mapped into
 126 fixed grids and some steps are suggested for the dynamic modeling. The main
 127 difference of the present research is that the microscopic traffic simulations
 128 are not only used for the sources (noise emission), but also for the mobiles
 129 receivers. Then, the modeling steps are as follow:

- 130 (a) Traffic model: Simulation of individual vehicle trajectories at each t .
 131 Matched to a fixed grid of sources.
- 132 (b) Noise emission: Calculation of the noise power of each individual vehicle
 133 at each t .

¹<https://vimeo.com/315221179>

- 134 (c) Mobile receivers: Simulation of individual bikes trajectories at each t .
135 Matched to a fixed grid of receivers.
- 136 (d) Sound propagation: Attenuation between fixed sources and receivers
137 grids to compute noise level at each receiver, whether they are static
138 or mobile.
- 139 (e) Indicators calculation: Sound level indicators to compare static and
140 mobile sampling.

141 The geographical information system OrbisGIS together with the Noise-
142 Modeling plug-in (v 2.2.0) (Picaut et al., 2011; Fortin et al., 2012) are used
143 for the noise emission and propagation computations. This version of the
144 plug-in is based on the CNOSSOS (Kephalopoulos, Stylianos and Paviotti,
145 Marco and Anfosso-Lédée, Fabienne, 2012) standard for road noise emission,
146 and the NMPB (Dutilleux et al., 2009) method for sound propagation. The
147 validity of a similar modeling chain to reproduce the spatio-temporal noise
148 variations in urban areas has been demonstrated in (Can et al., 2009, 2010).

149 *2.2.1. Fixed grids for sources and receivers*

150 Since the output of the simulations for traffic and mobile receivers could
151 bring infinite different positions for sources and receivers, which could have
152 a huge negative impact on the calculation time, the sources and receivers are
153 matched into fixed grids close enough not to alter the expected noise level.

154 Therefore, to place the fixed sources points, each road/street is taken as
155 a single lane and divided into equal segments of $D = 3$ m. A fixed point
156 is placed on one side of each segment and every vehicle is then attached
157 to its nearest fixed point (modeling chain step (a)). The grid of sources is

Figure 2: (a) Vehicles and (b) bikes mapped into a fixed grid. The fixed grid of the Bikes is displaced 1 meter perpendicular to the road.

158 finally created selecting only the fixed source points, P_s , that have a vehicle
 159 attached. Almost the same procedure is followed for the grid of receivers
 160 (modeling chain step (c)), but the positions of the fixed receiver points,
 161 P_r , are displaced 1 m perpendicular to the trace of the road to avoid an
 162 overlapping with the cars (Figure 2).

163 2.2.2. Vehicle noise emission

164 The input parameters for the CNOSSOS standard are obtained from the
 165 each second outputs from the SYMUVIA software, and from the actual char-
 166 acteristics of the zone under study. According to (Kephalopoulos, Stylianos
 167 and Paviotti, Marco and Anfosso-Lédée, Fabienne, 2012), five classes of ve-
 168 hicles are considered for the noise emission computation. For the present
 169 research, since the aim is to compare the differences between mobile and
 170 static sampling for traffic noise, three vehicle classes are considered: light
 171 vehicles (Cars), medium heavy vehicles (Buses) and heavy vehicles (Tram).

172 Since on a real scenario not all the vehicles emit the same noise level,

173 an uncertainty with a standard deviation of 2 dB was added to the noise
 174 power calculated for each vehicle (constant during its whole life). Thus,
 175 the spectrum power for every time-step and each vehicle $Lw_b(i, t)$ (dB) is
 176 computed for the b octave bands with a central frequency in the range 63 Hz
 177 - 8 kHz (modeling chain step (b)).

178 2.2.3. Attenuation matrix

179 To compute the attenuation between sources and receivers, the input
 180 parameters were configured to have an appropriate calculation time without
 181 affecting the accuracy. Thus, the calculation takes into account only the
 182 sources that are within a maximum radius of 250 m from a receiver (maximum
 183 propagation distance), and reflections and diffractions are computed only for
 184 walls within 50 m from the sources-receivers propagation line. The road
 185 surface is specified as dense asphalt concrete (Kephalopoulos et al., 2012)
 186 and the temperature is set to 20 °C. Other configured parameters for the
 187 computation of the attenuation of each octave band are:

- 188 • Reflection order: 2
- 189 • Diffraction order: 1
- 190 • Wall absorption: 0.2

191 Based on the condition that the acoustic propagation for the studied pe-
 192 riod does not change (Aumond et al., 2018b), and using as input the build-
 193 ings information and the fixed grids of sources and receivers, the attenuation
 194 $Att_b(x, y)$ is computed for each combination of $x \in Pr$ and $y \in P_s$ (modeling
 195 chain step (d)) with the spatial conditions previously mentioned.

196 2.3. Noise maps and indicators calculation

197 Using the power spectrum of each vehicle and the attenuation matrix for
 198 each b octave band, Subsections 2.2.2 and 2.2.3 respectively, the noise level
 199 at each x for any t can be computed as (modeling chain step (e)):

$$L_b(x, t) = 10 \log \left(\sum_{i \in I} 10^{[Lw_b(i, t) - Att_b(P_s(i), P_r(x))]} + 10^{\frac{L_{BK}}{10}} \right) \quad (1)$$

200 where $I = \{x \bowtie^{250} P_s\}^2$ and L_{BK} is the background noise set at 40 dB, which
 201 is relevant for the cases where there are not cars nearby a fixed or mobile
 202 receiver.

203 The L_b is representative of the interval of one second, with the error that
 204 this entails, since a fixed position is assumed for the whole second, when
 205 both, emitter and receiver are actually moving during this period. Once the
 206 L_b is computed for all the octave bands, the A-weighted equivalent level of
 207 each time-step is obtained (American National Standards Institute, 2009).

208 2.3.1. Reference and mobile noise maps

209 Two different types of noise maps are created: the reference noise map,
 210 which is based on fixed measurements and computed for the whole set of
 211 fixed receivers, and the mobile noise maps based on mobile measurements,
 212 which are the ones to be evaluated.

213 Thus, to obtain the final noise maps, a temporal aggregation for the
 214 whole simulation time T is performed for each receiver. Furthermore, to
 215 homogenize the results of the reference noise map, and to find the optimal

² $\{x \bowtie^y Z\}$ is a subset of the elements in Z that are within a radius of y meters from x .

216 aggregation radius for the mobile noise maps, a spatial aggregation of the
 217 surrounding receivers is also performed.

218 Therefore, for the total simulation time T and for each $x \in P_r$, each
 219 time-step samples $L_{Aeq}(x, t)$ are joint into a subset of P_r as:

$$L = \bigcup_{x \in X} \left\{ \bigcup_{t=1}^T L_{Aeq}(x, t) \right\} \quad (2)$$

220 where T is the total simulation time and $X = \{x \in P_r\}$ for the reference
 221 noise map or $X = \{x \in P_r\}$ for the mobile noise maps.

222 Then, the aggregated A-weighted equivalent level is computed as:

$$\overline{L_{Aeq}}(x) = 10 \log \left(\frac{1}{N} \sum_{l \in L} 10^{\frac{l}{10}} \right) \quad (3)$$

223 where N is the number of elements in L (Equation 2).

224 For the case of the reference noise map, all $x \in P_r$ are used for the spatial
 225 and temporal aggregations. For the case of the mobile noise maps, only the
 226 fixed points that are active at t are taken into account for aggregations.

227 2.3.2. Complementary indicators

228 For the whole simulation period, the number of bikes passes-by (B_{pb}) and
 229 the traffic flow (T_f) for each static receiver is computed. Moreover, since the
 230 type of road junctions, whether they are traffic lights, roundabouts, cross
 231 streets, etc. are shown to bring noise level variations (Chevallier et al., 2009;
 232 Estévez-Mauriz and Forssén, 2018), the distance to the nearest cross street
 233 (streets intersections D_{in}) is also computed. Then, the Root Mean Square
 234 Error (RMSE) between the reference and mobile noise maps is obtained as:

$$RMSE = \sqrt{\left(\frac{1}{N} \sum_{x \in P_r} (\overline{L_{Aeq}^{ref}}(x)^2 - \overline{L_{Aeq}^{mob}}(x)^2) \right)} \quad (4)$$

where L_{Aeq}^{ref} and L_{Aeq}^{mob} are the A-weighted noise levels from the reference and mobile receivers respectively and N is the number of receivers.

Thus, three types of noise maps are computed according to the following conditions:

(C₁) Optimal aggregation radius: Using all the receivers, the mobile noise maps are computed using Equation 2 for a spatial aggregation distance from 1 m to 100 m. The RMSE is computed for each aggregated noise map.

(C₂) Minimum passes-by: The RMSE is computed for subsets of P_r . First, the receivers are separated according to 4 traffic flow rates $Q = \{i, ii, iii, iv\}$ where **i**) 0 - 100 veh/hr, **ii**) 102 - 245 veh/hr, **iii**) 246 - 561 veh/hr and **iv**) 562 - 2185 veh/hr. Then, for each traffic flow, the receivers are grouped according to their number of bikes passes-by, $B_{pb} = \{1, \dots, 100\}$. Thus, RMSE is computed for each combination of Q and B_{pb} , i.e. $RMSE_{Q, B_{pb}}$.

(C₃) Distance to intersection error estimation: The RMSE is computed for subsets of P_r grouped according their distance to the nearest intersection, $D_{in} = \{1, \dots, 100\}$ meters, i.e. $RMSE_{D_{in}}$.

Before the RMSE calculations in (C₂) and (C₃), the maps are aggregated by the optimal radius as obtained in (C₁). The receivers were separated into traffic flows to enhance the rest of the parameters (Cristina et al., 2014).

256 Then, the ranges of traffic flow in (C_2) were chosen so that each category
257 has the same amount of receivers and the comparison be as homogeneous as
258 possible.

259 **3. Results**

260 *3.1. RMSE vs Aggregation radius*

261 As stated in (Can et al., 2014; De Coensel et al., 2007), the spatial ag-
262 gregation of short-term samples is necessary to deal with their high spatial
263 variations. Furthermore, in (Dekoninck et al., 2012) for the aggregation of
264 L_{Aeq} samples, a radius of 50 m is suggested to ensure that a minimum of
265 10 samples are aggregated in each point, since the typical speed of a bicycle
266 is 5 m/s. Thus, for the present research, the noise maps were computed
267 for aggregation radius from 1 m to 100 m according to Equation 3 and to
268 condition C_1 . Then, the RMSE for each map was computed with Equation
269 4. Figure 3 shows the RMSE as a function of the aggregation radius. It is
270 seen that the radius that minimizes the estimation error is 34 m. The lower
271 radius obtained for L_{Aeq} compared to the one suggested in (Dekoninck et al.,
272 2012), is obtained since the simulation limits the maximum speed to 5 m/s
273 which, would only be obtained in cases of free flow. The actual speed average
274 of bikes is 3.5 m/s, that for a radius of 34 m, gives around 19 samples for
275 each spatial aggregation.

276 *3.2. RMSE vs Pass-by*

277 The SYMUVIA output file gives to each vehicle a unique ID, then, in
278 order to calculate the number of passes-by or the traffic flow, the different

Figure 3: RMSE for mobile measurements aggregation from 1 m to 100 m. The minimum error is pointed with a circle.

279 IDs attached to each receiver are accounted. For cases where an ID appears
 280 more than 1 time at the receiver, which means that it stayed more than 1 s
 281 near to it, a time aggregation was performed and it is counted as 1 pass-by.

282 Figure 4 shows the RMSE according to different traffic flows from 1 to
 283 50 passes-by. It can be observed that, before a certain number of passes-by,
 284 the RMSE decreases as the passes-by increase. Except for traffic category
 285 i), after 20 passes-by the decrease in the RMSE is lower, which suggests a
 286 stabilization. Furthermore, about 42 passes-by brings almost the same error
 287 for the other 3 categories (approximately 0.5 dBA difference).

288 3.3. RMSE vs Distance to intersection

289 The distance to the nearest street intersection was computed for each of
 290 the fixed receivers. The RMSE for L_{Aeq} was then computed for 25 passes-by
 291 and for the 4 traffic categories. Figure 5 shows the mean error according to
 292 the distance to the nearest street intersection. It is observed that, except for

Figure 4: RMSE for mobile measurements as a function of the number of passes-by for different traffic flows.

category 1, the farther from the intersection, the lower the calculated RMSE.

Figure 6 shows a 3D bar plot of the RMSE as a function of the number of passes-by and the distance to the nearest intersection for traffic category 4. The plot was smoothed to better observe the possible patterns. It is seen that after a distance of 20 m from intersection, the number of passes-by gains more importance since the decrease in the RMSE is higher for each increment in the passes-by.

3.4. Noise maps

A map to represent the traffic count for the mentioned categories, as well as the number of passes-by (bikes) at each receiver point is shown in Figure 7. Furthermore, noise maps were computed for the whole simulation time for the reference receivers, the mobile receivers (aggregated by its optimal radius) and their noise level difference computed by subtracting the reference noise level minus the mobile noise level as follows:

Figure 5: RMSE for mobile measurements for 4 traffic categories as a function of the distance to the nearest intersection (1 m to 70 m).

Figure 6: RMSE for 1-50 passes-by and 1-50 m from intersection for L_{Aeq} estimation.

$$L_{ref-mobile}(x) = L_{Aeq}^{ref}(x) - L_{Aeq}^{mob}(x), \forall x \in P_r \quad (5)$$

where L_{Aeq}^{ref} and L_{Aeq}^{mob} stands for the L_{Aeq} of the reference noise map and the mobile noise map respectively. The resulting noise maps are shown in Figure 8. Although the reference and mobile noise maps seem to be similar at first sight, the map of the noise level differences (Figure 8c) highlights the discrepancies between them. If one compares Figure 8c to Figure 7, it can be appreciated that the highest estimation errors, are mostly observed for streets with low traffic flow and low number of passes-by. The histogram of the estimation error for the mobile sampling (Figure 8c) according to the number of receivers is shown in Figure 9. The mean value and the standard deviation is also shown. It is observed that 95% of the samples fall in the range $[-5.4, 5]$ dBA for L_{Aeq} estimation.

Finally, based on the three input parameters: B_{pb} , T_f and D_{in} , a linear regression analysis was performed to approximate the absolute error of the L_{Aeq} estimation. The independent variables were transformed into a logarithm function ($\log_{10}$) to match their non linear relation. Table 1 shows the results of the analysis. It is observed that there is a positive correlation ($p < 0.05$) with an explained variance about 15%. It is important to point out that, although the explained variance is low, it is an expected value since the moment of the measurement is what explains the largest part of the variance.

4. Discussion

The present research shows the possibility to perform mobile sampling with a certain precision, although some considerations should be taken into

Figure 7: Bikes passes-by and traffic counts for each receiver.

Table 1: Multiple linear regression between absolute estimation error in the L_{Aeq} estimates, and the independent variables B_{pb} , T_f and D_{in} . All variables are significant with a $p - value < 0.05$. The multiple and adjusted R^2 are both equal to 0.1554 and the residual standard error is 2.446.

	Coeff.	Std. err.	t-values.
(Constant)	7.33	$16.29E^{-03}$	450.2
B_{pb}	-1.75	$7.33E^{-03}$	-239.1
T_f	-0.60	$3.96E^{-03}$	-151.8
D_{in}	-0.82	$6.70E^{-03}$	-122.7

Figure 8: Reference noise map (a), mobile noise map (b) and difference between reference and mobile noise maps (c).

Figure 9: Histogram of the noise level difference for each receiver of the reference noise map minus the mobile noise map (L_{Aeq}).

329 account in order to improve the estimation accuracy, or if one wanted to put
 330 this sampling approach into practice.

331 To improve the estimation accuracy, Figure 3 shows that by aggregating
 332 the mobile samples, the RMSE can be reduced up to 3 dBA for the estimation
 333 of L_{Aeq} . In addition, Figure 4 shows that a minimum of passes-by could be
 334 set depending on the traffic flow. For the case of streets with low traffic flow,
 335 it is clear that the higher the number of passes-by the lower the estimation
 336 error. For the case of streets with higher traffic flow, a stabilization time
 337 related to the number of passes-by, similar to the one shown in (Torija et al.,
 338 2011), could be proposed as a stop parameter, since at a given number of
 339 passes-by, the estimation error seems to remain almost constant.

340 Furthermore, the present research showed that intersections introduce
 341 some uncertainty to the mobile measurement (higher than 2 dBA for dis-
 342 tances around 20 m). It is observed that the closer the intersection is,
 343 the higher the error. This result is in concordance to what is presented

344 in (De Coensel et al., 2007; Chevallier et al., 2009; Estévez-Mauriz and
345 Forssén, 2018; Can and Aumond, 2018), where the influence of the acceler-
346 ation/deceleration, which is mostly observed at the intersections, is studied
347 and some corrections are proposed for static noise mapping.

348 Although in Section 3.4 it is mentioned that 95% of the estimations falls
349 into a wide error range, $[-5.4, 5.0]$ dBA for L_{Aeq} , this range could be reduced
350 by setting some minimum sampling parameters. For example, if a minimum
351 of 30 passes-by and a distance to intersection higher than 30 m for the traffic
352 categories iii) and iv) is considered, the 95% confidence interval is reduced
353 down to $[-3, 2.2]$ dBA.

354 The present research proposes techniques to deal with the high spatial
355 and temporal resolution of the samples, that is, the spatial and temporal
356 aggregation, which, complemented with some minimum requirements help
357 to reduce the estimations errors. Anyway, the studied simulation would be
358 an ideal scenario for mobile sampling. If one wanted to put the methodology
359 into practice on a real scenario, several external issues that the simulation
360 neglects and that would certainly affect the actual sampling, should be taken
361 into account:

- 362 • Vehicle reflections: The simulations do not include the reflections that
363 would occur between the sources themselves (cars). Furthermore, in
364 (Montes González et al., 2015), the screening effect of the parked cars is
365 also shown as a source of uncertainty, which for the proposed sampling,
366 could probably be reduced by increasing the microphone height.
- 367 • Vehicle self generated and impulsive noise: Although the vehicle pro-
368 posed is a bike, which would have a low floor noise compared to a car

369 (Bennett et al., 2010), impulsive noise, probably due to potholes or
370 poor condition of traffic lanes, should be identified and processed.

- 371 • External noise sources: In a real scenario, several natural noise sources,
372 such as birds, wind, climatological variables, or human induced such
373 as constructions, commercial zones, schools, would be captured by the
374 sampling device, which are not considered in the simulation.

375 5. Conclusion

376 The present research tested the statistical requirements for noise map-
377 ping based on mobile measurements, under a simulation framework. It was
378 shown that it is actually possible to perform noise mapping based on mobile
379 measurements, however, some considerations should be set in order to reduce
380 the uncertainties.

381 In order to minimize the estimation error, a minimum number of passes-
382 by, which depends on the traffic flow, should be selected. Furthermore, an
383 optimal radius of 34 m for mobile samples aggregation to minimize the L_{Aeq}
384 estimation error is proposed. For the distance to intersection, some correction
385 could be set to compensate the error that it introduces.

386 Finally, in case that the mobile sampling is put into practice, some extra
387 considerations that should be addressed are also suggested, some of them
388 related to the vehicle itself such as reflections, self-generated noise and im-
389 pulsive noise, or to external noise sources such as those related to the nature
390 or human interactions.

391 Acknowledgments

392 The authors express their warm thanks to Ludovic Leclercq and Cécile
393 Bécarie, from LICIT, for sharing SYMUVIA and the traffic data from the
394 calibrated network used in this study, as long as precious recommendations
395 on the use of the model. Special thanks also to CONACyT for the support
396 with the grant (260828/409838).

397 References

- 398 Aletta, F., Kang, J., 2015. Soundscape approach integrating noise mapping
399 techniques: A case study in Brighton, UK. *Noise Mapp.* 2, 1–12. doi:10.
400 1515/noise-2015-0001.
- 401 Alsina-Pagès, R.M., Hernandez-Jayo, U., Alías, F., Angulo, I., 2017. Design
402 of a mobile low-cost sensor network using urban buses for real-time ubiq-
403 uitous noise monitoring. *Sensors (Switzerland)* 17, 1–21. doi:10.3390/
404 s17010057.
- 405 American National Standards Institute, 2009. ANSI S1.11: Specification for
406 Octave, Half-Octave, and Third Octave Band Filter Sets 552, 31pp.
- 407 Aumond, P., Can, A., Mallet, V., De Coensel, B., Ribeiro, C., Botteldooren,
408 D., Lavandier, C., 2018a. Kriging-based spatial interpolation from mea-
409 surements for sound level mapping in urban areas. *J. Acoust. Soc. Am.*
410 143, 2847–2857. doi:10.1121/1.5034799.
- 411 Aumond, P., Jacquesson, L., Can, A., 2018b. Probabilistic modeling

- 412 framework for multisource sound mapping. *Appl. Acoust.* 139, 34–43.
413 doi:10.1016/j.apacoust.2018.04.017.
- 414 Barrigón Morillas, J.M., Gómez Escobar, V., Méndez Sierra, J.A., Vílchez-
415 Gómez, R., Vaquero, J.M., Trujillo Carmona, J., 2005. A categorization
416 method applied to the study of urban road traffic noise. *J. Acoust. Soc.*
417 *Am.* 117, 2844–2852. doi:10.1121/1.1889437.
- 418 Bennett, G., King, E., Curn, J., 2010. Environmental noise mapping using
419 measurements in transit. ... *Conf. Noise ...*, 1795–1810.
- 420 Brocolini, L., Lavandier, C., Quoy, M., Ribeiro, C., 2013. Measurements
421 of acoustic environments for urban soundscapes: choice of homogeneous
422 periods, optimization of durations, and selection of indicators. *J. Acoust.*
423 *Soc. Am.* 134, 813–821. doi:10.1121/1.4807809.
- 424 Can, A., Aumond, P., 2018. Estimation of road traffic noise emissions: The
425 influence of speed and acceleration. *Transp. Res. Part D Transp. Environ.*
426 58, 155–171. doi:10.1016/j.trd.2017.12.002.
- 427 Can, A., Dekoninck, L., Botteldooren, D., 2014. Measurement network for
428 urban noise assessment: Comparison of mobile measurements and spa-
429 tial interpolation approaches. *Appl. Acoust.* 83, 32–39. doi:10.1016/j.
430 apacoust.2014.03.012.
- 431 Can, A., Leclercq, L., Lelong, J., Botteldooren, D., 2010. Traffic noise spec-
432 trum analysis: Dynamic modeling vs. experimental observations. *Appl.*
433 *Acoust.* 71, 764–770. doi:10.1016/j.apacoust.2010.04.002.

434 Can, A., Leclercq, L., Lelong, J., Defrance, J., 2009. Accounting for traf-
 435 fic dynamics improves noise assessment: Experimental evidence. *Appl.*
 436 *Acoust.* 70, 821–829. doi:10.1016/j.apacoust.2008.09.020.

437 Chevallier, E., Leclercq, L., Lelong, J., Chatagnon, R., 2009. Dynamic noise
 438 modeling at roundabouts. *Appl. Acoust.* 70, 761–770. doi:10.1016/j.
 439 apacoust.2008.09.009.

440 Chew, Y.R., Wu, B.S., 2016. Computers , Environment and Urban Systems
 441 A soundscape approach to analyze traf fi c noise in the city of Taipei ,
 442 Taiwan. *CEUS* 59, 78–85. doi:10.1016/j.compenvurbsys.2016.05.002.

443 CITI-SENSE, 2012. <http://www.citi-sense.eu/>. Accessed: 2017-03-14.

444 Cristina, L., Souza, L.D., Giunta, M.B., 2014. Computers , Environment and
 445 Urban Systems Urban indices as environmental noise indicators. *Comput.*
 446 *Environ. Urban Syst.* 35, 421–430. doi:10.1016/j.compenvurbsys.2011.
 447 06.001.

448 De Coensel, B., Botteldooren, D., Vanhove, F., Logghe, S., 2007. Microsim-
 449 ulation based corrections on the road traffic noise emission near intersec-
 450 tions. *Acta Acust. united with Acust.* 93, 241–252.

451 Dekoninck, L., Botteldooren, D., Int Panis, L., 2012. Guidelines for partic-
 452 ipatory noise sensing based on analysis of high quality mobile noise mea-
 453 surements. *Proc. 41st Int. Congr. Expo. Noise Control Eng. (Inter-Noise*
 454 *2012)* .

455 D’Hondt, E., Stevens, M., Jacobs, A., 2013. Participatory noise mapping
 456 works! An evaluation of participatory sensing as an alternative to standard

457 techniques for environmental monitoring. *Pervasive Mob. Comput.* 9, 681–
458 694. doi:10.1016/j.pmcj.2012.09.002.

459 Dutilleux, G., Defrance, J., Junker, F., Ecotière, D., Gauvreau, B., van
460 Maercke, D., Le Duc, E., Bérengier, M., Besnard, F., 2009. Road noise
461 prediction 2 - Noise propagation computation method including meteorological effects (NMPB 2008).
462

463 Estévez-Mauriz, L., Forssén, J., 2018. Dynamic traffic noise assessment tool:
464 A comparative study between a roundabout and a signalised intersection.
465 *Appl. Acoust.* 130, 71–86. doi:10.1016/j.apacoust.2017.09.003.

466 European Comission, 2002. Directive 2002/49/EC relating to the assessment
467 and management of environmental noise .

468 Fortin, N., Bocher, E., Picaut, J., Petit, G., Dutilleux, G., 2012. An open-
469 source tool to build urban noise maps in a GIS, in: Open Source Geospatial
470 Research and Education Symposium (OGRE), YVERDON-LES-BAINS,
471 Switzerland. pp. 9p, cartes.

472 Gaja, E., Gimenez, A., Sancho, S., Reig, A., 2003. Sampling techniques for
473 the estimation of the annual equivalent noise level under urban traffic conditions. *Appl. Acoust.* 64, 43–53. doi:10.1016/S0003-682X(02)00050-6.
474

475 Guillaume, G., Aumond, P., Chobeau, P., Can, A., 2019. Statistical study of
476 the relationships between mobile and fixed stations measurements in urban
477 environment. *Build. Environ.* 149, 404–414. doi:10.1016/j.buildenv.
478 2018.12.014.

479 Hakala, I., Kivel, I., Kivelä, I., Ihalainen, J., Luomala, J., Gao, C.,
480 2010. Design of low-cost noise measurement sensor network: Sensor
481 function design. Proceedings - 1st International Conference on Sensor
482 Device Technologies and Applications, SENSORDEVICES 2010 , 172–
483 179doi:10.1109/SENSORDEVICES.2010.39.

484 Jiménez, S., Genescà, M., Romeu, J., Sanchez, A., 2008. Estimation of
485 night traffic noise levels. Acta Acust. united with Acust. 94, 563–567.
486 doi:10.3813/AAA.918065.

487 Kanhere, S.S., 2011. Participatory Sensing: Crowdsourcing Data from Mo-
488 bile Phones in Urban Spaces. 12th IEEE International Conference on
489 Mobile Data Management (MDM) , 3–6doi:10.1109/MDM.2011.16.

490 Kanjo, E., 2010. NoiseSPY : A Real-Time Mobile Phone Plat-
491 form for Urban Noise Monitoring and Mapping , 562–574doi:10.1007/
492 s11036-009-0217-y.

493 Kardous, C.A., Shaw, P.B., 2014. Evaluation of smartphone sound measure-
494 ment applications. The Journal of the Acoustical Society of America 135,
495 EL186–92. doi:10.1121/1.4865269.

496 Kephelopoulos, S., Paviotti, M., Anfosso-Lédée, F., 2012. Common noise
497 assessment methods in europe (cnossos-eu).

498 Kephelopoulos, Stylianos and Paviotti, Marco and Anfosso-Lédée, Fabienne,
499 2012. Common Noise Assessment Methods in Europe (CNOSSOS-EU).
500 doi:10.2788/31776.

- 501 King, E.A., Rice, H.J., 2009. The development of a practical framework for
502 strategic noise mapping. *Appl. Acoust.* 70, 1116–1127. doi:10.1016/j.
503 *apacoust.*2009.01.005.
- 504 Kluijver, H.D., Stoter, J., de Kluijver, H., Stoter, J., 2003. Noise mapping
505 and GIS: Optimising quality and efficiency of noise effect studies. *Comput.*
506 *Environ. Urban Syst.* 27, 85–102. doi:10.1016/S0198-9715(01)00038-2.
- 507 Licitra, G., Ascari, E., 2014. Gden: An indicator for European noise maps
508 comparison and to support action plans. *Sci. Total Environ.* 482-483, 411–
509 419. doi:10.1016/j.scitotenv.2013.07.014.
- 510 Montes González, D., Barrigón Morillas, J.M., Rey Gozalo, G., 2015. The in-
511 fluence of microphone location on the results of urban noise measurements.
512 *Appl. Acoust.* 90, 64–73. doi:10.1016/j.*apacoust.*2014.11.001.
- 513 Morley, D.W., Hoogh, K.D., Fecht, D., Fabbri, F., Bell, M., Goodman, P.S.,
514 Elliott, P., Hodgson, S., Hansell, A.L., Gulliver, J., 2015. International
515 scale implementation of the CNOSSOS-EU road traffic noise prediction
516 model for epidemiological studies. *Environ. Pollut.* 206, 332–341. doi:10.
517 1016/j.*envpol.*2015.07.031.
- 518 Mydlarz, C., Salamon, J., Pablo, J., 2017. The implementation of low-cost
519 urban acoustic monitoring devices. *Appl. Acoust.* 117, 207–218. doi:10.
520 1016/j.*apacoust.*2016.06.010.
- 521 Ng, C.H., Tang, S.K., 2008. On monitoring community noise using arbitrarily
522 chosen measurement periods. *Appl. Acoust.* 69, 649–661. doi:10.1016/j.
523 *apacoust.*2007.01.003.

524 NoiseTube, 2008. <http://www.noisetube.net/>. Accessed: 2019-02-15.

525 Picaut, J., Fortin, N., Dutilleux, G., 2011. A simplified approach for making
526 soundmaps within a GIS software, in: Inter-Noise 2011, France. p. 6p.

527 Prieto, C., Barrigón, J.M., 2015. Stabilisation patterns of hourly ur-
528 ban sound levels. *Environ. Monit. Assess.* 187, 4072. doi:10.1007/
529 s10661-014-4072-3.

530 Prieto, C., Barrigón, J.M., Rey, G., Vílchez, R., 2016. Can weekly noise
531 levels of urban road traffic, as predominant noise source, estimate annual
532 ones? *J. Acoust. Soc. Am.* doi:10.1121/1.4966678.

533 Quintero, G., Balastegui, A., Romeu, J., 2018. Annual traffic noise levels
534 estimation based on temporal stratification. *J. Environ. Manage.* 206, 1–9.
535 doi:10.1016/j.jenvman.2017.10.008.

536 Quintero, G., Romeu, J., Balastegui, A., 2019. Temporal and spatial strat-
537 ification for the estimation of nocturnal long-term noise levels. *Environ.*
538 *Pollut.* 245, 666–674. doi:10.1016/j.envpol.2018.11.052.

539 Rana, R.K., Chou, C.T., Kanhere, S.S., Bulusu, N., Hu, W., 2010. Ear-Phone
540 : An End-to-End Participatory Urban Noise Mapping System , 105–116.

541 Rawat, P., Deep, K., Chaouchi, H., Marie, J., Singh, K.D., Chaouchi,
542 H., Bonnin, J.M., 2014. Wireless sensor networks: A survey on re-
543 cent developments and potential synergies. *J. Supercomput.* 68, 1–48.
544 doi:10.1007/s11227-013-1021-9.

545 Romeu, J., Genescà, M., Pàmies, T., Jiménez, S., 2011. Street categorization
546 for the estimation of day levels using short-term measurements. *Appl.*
547 *Acoust.* 72, 569–577. doi:10.1016/j.apacoust.2010.09.012.

548 Romeu, J., Jimenez, S., Genesca, M., Pamies, T., Capdevila, R., 2006.
549 Spatial sampling for night levels estimation in urban environments. *J*
550 *Acoust.Soc Am* 120, 791–800. doi:10.1121/1.2215219.

551 Safeer, H., Wesler, J., Rickley, E., 1972. Errors due to sampling in community
552 noise level distributions. *J. Sound Vib.* 24, 365–376.

553 Segura-Garcia, J., Felici-Castell, S., Perez-Solano, J.J., Cobos, M., Navarro,
554 J.M., 2015. Low-cost alternatives for urban noise nuisance monitoring
555 using wireless sensor networks. *IEEE Sens. J.* 15, 836–844. doi:10.1109/
556 *JSEN.2014.2356342*.

557 Sevillano, X., Socoró, J.C., Alías, F., Bellucci, P., Peruzzi, L., Radaelli, S.,
558 Coppi, P., Nencini, L., Cerniglia, A., Bisceglie, A., Benocci, R., Zam-
559 bon, G., 2016. DYNAMAP – Development of low cost sensors networks
560 for real time noise mapping. *Noise Mapp.* 3, 172–189. doi:10.1515/
561 *noise-2016-0013*.

562 Smartcitizen, 2011. <https://smartcitizen.me/>. Accessed: 2019-02-15.

563 Steele, C., 2001. Critical review of some traffic noise prediction models. *Appl.*
564 *Acoust.* 62, 271–287. doi:10.1016/S0003-682X(00)00030-X.

565 SYMUVIA, 2005. [http://www.licit-lyon.eu/themes/realisations/](http://www.licit-lyon.eu/themes/realisations/plateformes/symuvia/)
566 [plateformes/symuvia/](http://www.licit-lyon.eu/themes/realisations/plateformes/symuvia/). Accessed: 2019-01-12.

- 567 Torija, A.J., Ruiz, D.P., Ramos-Ridao, Á., 2011. Required stabilization time,
568 short-term variability and impulsiveness of the sound pressure level to char-
569 acterize the temporal composition of urban soundscapes. *Appl. Acoust.*
570 72, 89–99. doi:10.1016/j.apacoust.2010.09.011.
- 571 Wei, W., Van Renterghem, T., De Coensel, B., Botteldooren, D., 2016.
572 Dynamic noise mapping: A map-based interpolation between noise mea-
573 surements with high temporal resolution. *Appl. Acoust.* 101, 127–140.
574 doi:10.1016/j.apacoust.2015.08.005.
- 575 Wessels, P.W., Basten, T.G.H., 2016. Design aspects of acoustic sensor net-
576 works for environmental noise monitoring. *Appl. Acoust.* 110, 227–234.
577 doi:10.1016/j.apacoust.2016.03.029.
- 578 Zambon, G., Benocci, R., Brambilla, G., 2016. Cluster categorization of
579 urban roads to optimize their noise monitoring. *Environ. Monit. Assess.*
580 188, 1–11. doi:10.1007/s10661-015-4994-4.