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Faster and more accurate noise mapping combining meta-modeling and data assimilation

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Abstract
Urban noise mapping can be sped up replacing the traditional noise mapping model with a meta-model. In the present study, in the framework of the CENSE project, a meta-model was obtained by training on 2000 simulations of NoiseModelling software, on part of Paris. It is based on dimension reduction of inputs and outputs of NoiseModelling. The reduced model is then approximated by a statistical emulator. The resulting meta-model can closely reproduce any NoiseModelling noise map for Paris under any typical traffic condition, but with a computational time about 10000 times lower. The meta-model is then employed to assimilate acoustic measurements from 16 locations. State estimation, inverse modeling and joint state-parameter estimation are compared and evaluated using cross validation. The most accurate noise map is obtained with joint state-parameter estimation, without a priori knowledge about traffic and weather.

Keywords: Noise mapping, data assimilation, meta-model, sensor networks, CENSE project.

1 Introduction

Many countries have implemented policies and strategies to reduce noise pollution, of which noise mapping is a part. The directive 2002/49/EC requires for instance every European agglomeration with more than 100 000 inhabitants to produce a noise map every 5 years, as a starting point for the implementation of action plans to reduce noise pollution, but also as a tool for communicating between the different stakeholders [1]. As a response, model-based numerical engineering methods have been developed and are currently widely used to make road traffic urban sound maps: CNOSSOS-EU in Europe [2], FHWA in USA [3], ASJ-RTN in Japan [4] amongst others. These models provide a good compromise between accuracy and computation time, and made it possible to quantify the number of people exposed in cities to noise levels associated with health impacts. They are however criticized on three points. First, the quality of the input data and the accuracy of the model parameters strongly affect the quality of the noise maps produced [5]. Secondly, it focuses on noise sources that are considered annoying, and does not reflect the diversity in sources of the perceived sound mixtures, although research in soundscapes provides evidence on the importance to characterize this diversity [6]. Thirdly, this method is computationally expensive; thus, it only allows for the elaboration of maps based on long-term indicators and is not adapted to the production of time evolving noise maps.
Sound maps based on measurements can help to improve sound mapping [7][10]. Noise observatories enable to monitor sound levels evolution in urban areas with a fixed network of low cost noise level meters. Maps interpolated from the data obtained through fixed sound measurement stations have recently been produced [9]-[13], and form a useful tool to estimate the noisiness of a neighborhood or to give a global overview of the city sound levels. However, [14] showed that interpolation methods were defective when the spacing between sensors was too large.
Studies recently proposed to merge the benefits of the two approaches that is combining the spatial information from the model-based approaches and the temporal information from the observation-based approaches. [15] built an interpolating model based on observations and a method to propagate the observed sound level. [16]

assimilated observations from mobile phone microphones in order to improve a pre-calculated noise map. However, this process is useful only when a large number of mobile observations can be collected for this task. [17] inferred the noise mapping software inputs from noise observation by estimating the emission sources from the observed noise measurements in the vicinity of the roads by using a forecasting sequential approach rather than a more spatial approach. These methods can be adapted to estimate either long-term or dynamic 1-hour maps. The Life project “Dynamap" updated 1-hour noise maps by scaling the noise levels of pre-calculated noise maps using the observed differences between measured and calculated original grid data for different classes of roads [18][19]. However, the production of dynamic maps requires that noise or road traffic data are available continuously, which can be tedious.

The CENSE project relied on a two steps approach to combine measurements and modeling, in order to go towards faster and more accurate noise mapping:

- A meta-model (also sometimes called surrogate model) is built to statistically reproduce the behavior of the reference simulation software, Noisemodelling in this case;
- The meta-model is then employed to assimilate acoustic measurements from 16 locations. State estimation, inverse modeling and joint state-parameter estimation are compared and evaluated using cross validation.

This paper summarizes the results of the CENSE project in terms of meta-modelling and data assimilation. The reader can refer to the following papers for more details [20][21][22].

2 Materials

2.1 Case Study

For phasing and data availability reasons, the model was built on data produced on the city of Paris, and not on the Lorient measurement network of the CENSE project. The study area is located in the 13th district of Paris, France and covers an area of 3 km^2, and is described in details in [6]. It consists of an array of 25 microphones has been deployed across5 the study area in 2015, from which 16 have been selected for the present study. They have recorded the noise level $L_{f,i}$ in dB for every one-third octave from 63Hz to 20 kHz with a time step of Δt = 125ms, from January 1, 2015 to September 30, 2015. The spatial distribution of the 16 sensors is shown in Figure 1.

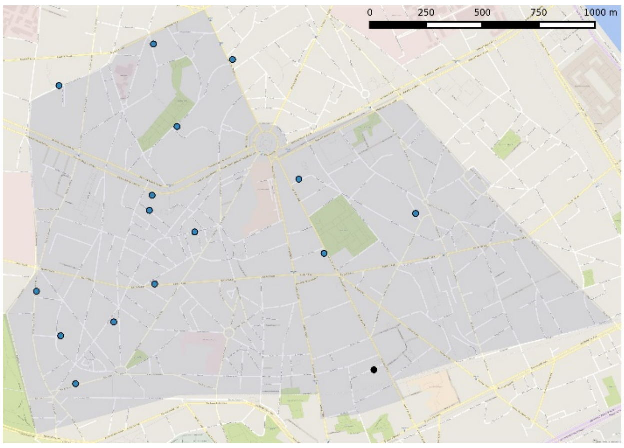

Figure 1. Distribution of the noise level meters across the studied section

2.2 Meta-Model

2.2.1 NoiseModelling

The noise mapping software used in this study by which the meta-model is generated is NoiseModelling (Aumond et al., 2020a). It is an open source software designed to produce1 noise maps, which implements the CNOSSOS-EU guidelines. It uses as input traffic, topographic and meteorological data. The process can be summed up by the following steps: the input traffic data along each road is discretized into a set of punctual noise sources. NoiseModelling computes the emissions. Then NoiseModelling computes the transmission paths between the sources and the receivers, taking into account the distance propagation, the number of reflections and diffractions. The software then computes the attenuation along each path. The sound level at a receiver is finally calculated from the contributions of all sources.

2.2.2 Meta-model method

The meta-model is built in three steps:

- The generation of the training sample;
- The dimension reduction, through a PCA, which aims to select a reduced amount of maps that explain most of the variance of the noise maps of the training sample;
- The kriging, which interpolates with a statistical method the projected values of the training sample onto the basis vectors of the reduced subspace.

The training sample is made of 2000 simulations run with model input parameters defined a so-called design of experiment. The parameters are associated with variation ranges (defining the parameter space) and then drawn with Latin Hypercube Sampling (LHS) so that they “uniformly” cover the parameter space.
The dimension reduction is carried out with principal component analysis (PCA) on the training sample. It leads to the representation any model output as a linear combination of PCA maps. Each PCA map represents a typical variation observed among the training maps. Any output map of the training set is well reproduced by a linear combination of 4 PCA maps with weights that depend on the model input parameters.
Each weight of the aforementioned linear combination can be seen a function that depends on the model input parameters. This function is unknown but is approximated using kriging applied to the training set. One kriging is carried out for each weight, independently.
The meta-model finally consists in applying the kriging, for each weight, at for any given input parameters. The resulting weights are used to linearly combine the PCA maps, which yields a noise map similar to that of the complete model run with the given parameters.
Once the meta-model is built, each call with new input parameters takes a very small amount of time (100ms versus ~ 1 h for the complete model). For more details about the meta-model construction, the reader can refer to [22].

2.3 Real-time observations

All the noise data is given in global value and in dB(A) because the meta-model is designed to give an output in dB(A). The real-time 1-hour traffic data on the main roadways of Paris is available online on the city of Paris open data platform. The real-time weather data has been taken from the Montsouris weather station near the study area, it is also on open access online. The weather station updates its data every hour in real time.

2.4 Data assimilation methods

2.4.1 Purpose of the data assimilation

Data assimilation is the process of combining a noise model simulations and field observations, in order to build an improved representation of the real noise levels, at least at simulated points (i.e., at model receptors). One difficulty of the task is that only part of the simulated values (at the model receptors) are observed. Indeed there are only a few point observations while a numerical simulation includes many receptors (on a grid or a more complex mesh). Actually, more often than not, observed locations do not even coincide with any model receptor.
In our context, the data assimilation will make use of a model or a model simulation (simulated noise map) and field observations at a given time, in order to produce another noise map closer to the real noise map. It can be seen as a correction on the simulated noise map, induced by the additional information brought by the observations.

2.4.2 Data assimilation methods

Among all the data assimilation approaches, we compared state estimation, inverse modeling and a joint state-parameter estimation.

- The state estimation applies a direct correction on a simulation map. It assumes the simulated map is an priori map with some unknown error at every point of the map. This defines an error map, which is the difference between the simulated map and the real noise map. This error map (defined at the model receptors) can be represented as a random vector, assumed to have zero mean and some variance (matrix) B. The observations are also imperfect and the observational error can also be seen as a random vector (one component for each observed location), with zero mean and some variance (matrix) R. Relying on previous definition, we compute the so-called best linear unbiased estimator (BLUE) which is an improved noise map whose error has minimum variance.
- Another approach is called inverse modeling (IM). In this case, we do not correct directly the simulated noise map, but instead the input parameters of the noise model, or in our case, of the meta-model. The method allows to determine better parameters, which with the simulated map gets closer to the observations.
- Joint state-parameter estimation (JSPE) combines both approaches: the parameters are improved and also a correction of the resulting noise map is corrected. This allows for further flexibility and gives more room for improvement.

Note that we can rely on a priori parameters (i.e., assumed parameters for the given situation, before assimilating the observations), or even try to find the input parameters only using the observations, without any first guess on the parameters.

2.5 Compared interest of different methods

Both methods, IM and JSPE, can work with or without prior knowledge of the input parameters, four optimization algorithms are therefore analyzed. Table 1 sums up the data necessary to perform the optimization algorithm for each cost function. If satisfying results are obtained with optimization algorithms that do not need a priori parameters, then it is possible to expand the inverse modeling data assimilation processes to a wider range of urban areas where the input parameters values are not known.

optimization algorithms	*a priori* parameters p	covariance matrices B and R
Inverse modeling	✗	✗
Inverse modeling with *a priori* parameters	✓	✗
JSPE	✗	✓
JSPE with *a priori*	✓	✓

3 Results

Methods are compared through a leave-one-out cross validation, which consists in removing the observations of a given microphone from the data assimilation process. Only the observations from the other microphones are used to correct the noise level distribution. This procedure is carried out for all microphones, one by one, where only one microphone is removed at a time. The metrics used for comparison are The Bias and RMSE. Results are detailed in [22]. In brief, the distribution of the bias is narrower for the inverse modeling than for the meta-model only. It is even narrower when the JSPE is used. All the optimized cost function based algorithms show better results than the regular BLUE data assimilation procedure for both error margins 1 dB and 3 dB whether we consider the approach with or without accounting for prior knowledge of the input parameters. The JSPE with a priori parameters shows the best results when considering RMSE. The better performance of the JSPE is explained by the consideration of the background error covariance matrix.
The method can be illustrated by visualizing the correction map when a specific noisy event occurs (a popular street festival on the 21st of June). It shows that the positively corrected area is a lively neighborhood with a high density of bars and restaurants.

4 Conclusion

Several ways of generating noise maps have been evaluated under the CENSE project, in order to take into account an observation network in the evaluation:

- The first step, consisted in designing a meta-model built in order to reproduce the output of a noise mapping software (in our case NoiseModelling) of a given area where the inputs are variations of the noise sources parameters such as the speed and the flow rate of the vehicles, of the noise propagation such as the reflection coefficient of the buildings or the temperature. It is generated by a learning sample of input parameters and the resulting noise maps computed by the noise mapping software. The resulting meta-model is a linear combination of a reduced set of statistically significant normalized noise maps whose weights are interpolation functions of the projection of the output noise maps onto the maps of the reduced basis. This method allows to fairly reproduce the output of the noise mapping software with a much lower computation time, and then, among other applications, to computed dynamic noise maps in real time.
- The second step is to include the noise level observed through noise level meters scattered across the study area through two methods, the Best Linear Unbiased Estimator (BLUE), and the inverse modeling and Joint State Parameter Estimation. The BLUE method adds a correction layer to a noise map generated by the meta-model, called background, whose input parameters are based on ground traffic and weather observations. The correction layer is built with an estimation of the background and observation matrices. The RMSE is reduced by 30% when estimating the performance of this process through a leave-one-out cross-validation method. The inverse modeling computes the input parameters of the metamodel which best fit with the observations with an optimization algorithm. This

method generally gives better results than the BLUE method at the cost of a longer computation time due to the exploration part of the optimization algorithm. In addition, this method is suitable for areas where no traffic nor weather ground measures are observed. It is then available for a wider range of study areas.

This work opens up new research perspectives:

- First, the meta-model created in chapter II which has been used for data assimilation purposes can be used for several other applications which have not been explored yet in this work. Some applications can be done in sensitivity analysis, and uncertainty propagation. An other domain of sensitivity analysis requires a very large amount of calls to the model, the variance based sensitivity analysis and the computation of the so-called Sobol indices (Sobol, 1990). The Sobol indices of the input parameters of a noise mapping reference software can only be computed with the help of a meta-model [25].
- Second, the meta-model used in this study for data-assimilation only required a limited amount of input parameters (dim p = 7). However, it is possible to build a richer meta-model with a larger amount of input parameters. In addition, it is possible to enrich the weather data. In this study, only the temperature has been considered as an input, but it is possible to add wind direction and intensity, hygrometry, probability of of occurrence of favorable atmospheric condition, etc.) which would lead to a much richer and more complex meta-model and might better approach the real dynamic noise distribution.
- Third, In this study, the distribution of the observation points across the study area was given as an input. One may wonder if, for a given quantity of noise level meters, some distribution give better results than others when conducting the data assimilation process. The CENSE network deployed in Lorient could support this research.

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