METHODS FOR QUANTIFYING THE UNCERTAINTY
IN NOISE MAPPING

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SUMMARY

This paper discusses two techniques to tackle the problem of dealing with and quantifying the uncertainty in noise maps. A Monte Carlo type approach and a fuzzy technique are examined. Both techniques are able to map the uncertainty in the input to a measure of uncertainty of the noise maps produced from it. A theoretical comparison between both approaches is discussed. The fuzzy technique has a clear advantage in processing speed and can handle more aspects of uncertainty. The Monte Carlo technique is however preferred when the uncertainty distributions and mechanisms are well known. Real life examples of the techniques are shown.

INTRODUCTION

Noise mapping is a tool that is gaining increasing support in policy support and decision making. Regions covered by noise mapping projects continue to grow in response to a more global policy strategy and the demand from governments to provide noise maps for important noise sources. The European Union insists on Member States to report noise maps of agglomerations with more than 50.000 inhabitants and for large infrastructure. Gathering the data needed and preparing of the data has become one of the most important problems in current noise mapping. Data is lacking or is of poor quality causing the noise maps to loose credibility. When noise maps are used in a legal context it is even more important to provide correct results and provide a founded uncertainty on the result.

The problems that pop up in a noise mapping project come from several sources. Due to the many parties involved in providing data differences in format, encoding and geo-mapping are a first source of error and uncertainty. Even for well-defined data sets small differences in projection of georeferenced data may cause great problems that are difficult to solve automatically. Roads may be extracted from construction plans and houses from processing satellite images or aerial photographs causing small differences in projections. As a consequence roads may be in buildings or too close to facades leading to overestimated exposure.

Traffic models are often based on virtual links between cities without using the actual roads between them. The projection of the final modeling results onto the real roads is an important source of emission uncertainty.

The Workgroup Assessment of Exposure to Noise (WG-AEN) has formulated to a certain degree the expected accuracy of several methods and their complexity and expected cost. Although this provides a global sense of accuracy no exact defined uncertainty measure is used. This is one of the

problems the Imagine project tries to solve by quantifying the accuracy and uncertainty of the methods used throughout the noise mapping process. This paper discusses methods on how to obtain uncertainty estimates from simulation and how to use them in real world noise mapping.

MODELING UNCERTAINTY

All real-world information is tainted by uncertainty to a certain degree. In many applications this imperfection is however silently neglected. It may however be clear that uncertainty in noise mapping is clearly present and can not be neglected. Two types of uncertainty can be discriminated. *Soft* uncertainties are uncertainties that can be quantified or estimated. An example is the uncertainty about the ground reflection of an unknown open area. The exact reflection may not be known but based on the distribution of the types soil a distribution can be computed. Also when ground reflection is extracted from satellite imagery a rough estimate of the ground impedance can be made which causes a soft uncertainty on it. *Hard* uncertainties [10] occur when even the range of possible outcomes is unknown. An example is missing geometry. The effects of reflections and diffractions can not be set out in a distribution. The focus in this paper will be on soft uncertainties as they are the most prevalent in noise mapping.

Uncertainty can also be split up between model and data uncertainty. Model uncertainty specifies that a model is only a reflection of reality and may and will miss some features that can have an impact on the accuracy of the result. Data uncertainty relates to imprecise or lacking input data.

Uncertainties in Noise Mapping

Uncertainty emerges at several places in the noise mapping tool chain. The tool chain roughly follows the DPSIR (Driving Forces, Pressure, State, Impact and Response) chain model often used in environmental impact modeling. If we look at the bottom of the chain we find the driving sources that are the traffic, industrial, railway and aircraft sources. Traffic intensities and speed distributions are often measured at large access roads and highways, but even then the number of measurements is limited due to practical or economical reasons. Traffic models of various kinds are employed to fill in the missing data and can magnify problems with calibration data. An additional problem is that some models do not provide the necessary statistics about vehicle speed and acceleration and estimates have to be made or generalizations used.

Noise emissions from the traffic are based on standardized models like the Nord2000 or Harmonoise model. Although the error on these models is in general quite low for streams of traffic, detailed traffic data is necessary to operate within a 1dB margin. Effects of ignoring speed and/or acceleration can easily add up to 5dB in traffic interchange areas.

Propagation models are probably the most known source of uncertainty in noise mapping. They are complex and require huge amounts of data, geometric or other. For large-scale noise mapping the required detailed data is often lacking and forms the most important source of uncertainty. Geometry is often badly matched to the road network and data about local meteorological conditions is frequently missing.

The uncertainty discussed above was of numerical nature. In noise mapping there is also an important geometric problem to be solved. Engineering models used for large-scale noise mapping are ray based and hence use some kind of ray path constructor. The impact of having imprecise geometry for the buildings and infrastructure can be large. Receivers can come into the line of sight of important sources due to slight changes in geometry. The use of Fresnel zones can limit this effect but at a great cost in computer time and algorithmic complexity.

The algorithm used to construct paths also has an impact on accuracy. Sweeping the space seen from the receiver by shooting rays could lead to missed sources. Better, but often slower,

techniques make sure that no source-receiver-paths are missed up to a given number of reflections and diffractions. Obviously the number of reflections and diffractions used to find paths plays a role in the final accuracy. In general it is hard to estimate the loss of accuracy due to geometric data or model uncertainty.

Techniques

The techniques discussed in this section are able to solve the problem of numerical uncertainty in the noise mapping process. We introduce the concept of *extended numbers*. We discuss two flavors extended numbers: *probabilistic numbers* and *fuzzy numbers*.

A probabilistic number is given by a mapping of the real axis to the closed interval [0,1] given that the integral over the real axis is exactly 1 corresponding to a probability distribution. Operations on *probabilistic numbers* are defined in terms of the cumulative distribution of the underlying probability distribution. The probability distribution of the new probabilistic number is then obtained by derivation. Equation 1 computes the cumulative distribution of the product of two *probabilistic numbers*:

$$F_{A \cdot B}(x) = \int_{-\infty}^{+\infty} \Pr[A \le x / b \wedge B \le b + db] db$$
$$= \int_{-\infty}^{+\infty} F_A(x / y) f_b(b) db$$

(1)

A fuzzy number is defined by a mapping of the real axis to he closed interval [0,1] given that the supremum of the image is 1. The mapping is also called a possibility distribution [7]. Operations on fuzzy numbers are based on the extension principle [4][7] that allows extending mathematical operations on crisp numbers to operations on fuzzy numbers. Equation 2 shows how to extend the product:

$$\mu_{A \cdot B}(y) = \mu_C(y) = \sup_x \min\{\mu_A(y / x), \mu_B(x)\}$$

(2)

where μ_X is the possibility distribution of the fuzzy number X.

Numerical Representation

Both types of extended numbers work with underlying distributions. Several techniques exist to represent the distributions and we refer to [6] for a more elaborate discussion. The parametric form is the most space efficient but some results of computations cannot be rewritten in parametric form.

Representing distributions with a large number of samples are the easiest to perform operations on but are the slowest. A piecewise linear approximation of the underlying distribution allows to perform fast computations while being space efficient. When the underlying distributions are convex some important simplifications can be made in the computation schemes leading to significant improvements in speed. Specifically, the calculus on the fuzzy numbers collapses to the calculus on intervals.

Measuring Uncertainty

There is no single numerical definition of uncertainty. Uncertainty can be measured in several ways in both frameworks. A common measure of uncertainty is the extent (often called *support*) of the distribution. The width of the extent is a first indication of the total uncertainty present in the computation at a given position. When theoretical distributions are used which extend over the whole real axis this measure is of no use. Taking the *bandwidth* of the distribution is often a better

idea. The bandwidth is the width of the distribution where it has 0.5 probability or possibility. Skewness of the uncertainty is measured by subtracting the most likely value (also called the *mode*) from the expected value, respectively defined as the value with the highest probability/possibility and the average of the distribution under consideration.

The shape of the distribution is measured by taking the entropy. Low entropy is an indication of sharp shaped distributions. The pointier the distribution is the less uncertainty is present in the computation. In the limit the distribution collapses to a single crisp value indicating absolute certainty. The opposite is maximum entropy where all values of the domain have an equal probability/possibility. Entropy is measured for probability distributions using the Shannon entropy [9]. Measuring entropy in the possibilistic framework is less straightforward; we employ the method of Klir [8]. Although both methods measure information content their absolute values are not comparable. An increase of the Shannon entropy will however also dictate an increase in the Klir entropy. Direct absolute comparison of uncertainty measures between the two frameworks is in general impossible.

Micro/Macro Architecture

The extended numbers can be put to use at several places in the noise mapping tool. The first option is to wrap an existing noise mapping architecture in a higher/macro level uncertainty module. This module performs a number of simulations and sweeps the parameter space. For each sample of the parameter space a new noise map simulation is performed. Although this is conceptually and practically the easiest solution some problems occurs. The relation between input and output may be non monotonic which prevents simulation of only two sample points on an input variable to gather the desired output sensitivity. If correlation between input variables has a significant effect on the output then the number of simulations grows exponential in the number of input variables. Each input variable's output sensitivity has to be computed in function of the other variables.

A better option is to handle the uncertainty at a micro level. Operations on regular floating point numbers are replaced by their extended counter part. The complete noise mapping tool is transformed. For the end user there is no visible change except for the input that the tool expects. This may still be exact, crisp, numbers but distributions are also accepted. Just like a regular noise mapping process, the tool is run once to compute the noise map. During this computation the extended numbers are used. The final result is a noise map together with the global output sensitivity.

Application

The first application of the technique is on an artificial environment. A single point source is placed in a street canyon in front of a side street. Different aspects of uncertainty are considered in the computation of figures 1 and 2:

- Source placement uncertainty: because often the exact position of the road is not known in street canyons a maximum displacement of 3m is taken into account. This translates into an uncertainty in the direct neighborhood of the source but the effect diminishes rapidly with the distance to the source.

- Uncertainty of ground effect: the ISO9613 [1] ground model is used where the G parameter is only known within a Gaussian distribution with mean of 0.2 and standard deviation 0.01. The relative importance of the ground effect on longer distances means that the uncertainty will also grow with distance for this effect.

- Reflection coefficient of façade: the reflection coefficient is expressed as a real relative impedance. The relative impedance used is 1/17 with a standard deviation of 0.005, corresponding to a mean perpendicular absorption coefficient of 0.8. The use of impedances allows the uncertainty to depend on the angle of coincidence of the incoming ray.

- Model uncertainty: the propagation model is only accurate for short distances. Longer distances show an increasing spread. This is partly due to instable meteo conditions. The uncertainty on the level takes a Gaussian shape with standard deviation linearly increasing from 0 to 2.5dB at 1.5km path length.

Other aspects of uncertainty are available in the model but were not used in the examples:

- Discretisation uncertainty: the model uses point sources, whereas line sources may be a more accurate approximation of reality. Typically the space between two successive point sources is kept around 10m. Because the distance to the façade is also of that order some uncertainty arises about the real façade levels. Close to the point source it is a slight overestimation while between two point sources the value is a small underestimate.

- Source emission uncertainty: the power spectrum may not be known exact due to the traffic data used to estimate the emission.

The fuzzy approach uses possibility distributions with 8 control points and a linear interpolation between them. The computation of the noise map with the fuzzy approach took about 5 times longer than the computation of a single sample of the Monte Carlo approach. In the fuzzy approach 8 times more information is processed. The use of interval calculus assures that the computation time increases linearly with the chosen level of discretisation of the uncertainty on the input variables. For real world environments this factor drops typically to around 3. In this artificial example the trace time is very small to the time needed to compute the acoustical attenuation.

For the Monte Carlo approach 200 runs were used to sample the uncertainty on the input variables. From figures above it is clear that the averaged value from the Monte Carlo approach and the most likely value from the fuzzy approach match very closely. The uncertainty measure used in all figures is the support of the respective distributions. The figures show the general tendency of the Monte Carlo approach to flatten out the uncertainty. In areas where no single factor of uncertainty is dominant the Monte Carlo approach smoothes the picture while the fuzzy approach takes the worst-case value.

Figure 3 shows the fuzzy technique for a real world environment. An excerpt of a simulation of an urban area is depicted for a limited number of sources. The uncertainty computed by the Monte Carlo approach contains more noise, which is to be expected from a random sampling technique. The noise is not present in the averaged value. Taking the averaged value instead of the most likely value in the probabilistic approach is done for computational reasons. To estimate the most likely value in a probability distribution some analysis of the distribution is needed, while the average is easy to compute. The average will be the most likely value for convex distributions where the average is equal to the median value.
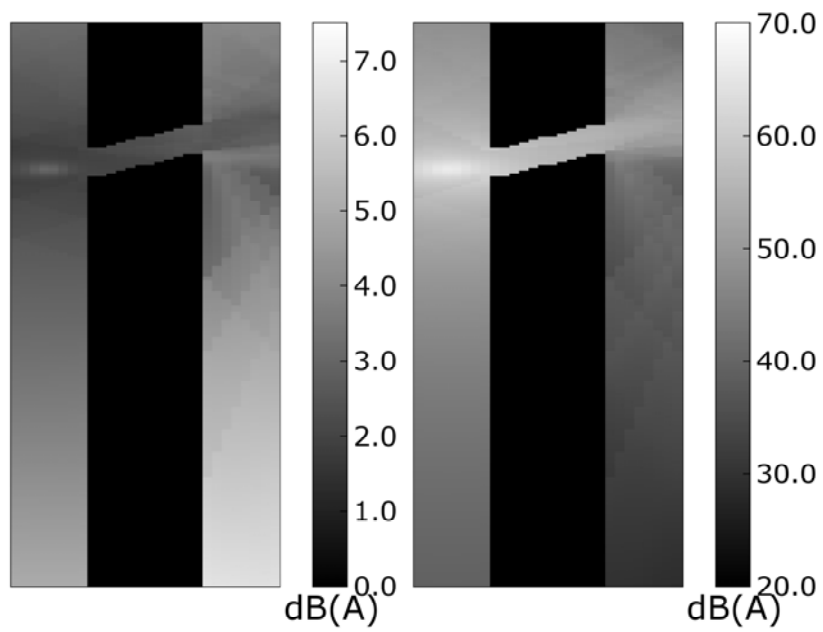
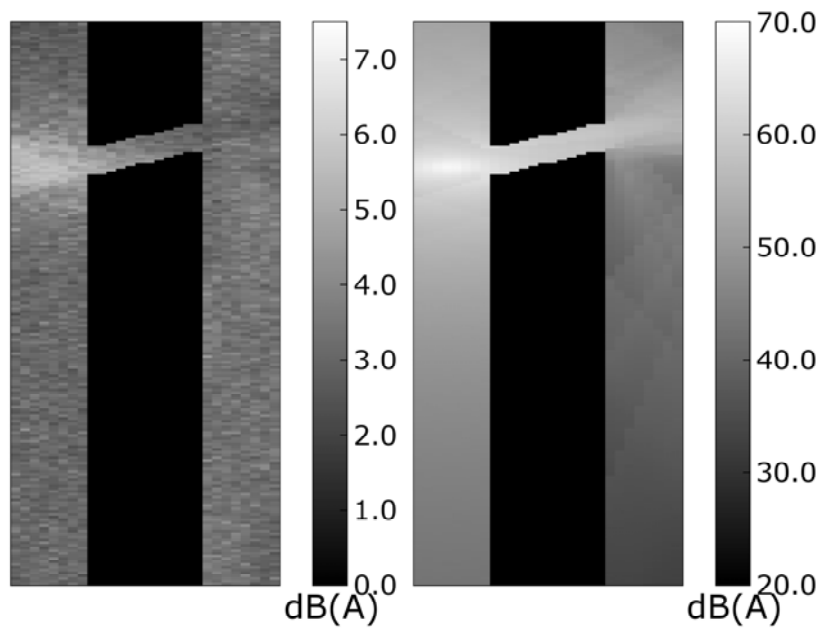*Figure 1 Uncertainty (l) and most likely value (r) using fuzzy approach*

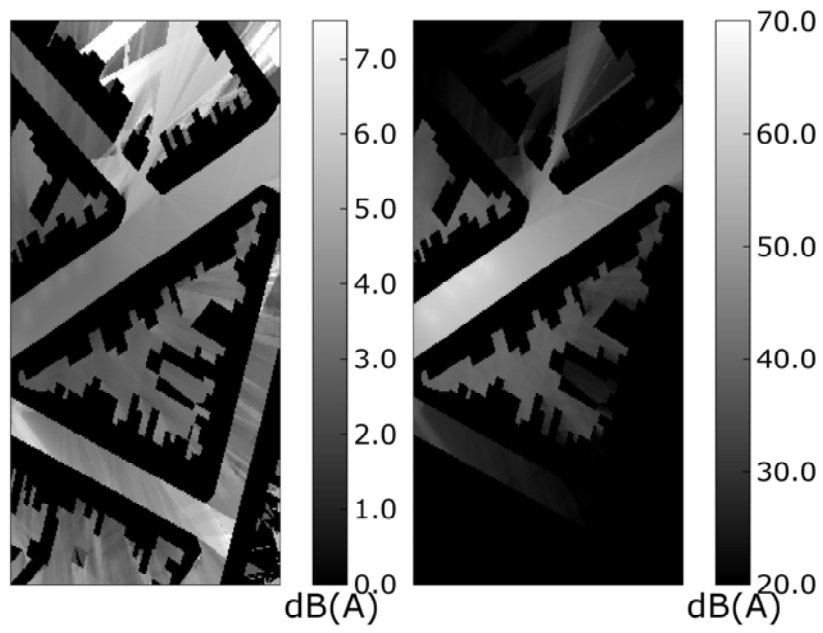*Figure 2 Uncertainty (l) and averaged value (r) for Monte Carlo approach*

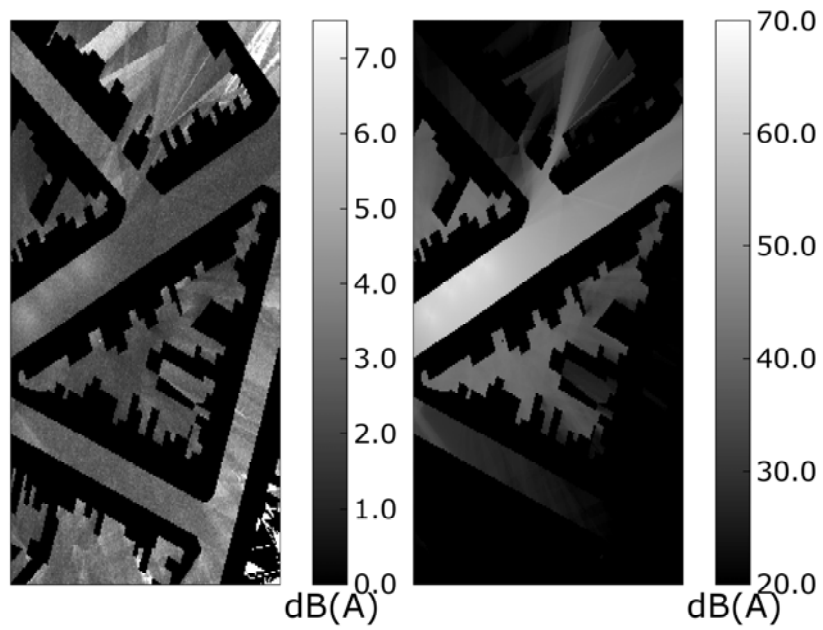*Figure 3Uncertainty(l) and most likely value (r) for fuzzy approach*

Figure 4 Uncertainty (l) and averaged value (r) for Monte Carlo approach

CONCLUSIONS

Two methods are presented to deal with uncertainty in noise mapping: a Monte Carlo method based on probability and a fuzzy method. Both techniques prove useful but the fuzzy method has the definite speed advantage. The interpretation of the results is however not as straightforward as the more familiar probabilistic approach. The fuzzy technique suits its purpose very well of showing areas in the noise map where problems with accuracy may occur.

ACKNOWLEDGEMENTS

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