Stochastic modelling of 3D electric field in children brain exposed to 50 Hz magnetic field

Emma Chiaramello, Marta Parazzini, Serena Fiocchi, Marta Bonato, Laurent Le Brusquet, Paolo Ravazzani

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E. Chiaramello[1], M. Parazzini[1], S. Fiocchi[1], M. Bonato[1], L. Le Brusquet[2] and P. Ravazzani[1]
[1] *Istituto di Elettronica e di Ingegneria dell'Informazione e delle Telecomunicazioni IEIIT CNR, Milano, Italy*
[2] *Département Signal et Statistiques Centrale Supélec Paris France*

***Abstract*—This study focused on the evaluation of the electric field induced in the brain grey matter of a 5 years child when exposed to uniform magnetic field at 50 Hz with uncertain orientation. An innovative approach that combines Principal Component Analysis (PCA) and Gaussian process regression (Kriging method) in order to build space-dependent surrogate models was applied and validated. Preliminary results showed the feasibility of the approach.**

***Keywords*— stochastic dosimetry, ELF-MF exposure, surrogate modelling.**

I. Introduction

THE ubiquity of Extremely Low-Frequency Magnetic Fields (ELF-MF), such as those generated by transmission of electricity power lines, contributes to the raising of public awareness over the potential adverse health effects due to the interaction of ELF-MF with the human body. The exposure to ELF-MF of high amplitude causes well known acute biological effects on the nervous system, such as nerve stimulation and induction of retinal phosphenes [1]. Starting from the late 1970s, many studies focused on a possible association, firstly suggested by [2], between long-term exposure to ELF-EMF and an increased risk of childhood cancer (see e.g. [3]), leading the International Agency for Research on Cancer (IARC) [4] to classify ELF-MF as "possibly carcinogenic to humans" (2002).

Many studies investigated the exposure to magnetic field at the specific frequency of 50 Hz, particularly focusing on children [5], [6] and fetuses [5], [7]–[10], for their precocity of exposure. Most of these studies investigated the assessment of the compliance to exposure guidelines when considering few specific exposure scenarios, providing no information about how the exposure changes in realistic and highly variable scenarios. Such an assessment is indeed a challenging task, due to the intrinsic variability of the parameters that influence the exposure, (e.g. morphology, anatomy and posture of the exposed subject, reciprocal position of the source and the exposed subject, polarization of the EMF field [11]). Classical electromagnetic computational techniques typically involve highly time-consuming simulations to obtain 3D spatial distributions of the electromagnetic fields induced in human tissues, making almost impossible to characterize how the exposure changes in variable conditions. Recently, stochastic dosimetry has been proposed as a method to face variability of the EMF exposure scenario in the assessment of exposure. Stochastic dosimetry uses statistics to build surrogate models able to replace by analytical equations the heavy numerical simulations that would be needed to describe the highly variable exposure by electromagnetic computational techniques. Stochastic dosimetry proved to be a useful method to assess the EMF exposure both at radio frequency [12], [13] and at low frequency [10]. All these studies were exclusively dealing with surrogate models of EMF univariate variables, e.g. the 99th percentile calculated on the 3D domain of root mean square tissue-specific values of the electric field induced by ELF-MF [14]. However, a complete assessment should involve the complete description of the 3D spatial distribution the induced electric field in each tissue of the exposed subjects in variable conditions, as different spatial localization could involve different effect on the tissues. Such an assessment involves creating surrogate models able to describe the 3-dimensional spatial localization of the electric field induced in each tissue. Some recent studies focused on the developing of non-intrusive methods (i.e. methods in which the phenomenon to be approximated is treated as a "black-box") for building surrogate models of space-temporal variables [15]–[17]. To the best of our knowledge, these methods were never applied before in the stochastic dosimetry framework.

In this study, the variability of the 3-dimensional spatial distribution of electric field induced in children brain tissues when exposed to a uniform 50 Hz magnetic field with uncertain orientation was investigated. An innovative approach that combines Principal Component Analysis (PCA) and Gaussian process regression (Kriging method) [15] in order to build space-dependent surrogate models was applied and validated.

II. Materials and Methods

Fig. 1 shows a schematic view of the exposure scenarios (left side) and the flow chart of the experimental procedure (right side). The electric field induced in the brain grey matter of a 5 years child was assessed by varying the orientation of a perfectly homogeneous 50 Hz $\boldsymbol{B}$-field of 200 μT of amplitude, using 3D surrogate models. Each surrogate model describes how the 3D variable of interest Y (i.e., the electric field induced in the brain) was affected by the variability in the input parameters X (i.e., the different orientation of the $\boldsymbol{B}$-field). Three main steps composed the experimental procedure. The first step, namely, "design of the experiment," consisted of using deterministic dosimetry, that is, dosimetry based on computational methods, for the evaluation of a set of N experimental observations Y_0 of the variable of interest Y, needed for the construction of the surrogate models. The second step, namely, "3D surrogate modelling," focused on the development of a surrogate model

$\hat{Y}$. The surrogate model thus obtained was validated in the "validation" step. Details about each step are as follows.

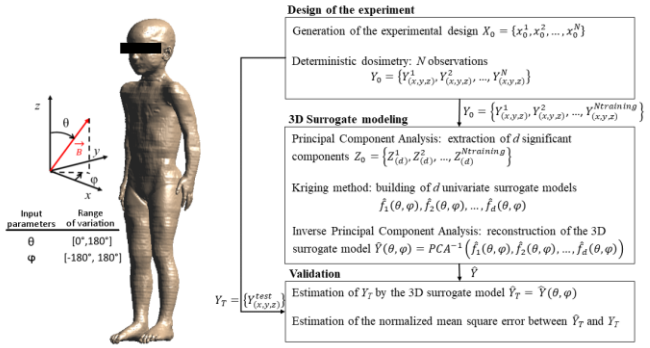

Fig. 1: Schematic view of the exposure scenarios and flow chart of the experimental procedure.

A. *Design of the experiment*

The random input vector X was defined as the two spherical angles theta (θ) and phi (φ), which characterized the ***B***-field orientation (see Fig. 1). The experimental design X_0 has been generated using a Latin Hypercube Sampling (LHS), using a selection criterion based on the maximum of the minimum distance between the points [18]. The variable of interest Y is the root mean square value of electric field induced in the child grey brain matter averaged on a 2 mm side cube, obtained by deterministic dosimetry based on Magneto Quasi-Static low frequency solver implemented on the simulation platform SEMCAD X (Schmid & Partner Engineering). The simulations were conducted using the 5 years Roberta model from the Virtual Classroom [19]. The dielectric properties (permittivity and conductivity values) in each tissue of the children were assigned according to the data available in literature [20], [21]. A total number of N = 150 simulations, corresponding to 150 different orientations of ***B***-field were carried out to obtain the set of observation Y_0. Each observation is a matrix with dimensions 452x258x1494.

B. *3D Surrogate modelling*

Similarly to the approach proposed by [15], the 3D surrogate modelling procedure is based on three main steps. First, a kernel PCA with linear kernel was applied. The rationale of using PCA is that the electric field induced at nearby spatial coordinates could be hypothesized to be highly correlated [22], and thus can be efficiently represented by a few d components.

As a second step, the Kriging method (see, e.g. [15]) was applied to develop a separate surrogate model for each of the d components identified by PCA. Kriging (a.k.a. Gaussian process modelling) is a stochastic interpolation algorithm that assumes that a model output a realization of a Gaussian process indexed by $x \in D_X \subset \mathbb{R}^M$. A Kriging surrogate model is described by the following equation:

$$M^K(x,\omega) = \beta^T f(x) + \sigma^2 Z(x,\omega) \quad (1)$$

where $\beta^T f(x)$, is the mean value of the Gaussian process and it consists of the regression coefficients $\{\beta j\ ,\ j = 1, \dots, P\}$ and the basis functions $\{fj\ ,\ j = 1, \dots, P\}$, σ^2 is the variance of the Gaussian process and $Z(x, \omega)$, a zero mean, unit variance, stationary Gaussian process. The underlying probability space is represented by ω and is defined in terms of a correlation function R (a.k.a. correlation family) and its hyperparameters θ. In this study, a Matérn correlation function R was used and its hyperparameters σ^2 and θ were estimated by Maximum Likelihood Estimation (MLE).

The third step in the 3D surrogate modelling procedure consisted of using the inverse Principal Component analysis to reconstruct, from the univariate surrogate models $\hat{f}_1$, $\hat{f}_2$,…, $\hat{f}_d$ obtained by Kriging method, the 3D spatial distribution of the electric field induced in the brain of the child. For more details about each step and about the whole 3D surrogate modelling procedure, see [15].

C. *Validation*

The validation of the 3D surrogate model was based on a leave-one-out cross-validation approach, a technique developed in statistical learning theory (see, e.g., [23]) and here used to reduce at minimum the size of the experimental design. To that purpose, the set of observation Y_0, obtained by deterministic dosimetry from the experimental design of size N, was recursively divided into two subsets: $Y_{training}$, containing all the observations except for the i^{th} one, and Y_{test}, containing only the excluded observation. A 3D surrogate model $\hat{Y}$ was built using the subset $Y_{training}$ and then its prediction of the excluded i^{th} point ($\hat{Y}_T(\theta_i, \varphi_i)$) was compared with Y_{test}. The normalized Mean Square Error (MSE) was calculated by computing the mean of the errors calculated at each iteration, as:

$$MSE = 100 * \sum_{i=1}^{N} \frac{\|\hat{Y}_T(\theta_i,\varphi_i) - Y_T\|^2}{\|Y_T - mean(Y_0)\|^2} \quad (2)$$

III. Results

Fig. 2 shows the leave-one-out MSE versus the number d of principal components considered in the 3D surrogate modelling procedure. For d equal to 5, the MSE was equal to 0.34%, thus indicating that a very low number of components was sufficient to represent the 3D distribution of the electric field induced in the brain grey matter.

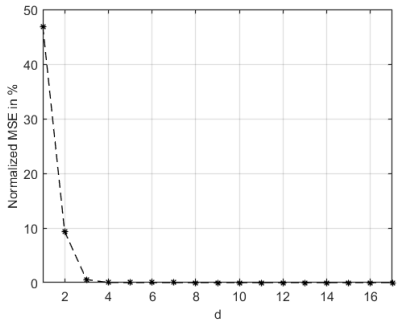

Fig. 2: Leave-one-out MSE versus the number d of components considered in the 3D surrogate modelling procedure

Fig. 3 shows, as an example, the spatial distribution of the electric field induced on one slice of the brain obtained for one specific orientation (θ and φ equal to 89° and 72°, respectively) of the incident ***B***-field by the 3D surrogate model (fig. 3a) and by deterministic dosimetry (fig. 3b). Fig. 3a and fig. 3b appear to be almost identical, confirming the

feasibility of the proposed approach

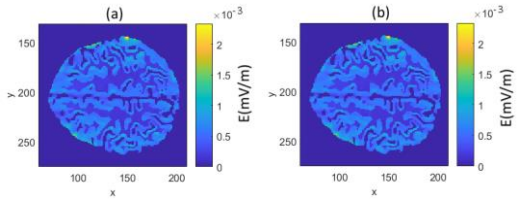

Fig. 3: Spatial distribution of the electric field induced on one slice of the brain grey matter obtained by 3D surrogate model (a) and deterministic dosimetry (b).

IV. Conclusion

Preliminary results showed that the proposed approach is feasible to assess the 3D spatial distribution of the electric field induced in human tissues when exposed to a uniform magnetic field with variable orientation. 3D surrogate models will be created to assess the variability of the spatial distribution of the electric field induced in different tissues of children of different ages. The proposed method will allow not only to assess the exposure to ELF-MF in variable conditions in terms of univariate variables resuming the level of exposures, but to investigate how the spatial distribution of the EMF field induced in the human tissue is influenced by the variability intrinsic to realistic exposure scenarios.

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