Innovative stochastic modeling of residential exposure due to a WiFi source placed in uncertain position

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Abstract

This study focused on the exposure evaluation of the electric field 2D spatial distribution of the E-field in a one-floor apartment when a WiFi source is placed in uncertain position. An innovative approach that combines a Principal Component Analysis and Kriging model in order to build space-dependent surrogate models was applied and validated. Results showed the feasibility of the approach.

Introduction

The continuous development of new wireless communication technologies contributes in raising the public concern for potential health effects of Radio Frequency Electromagnetic Field (RF-EMF) exposure [1]. A huge research effort was done in last years to assess the levels of exposure to RF-EMF, resulting in a wide variety of studies (see, e.g. [2]). All these studies, provided a limited picture of the RF-EMF exposure, strictly related to the exposure scenarios in which the assessment was carried out. However, the rapid evolution of technology requires a similar evolution in the methods of assessment of the exposure, to face the increasing complexity of the exposure scenarios. This is particularly needed in indoor environments, were people spend more than 80% of their time. Here, the RF-EMF levels depend on outdoor sources such as mobile phone antennas, as well as on indoor sources such as e.g. mobile phone handsets, WIreless Fidelity (WIFI) sources etc. The contribution of the outdoor sources is attenuated by building walls. The number and locations of indoor sources are not known, especially for residential environments. All these aspects cause the assessment of RF-EMF exposure in residential scenarios to be a challenging task. In this paper, we focus on indoor sources.

A promising approach to manage uncertainty and variability of the exposure scenarios was found to be stochastic dosimetry [3], an innovative approach based on ad hoc stochastic methods to build surrogate models, i.e. models with statistical properties similar to the phenomenon under interest, but with a simple functional form useful to propagate the uncertainty and variability of the parameters known to influence the exposure scenarios.

This study aims at obtaining a complete description of the RF-EMF exposure in a realistic apartment due to the presence of a WiFi source placed at uncertain positions. In order to obtain the 2D spatial distribution of E induced in the whole apartment for each position of the WiFi source, a recently proposed stochastic method combining Principal Component Analysis (PCA) and Kriging method [4] was used. The main novelty of this method is to firstly apply PCA to high dimensional output, such as the 2D spatial distribution of the *E* in the apartment. PCA, through an orthogonal transformation, allowed capturing the main stochastic features by means of a small number of non-physical variables, which can be predicted by surrogate models. The set of observations needed to develop the 2D surrogate models of the exposure was obtained by the WiCa Heuristic Indoor Propagation Prediction (WHIPP) tool, a set of heuristic planning algorithms developed for network planning in indoor environments [5].

Materials and Methods

Fig. 1 shows a schematic view of the exposure scenarios: the electric field *E* induced in each point of a one-floor apartment was assessed by varying the coordinates of a WiFi source, using a 2D surrogate model. The 2D surrogate model describes how the 2D variable of interest Y (i.e., the E induced in each point of the apartment) was affected by the variability in the input parameters X (i.e., the coordinates describing the WiFi source position).

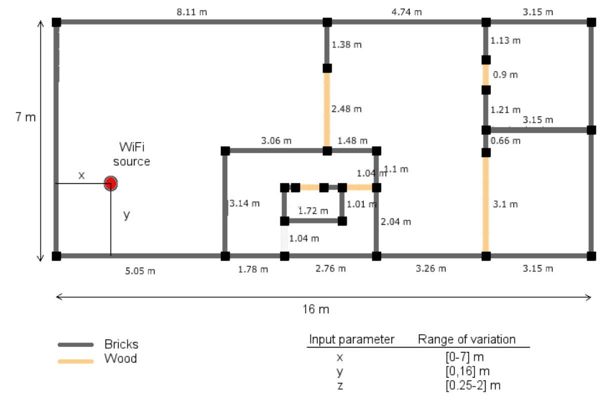

Fig. 1. Schematic view of the exposure scenario.

Design of the experiment

The considered apartment is 16 m long and 7 m wide and includes six distinct rooms of different sizes. The random input vector X was defined as the three coordinates *x*, *y* and *z*, which characterized the position of the WiFi source (the ranges of variation are reported in Fig.1). The experimental design $X_0 = \{X^1, \dots, X^N\}$, with N equal to 200, corresponding to 200 positions of the WiFi source, has been generated using a Latin Hypercube Sampling [3]. The set of 200 experimental observations Y_0 of the variable of interest Y was obtained by the WHIPP tool [5]. For each set of coordinates $X = \{x, y, z\}$, the variable of interest Y is a matrix containing the root mean square value of *E* for 2821 points spaced by 20 cm calculated at a height of 130 cm from the floor. The WHIPP algorithm, used to predict the *E* field values over the apartment floor for each WiFi source position defined in the experimental design, is a heuristic planning algorithm, developed and validated for the prediction of path loss in indoor environments, taking into account the effect of the environment on the wireless propagation channel [5]. The WiFi source considered in this study had Equivalent Isotropic Radiated Power equal to 20 dBm and working frequency equal to 2400 MHz.

Surrogate modeling

The 2D surrogate modelling procedure is based on three main steps [4]. First, a kernel PCA with linear kernel was applied. The rationale of using PCA is that the E induced at nearby spatial coordinates could be hypothesized to be highly correlated, and thus can be efficiently represented by a few *d* components. The central idea of PCA is to project the original *D* dimensional data $y \in \mathbb{R}^D$ into a space were the variance is maximized in the first few principal components:

$$Y = Wz + \mu + e \tag{1}$$

where *W* refers to the matrix of eigenvectors of the data covariance matrix corresponding to the *d* largest eigenvalues, $z \in \mathbb{R}^d$ refers to the vector of principal components scores, μ is the mean value of the data and *e* is the residual error.
As a second step, the Kriging method was applied to develop a separate surrogate model for each of the *d* (non-physical) components identified by PCA. Kriging method 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 scalar Kriging surrogate model is:

$$M^K(x, \omega) = \beta^T f(x) + \sigma^2 Z(x, \omega) \tag{2}$$

where $\beta^T f(x)$ is the mean value of the Gaussian process, σ^2 is the variance of the Gaussian process, $Z(x, \omega)$ is a zero mean, unit variance, stationary Gaussian process conditioned in such a way that $M^K(x_i, \omega)$ is equal to $z_i^{(c)}$ $\forall i$. The term ω describes outcomes of the underlying probability space with a correlation function *R* and its hyperparameters ϑ. The correlation function $R = R(x, x', \vartheta)$ models the dependence structure between values at points *x* and *x'*, and depends on the hyperparameters ϑ. In this study, no basis function was used ($P = 0$) and a Matérn correlation function *R* was used. The hyperparameters σ^2 and ϑ were estimated by Maximum Likelihood Estimation (MLE).
The third step in the 2D surrogate modelling procedure consisted of using the inverse PCA to reconstruct, from the univariate surrogate models $\widehat{z^{(1)}}$, $\widehat{z^{(2)}}$, …, $\widehat{z^{(d)}}$ obtained by Kriging method, the 2D spatial distribution of E in the apartment.
The validation of the 2D surrogate model was based on a leave-one-out cross-validation approach: the set of observation Y_0 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 2D surrogate model $\hat{Y}$ was built using the subset $Y_{training}$ and then its prediction of the

excluded i^{th} point was compared with Y_{test}. The normalized Mean Square Error (MSE) was calculated by computing the mean of the errors calculated at each iteration.

Assessment of the exposure

Once the 2D surrogate model has been obtained, the E field values in each points of the apartment were assessed for a high number of positions (i.e. 10.000) of the WiFi source. In order to take into account that WiFi data packets are transmitted in bursts and not continuously, the *E* field values were rescaled by duty cycle values equal 0.25%, 1.08% and 10.69%, corresponding to duty cycle values measured when surfing new site, using a Skype video call and watching a You Tube video at 1080p for a physical data rate equal to 54 Mbps [6].

Results

Fig. 2 shows the leave-one-out normalized mean square error (MSE) versus the number *d* of principal components considered in the 2D surrogate modelling procedure. For *d* equal to 88, the normalized MSE was equal to 5%, thus indicating that an acceptable number of components was sufficient to represent the 2D distribution of the E field in the whole apartment.

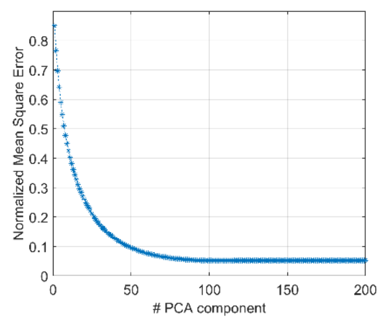

Fig. 2. Leave-one-out normalized MSE versus the number *d* of components considered in the 2D surrogate model.

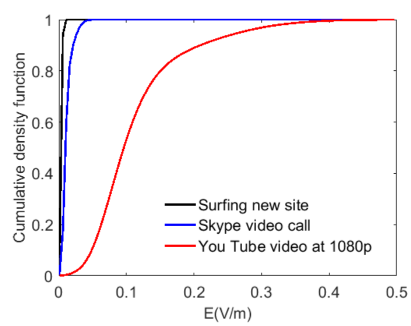

Fig. 3. Cumulative density functions of the E values for the three usage of the WiFi for 10.000 different positions of the source.

Fig. 3, shows, as an example of the results that are be obtained with the 2D surrogate model, the cumulative density functions of the *E* values obtained in the whole apartment for 10.000 different positions of the source, for the three usage scenarios of the WiFi (surfing new site, using a Skype video call and watching a You Tube video at 1080p). The probability density functions of the *E* values could be approximated by Gamma distributions with parameters a = 2.63 and b = 0.001, for the “Surfing new site” usage (with R^2 = 0.95), a = 2.64 and b = 0.004, for the “Skype video call” usage (with R^2 = 0.96), and a = 2.64 and b = 0.04, for the “You Tube” usage (with R^2 = 0.95).

Conclusions

Preliminary results showed that the proposed approach is feasible to assess the 2D spatial distribution of the E-field in a one-floor apartment when a WiFi source is placed in uncertain position. The developed 2D surrogate model allows obtaining a complete description of the level of exposure in the whole apartment for each possible position of the source with a very low computational cost. This could be used to obtain a description of the exposure in the different rooms, thus obtaining different probability density functions for rooms of different sizes or different shapes. The possibility of achieving this type of information will be fundamental for obtaining a full evaluation of the RF-EMF exposure with the upcoming 5G technologies.

Acknowledgments

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