Optimisation de l´échantillonnage spatial des mesures non destructives - développement théorique et étude de cas

Carolina Gomez-Cardenas

Optimal spatial sampling for non-destructive testing measurements

C. Gomez-Cardenas[a], ZM. Sbartaï[a], JP. Balayssac[b], V. Garnier[c], D. Breysse[a]

a. *Institut de Mécanique et d'Ingénierie (I2M), dpt GCE, Université Bordeaux 1, CNRS, INRA, 351 cours de la libération, 33405 TALENCE Cedex*
b. *Laboratoire Matériaux et Durabilité des Constructions (LMDC), NSA-UPS, INSA-GENIE CIVIL, 135 Av. de Rangueil, 31077 TOULOUSE Cedex*
c. *Laboratoire de Mécanique et d'Acoustique – Laboratoire de Contrôle Non Destructive (LMA-LCND), Avenue Gaston Berger, 13 625 AIX EN PROVENCE Cedex1*

Résumé :

Les techniques de Contrôle Non Destructif (CND) sont incontournables pour ausculter les ouvrages afin d'évaluer les propriétés du béton ou de détecter des anomalies (fissures, pathologies, etc). À cause de contraintes budgétaires, une méthodologie optimale pour évaluer l'intégralité de l'ouvrage à moindre coût est donc nécessaire. Cet article présente une optimisation spatiale des mesures de CND basée sur leur corrélation spatiale. Elle est faite en deux étapes. La première, consiste à déterminer les relations entre le nombre de mesures et les valeurs des fonctions objectives pour une grille régulière en utilisant l'interpolation spatial par krigeage. La deuxième, consiste en l'optimisation de la position des mesures de CND en utilisant une méthode d'optimisation d'échantillonnage spatial développée dans cette étude. Le développement théorique sera présenté ainsi que quelques résultats sur des donnés simulés et réelles (vitesse ultrasonore).

Abstract :

Non-destructive testing techniques (NDT) are essential to auscultate structures in order to assess properties or detect anomalies (cracks, pathologies, etc.) in the concrete. Due to budget limitations, an optimal methodology to estimate the integrity of a structure with a minimum cost is required. This paper presents a spatial optimization for NDT measurements based on their spatial correlation. This optimization is done in two steps. First, the relationship between the number of measurements organized in a regular grid and its respective fitness function value are determined using the kriging method. Then, using an optimisation spatial sampling method developed for this study (OSSM), a minimization of the fitness function is obtained by changing the positions of a chosen number of NDT measurements. The theoretical development as well as some results obtained with both simulated and real data (ultrasonic pulse velocity) will be presented.

Mots clefs : CND, surveillance, structure béton, optimisation, variabilité spatiale

1 Introduction

Non-destructive testing techniques (NDT) are used not only for detecting anomalies, but they are also essential to estimate the mechanical properties of a concrete structure and their spatial variability. Thus, NDT techniques constitute a powerful tool for reducing the budget of maintenance and repair. Among the NDTs there are techniques that are fast and not expensive, as ultrasonic pulse velocity, rebound hammer, radar, etc. In the case of this study, a fast technique is used to obtain a general view of the spatial distribution for a particular property of the concrete (strength, porosity, moisture, etc.). Then, a complimentary study with a higher quality technique (sensitive to the same property) may be performed in the critical zones. Such approach would allow an efficient characterization of the property taking advantage of the two types of NDT with a convenient cost/benefice ratio.

Nonetheless, to profit the most of a high quality NDT in an already pre-auscultated structure, it is imperative to carry out an optimal spatial sampling. To this aim, the most common algorithm employed is the Spatial

Simulated Annealing (SSA) [7]. Even though this procedure is commonly found in geostatistics applications [3], it has been widely used in other domains such as radioactive releases [4], ecosystem studies [6], etc. In this work, an original optimization spatial sampling method (OSSM) inspired on the SSA was developed and tested with three different fitness functions: the traditional mean kriging standard deviation, the mean prediction error and the variance estimation error. The performance of this OSSM was explored with simulated data inferred from a specified spatial correlation and also with ultrasound velocity measurements taken in a thermic central located in Le-Havre – France.

2 Methods and materials

2.1 Variogram and Kriging

Due to the concrete's inhomogeneity, there will often be spatial variability while auscultating a structure made out of this material. However, most of the times it can be said that for a given number of measurements distributed in a surface, those that are close by will have certain resemblance, while the distant ones will not have any. This spatial dependence can be represented in a form of a statistical function known as the variogram, which is defined as half the variance of the difference between two data from two different locations separated by a distance h (1) [1].

$$\gamma(h) = \frac{1}{2} Var[Z(x) - Z(x+h)] \tag{1}$$

For a series of observed measurements with a limited series of pairs separated a distance h (N(h)), an empirical variogram can be determined as:

$$\gamma_e(h) = \frac{1}{2\,N(h)} \sum_{i=1}^{N(h)} [Z(x_i) - Z(x_i + h)]^2 \ . \tag{2}$$

For each empirical variogram, a model can be fitted by the least squares method to obtain parameters that can be used later to fill the matrices needed for the kriging. Figure 1 shows an example of the spherical model fitted to an empirical variogram. Here, three main parameters can be inferred: nugget (Co) that describes the variance of a measurement made several times in the same location, sill (S) that represents the global variance and range or correlation length (a) which represents the maximum distance where data are correlated.

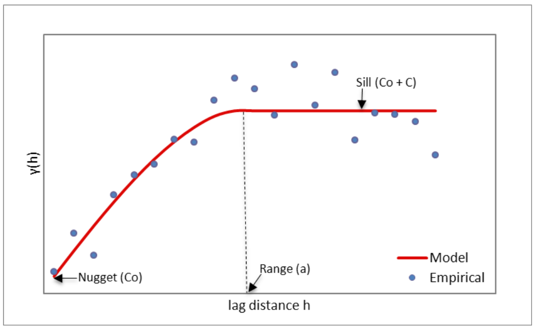

FIG. 1 - Empirical variogram and the fitted model with its parameters.

The kriging being a widely-used method for spatial interpolation can predict an unobserved measurement (Z*) using the weights of the surrounding observed measurements according to the variogram values and assuming a constant expected value as:

$$Z^* = \sum_{i=1}^{N} \lambda_i \, Z_i \ , \tag{3}$$

where λ_i is the weight of the ith observation. The kriging variance, which represents the variance of the estimation error, can be written as:

$$\sigma_k^2 = Var(Z) + \sum_{i=1}^{N} \sum_{j=1}^{N} \lambda_i \lambda_j \, Cov\,(Z_i\,, Z_j) - 2 \sum_{i=1}^{N} \lambda_i \, Cov(Z^*, Z_i) + 2\mu\left(\sum_{i=1}^{N} \lambda_i - 1\right), \tag{4}$$

where μ denotes a Lagrange multiplier, used on the ordinary kriging [2] to estimate the weights of each observed measurement.

2.2 Optimization algorithm

Considering a set (S) of N number of measurements, the sampling density reduction problem consists of choosing a subset (s_o) of n points initially located in a regular grid d_o and that must be moved, always to candidate locations in S, to best approximate the spatial distribution of the NDT measurements.

In order to do this, an algorithm inspired by the Spatial Simulated Annealing (SSA) was developed. The optimization spatial sampling method developed in the present study (OSSM) starts with an initial configuration s_o of N points distributed on a regular grid d_o. This configuration is changed by relocating one point of s_o to a random candidate location in D. When the new configuration s_1 is established, the fitness function is evaluated. This configuration will be accepted with a probability of acceptance P calculated with a step function described in (5):

$$\begin{aligned} \Delta &= J_o - J_1 \\ P = 1 &\quad If\ \Delta \leq 0, \\ P = 0 &\quad If\ \Delta > 0, \end{aligned} \tag{5}$$

where J_o is the fitness function value for s_o and J_1 is the fitness function value for s_1.

Three fitness functions were explored for the optimization algorithm:

2.2.1 Mean kriging estimation error standard deviation (MKSD)

In each iteration of the algorithm, to evaluate J_1, it was used the ordinary kriging. This spatial interpolation method does not only estimate unobserved measurements, but it also predicts the kriging variance for each estimated value. Hence, the first fitness function used is the mean of the square root of the kriging variance estimated for all the points, and normalized with respect to the mean of the N original points (Mean_R).

$$MKSD = \frac{\sigma_k^2}{Mean\_R}\ (\%) \tag{6}$$

2.2.2 Mean prediction error (MPE)

This function is the mean of the prediction error evaluated across all the points, and normalized with respect to the average of the N original points.

$$MPE = \frac{|Z - Z^*|}{Mean\_R}\ (\%) \tag{7}$$

2.2.3 Variance estimation error (VEE)

This function is the relationship between the variance of n known measurements (V_i) and the variance of the N original measurements (V_N).

$$VEE = 1 - \frac{V_i}{V_N}\ (\%) \tag{8}$$

The algorithm developed in this work differs from the SSA in a few aspects: (i) while the SSA works in a continuous domain, the original domain is discretized in the grid D, (ii) it does not use the Metropolis Accepting criterion (MAC), but a step function criterion, which was found to give better results than MAC since the resulting fitness function values after the optimization were smaller. Furthermore, the optimization process ran faster. (iii) There is no need of employing a cooling factor (as in SSA) because the new location of the perturbed point is chosen randomly between the candidate locations in D.

3 Simulated data

The potential of the OSSM proposed above with each of the three fitness functions was explored in a field of 9m x 9m, with 49 known points, regularly separated each 1.5 m that was simulated using a Fourier Integral Method [5]. This field was generated using a spherical variogram, with a nugget equal to 0, a sill equal to 4.56 and a range of 2.6 m. It was an unconditional simulation with a mean of 9.94 and a variance equal to 4.13 (figure 2a).

Figures 3 show the relationship between each fitness function for a regular grid and the number n of known points. As expected, all the fitness functions decrease as n increases. However, raising the number of n is not the only way to reduce the value of the fitness function. The OSSM can improve the fitness function values for each *n* just by relocating the points in the space passing from a regular grid to an irregular one.

For a clearer view of the impact of the OSSM, as an example it is going to be assumed that there is a budget for performing 16 measurements on the considered field. The first step for the optimization is obtaining a kriging map for a regular grid with a 3 x 3 m (figure 2b); the fitness function initial values are shown in table 1.

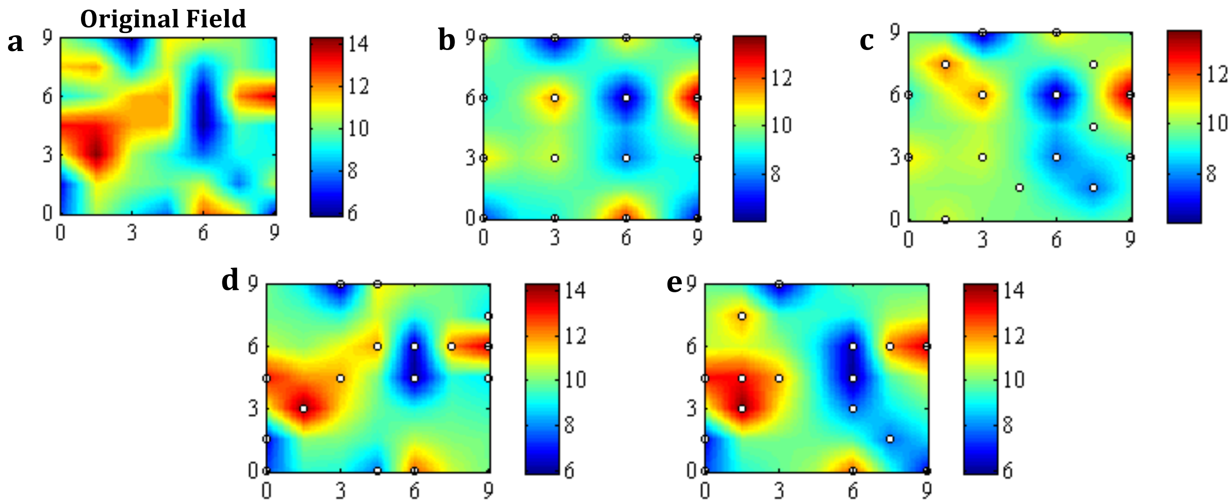

FIG. 2 - (a) Simulated field. (b) Kriging map obtained with a regular grid of 3m x 3m and 16 known values and Kriging maps obtained after the OSSM with each fitness function. (c) MKSD. (d) MPE. (e) VEE.

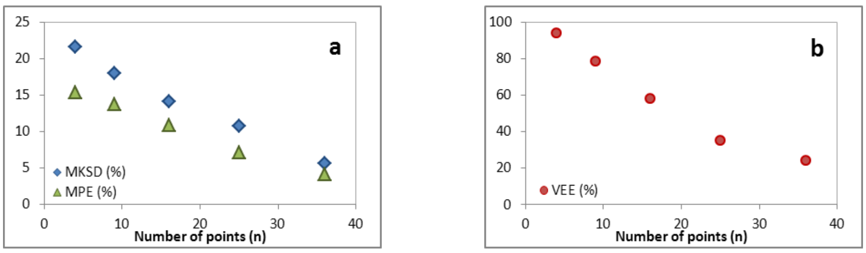

FIG. 3 - Relationship between each fitness function and the number of known points for a regular grid. (a) MKSD and MPE. (b) VEE.

Second, from the initial values of fitness functions obtained with the regular grid, the OSSM is applied during 4000 iterations to obtain the final fitness function values shown in Table 1. Here, in the case of the optimization with MKSD as the fitness function, the value of MKSD only had a diminution of 0.39% from a regular grid to an irregular grid. Additionally, the kriging map obtained with this fitness function (figure 2c) is not a good representation of the original field. Moreover, the variance obtained at the end of the optimization is not only significantly inferior to the real variance, but also resulted less than the variance obtained with a regular grid. Several optimizations were carried out on different sets of simulated data employing this fitness function and a low performance of the algorithm was always observed.

	Original Statistique Values	BEFORE OSSM (n=16)			AFTER OSSM (n=16)		
		MKSD	MPE	VEE	MKSD	MPE	VEE
FFV (%)	-	14.06	10.84	57.76	14.00	5.54	13.72
Mean	9.94	9.42			9.70	9.97	9.82
Variance	4.13	1.74			1.51	3.15	3.56
MPE (%)	-	10.84			11.78	5.54	7.52

TAB.1 - Initial fitness function values (J_o) for a regular grid composed of 16 known value and final fitness function values (J_1) for an irregular grid composed of 16 known values after 4000 iterations of OSSM.

In the case of the optimization with MPE as the fitness function, the value of MPE had a diminution of 48.9% from a regular grid to an irregular grid. Additionally, Figure 2d reveals that the kriging map obtained resembles the original field. Furthermore, this fitness function seems to give more importance to the zones where the variability is stronger. Finally, in the case of the optimization with the VEE as the fitness function, the value of VEE had a diminution of 76.2% passing from a regular grid to an irregular one. Also, the obtained kriging map (Figure 2e) represents in good agreement the original field. In spite of the optimal results obtained with the MPE and VEE fitness functions, it should be highlighted that the MPE leads to a smaller mean prediction error in the kriging map than VEE while on the other hand, the VEE provides a variance closer to the global variance than the MPE. Thus, a thoughtful consideration of this compromise should be taken before selecting the most suitable fitness function for analyzing a particular set of data.

4 Case study: Spatial sampling design for ultrasound measurements

A series of 30 ultrasound measurements for pre-auscultation of a concrete wall was made in Le-Havre – France, as part of two French national projects: C2D2-ACDC and EVADEOS. Figure 4a displays the velocity of the ultrasound waves at different locations of the wall along a straight longitudinal line. Figure 4b shows the corresponding variogram of these measurements from which an exponential variogram model was fitted with a nugget equal to 0 m/s, a range of 0.62m and a sill equal to 1 426 m/s.

a

b

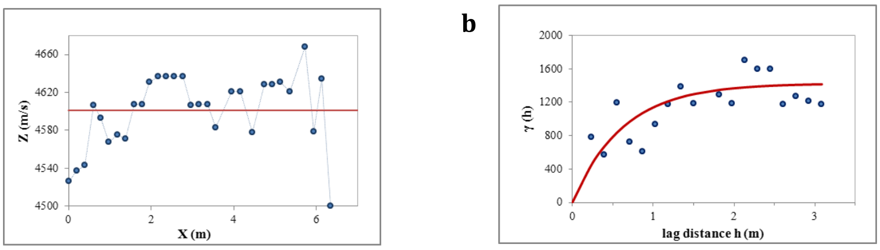

FIG. 4 - (a) Ultrasound measurements (points) and its corresponding velocity mean value (horizontal line). (b) Empirical variogram (points) and the respective exponential fitted model (line) of the series in (a).

The impact of the OSSM in this case study was explored with different sampling sizes (n_s). Figure 5 shows the relationship between n_s and two fitness functions – MPE and VEE – with n_s organized in a regular grid (before the OSSM) and then arranged in an irregular grid (after the OSSM). The MKSD was not taken into account due to the ineffectiveness of the function, previously demonstrated in the simulated data example.

a

b

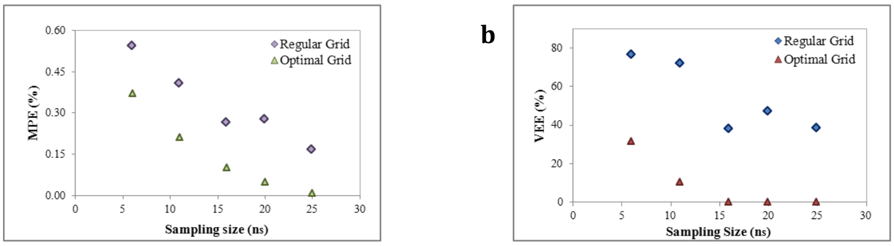

FIG. 5 - Relationship between the sampling size n_s and MPE (a) or VEE (b) fitness function for a regular grid before OSSM and an optimal grid after OSSM.

It is worth noting that the relative mean error with respect to the mean of the original measurements is 0.66%, which means that most of the ultrasound velocity values are close to the mean of the series (See figure 5a). Hence, it is not surprising that in Figure 5a all the MPE values are below 1%, even in the worst considered case with $n_s = 5$ in a regular grid.

As for figure 5b, it can be inferred that if n_s is reduced to 16, the new global variance is equal to that obtained with the original 30 measurements. This can be explained due to the VEE passing from 38.36 % with n_s organized in a regular grid to a VEE equal to 0% after OSSM. Moreover, the MPE obtained with n_s =16 and the VEE as the fitness function is only 0.16%. This value is very close to the MPE = 0.1% attained with the same n_s but with MPE as the fitness function. Finally, figure 6 shows that the kriging plot obtained with n_s = 16, VEE as the fitness function and organized in an irregular grid after OSSM, is also similar to the original set of ultrasound measurements.

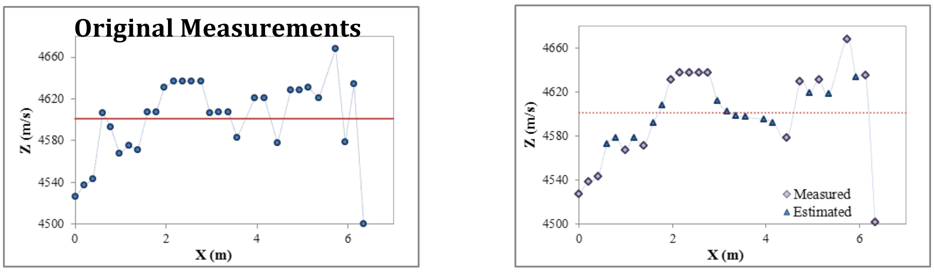

FIG. 6 - Original ultrasound set of measurements and Kriging plot after the OSSM obtained with n_s = 16 and VEE as the fitness function.

5 Conclusions

This study proposes an approach that may allow the efficient characterization of any concrete property by taking advantage of NDT (techniques which are sensitive to the same concrete property) with a convenient cost/benefice ratio. Here, a preliminary study of a structure is carried out with a NDT technique. Then, to select the most reliable and critical zones for a complementary diagnosis (High quality NDT, coring, semi-destructive tests, etc.) an optimization spatial sampling method (OSSM) was developed. Three fitness functions were tested to observe their effectiveness in the OSSM: MKSD, MPE and VEE. These functions were analyzed for a simulated field in the case of 16 known points (n) and also for ultrasound velocity measurements made in Le-Havre – France, for a sampling size of 16 (n_s).

The MKSD fitness function did not provide an improvement in the representation of the simulated field from n organized in a regular grid to n arranged in an irregular grid after OSSM. Additionally, the MPE value calculated after OSSM with this fitness function was more important than the one obtained with n arranged in a regular grid. Furthermore, the global variance calculated after OSSM is almost the same as that obtained with a regular grid.

The MPE and the VEE as the fitness functions showed an important improvement in the representation of both cases of study (simulated field and ultrasound velocity measurements). The use of these two functions significantly reduced the MPE value and increased considerably the global variance value from a regular grid to an optimal irregular grid not only in the case of simulated data, but also in the ultrasound velocity measurements on-site.

Further works for improving the OSSM proposed in this study include the combination of MPE and VEE into a single fitness function. This way, a good compromise between the minimization of the MPE value and the approximation to the global variance could be achieved.

6 Acknowledgements

The French National Research Agency (ANR) is gratefully acknowledged for supporting the ANR-B&VD EvaDéOS project.

7 References

[1] Barnes, R., Variogram Tutorial, Global Software, Inc.
[2] Bohling, G., Kriging, C&PE 940, 2005.
[3] Ferreyra, R.A., Apeztegui, H.P., Sereno, R., Jones, J.W., Reduction of soil water spatial sampling density using scaled semivariograms and simulated annealing, Geoderma, vol. 110, 2002, p. 265-289.
[4] Melles, S.J., Heuvelink, G.B.M., Twenhöfel C.J.W., Van Dijk, A., Hiemstra, P.H., Baume, O., Stöhlker, U., Optimizing the spatial pattern of networks for monitoring radioactive releases, Computers & Geosciences, vol. 37, 2011, p. 280-288.
[5] Pardo-Igdzquiza, E., Chica-Olmo, M., The Fourier Integral Method: An efficient spectral method for simulation of random fields, Mathematical Geology, vol. 25, n° 2, 1993.
[6] Stein, A., Ettema, C., An overview of spatial sampling procedures and experimental design of spatial studies for ecosystem comparisons, Agriculture, Ecosystems and Environment, vol. 94, 2003, p. 31-47.
[7] Van Groeningen, J.W., Siderius, W., Stein, A., Constrained optimization of soil sampling for minimization of the kriging variance, Geoderma, vol. 87, 1998, p. 239-259.