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Stochastic Exposure assessment to 4G LTE femtocell in indoor environments

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Abstract

The exposure of an 8-years child moving in a room to a 4G LTE femtocell with uncertain position was assessed by stochastic dosimetry based on sparse low rank tensor approximation method (sparse LRA). The Specific Absorption Rate (SAR) was estimated in all the possible positions of femtocell and child. Results showed that, for all the possible positions in the room, the exposure values were significantly below the International Commission of Non-Ionizing Radiation Protection (ICNIRP) guidelines for general public exposure. The variation of the distance between femtocell and child influenced greatly the exposure, resulting in Quartile Coefficient of Dispersion value equal to 67%.

1. Introduction

One of the most promising solutions to improve the performance of wireless communications in indoor environments is to deploy low power base stations, such as femtocells, within home and office environments [1]. Deployment of femtocells offers advantages in terms of efficiency and cost, as it provides enhancing of the coverage and capacity of mobile service, without requiring installation of additional local-area base stations [1]. Due to the key role that femtocells will play in next future of wireless communications scenarios, the evaluation of the possible health impacts of the exposure to radio-frequency electromagnetic fields (RF-EMF) due to the femtocells deployment is fundamental [2], especially for children and fetuses [3].

The position of the femtocell in a room may be highly variable, and depends on many features, e.g., the room size, its position in the building or the furniture. This involves the femtocell to be more or less close to the subjects staying and moving in the room, thus a complete assessment of the exposure should take into account these aspects of variability.

Previous studies on the assessment of adult human exposure to RF-EMF due to femtocells in various indoor environments [4-7] focused only on the assessment of the compliance to guidelines for few specific exposure scenarios, providing no information about how the exposure changes in uncertain and variable scenarios.

Stochastic dosimetry, an innovative approach based on statistics to build surrogate models, has been proven an efficient tool to account for uncertainty in EMF exposure [8-10], such as that arising from the variability in the femtocell position. The surrogate models obtained by the stochastic approach could be used for different types of analysis, e.g. evaluation of statistical moments, estimation of the probability density function, sensitivity and reliability analysis [11].

Among the different statistical approaches that can be used to build the above introduced surrogate models, a new method based on polynomial functions called Low Rank tensor Approximation (LRA) [11-12] was recently proposed. The advantage of the LRA method is that the number of unknowns grows only linearly with the input dimensions, thus sounding very promising when dealing with a high number of parameters. Combining the Least Angle Regression algorithm (LARS) [13] and the LRA method allows retaining only a subset of the most significant terms of the polynomial functions, thus obtaining a sparse version of the LRA method [14].

In this study, the exposure assessment of an 8-years child to a 4G LTE femtocell in an indoor environment has been performed using the sparse LRA method. This will allow evaluating how the variations in the positions of the femtocell and the child in the room could affect the exposure.

2. Materials and Methods

Fig. 1 shows a schematic view of the exposure scenarios: the Specific Absorption Rate (SAR) induced in child tissues has been assessed by varying the position of the 4G LTE femtocell (operating at 2.6 GHz) on the wall and the position of the child in a 3x4 m^2 room. The position of the femtocell was described by two coordinates, i.e. the horizontal location L and the height z, while the position of the child was described by three coordinates, i.e. the position on the floor, (coordinates x and y), and the rotation θ along the vertical axis. The ranges of variation of the coordinates of the femtocell and the child are reported in Fig. 1. The exposure was evaluated in terms of Whole-Body SAR (WB SAR), for different positions of the source and the child using surrogate models based on sparse LRA.

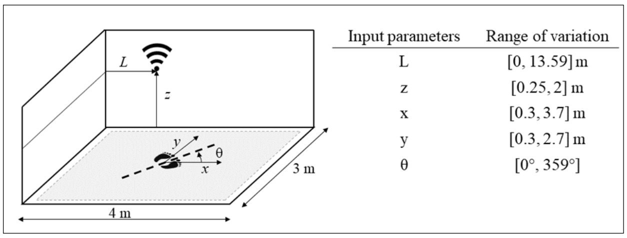

Figure 1. Schematic view of the exposure scenario.

LRA [11] is a non-intrusive method for developing surrogate models as a finite sum of rank-one functions:

$$Y_{LRA} = \sum_{l=1}^{R} b_l w_l = \sum_{l=1}^{R} b_l \left(\prod_{i=1}^{M} v_l^{(i)}(X_i) \right) \qquad (1)$$

where w_l is the l-th rank-one function obtained as product of univariate functions of the components of X_i, v_l (i) denotes a univariate function of the components of X_i in the l-th rank-one component, M is the number of input variables, b_l (l = 1,…, R) are scalars that can be viewed as normalizing constants and R is the rank of the decomposition. By expanding $v_l^{(i)}$ into a polynomial basis [11] that is orthonormal with respect to the marginal distribution f_{Xi}, the surrogate model reads as:

$$Y_{LRA} = \sum_{l=1}^{R} b_l \left(\prod_{i=1}^{M} \left(\sum_{k=0}^{p_i} z_{k,l}^{(i)} P_k^{(i)}(X_i) \right) \right) \qquad (2)$$

where $P_k^{(i)}$ denotes the k-th degree univariate polynomial in the i-th input variable, p_i is the maximum degree of $P_k^{(i)}$ and $z_{k,l}^{(i)}$ is the coefficient of $P_k^{(i)}$ in the l-th rank-one component.

The choice of the proper polynomial basis $P_k^{(i)}$ that would be used to build up the LRA model is based on the criteria of orthonormality to the marginal distributions of the input parameters Xi: as in this study the input parameters Xi were supposed to be uniformly distributed, the Legendre polynomials have been used [see, e.g. 11].

In order to estimate the unknown parameters, i.e. the polynomial coefficients $z_{k,l}^{(i)}$ and the normalizing coefficients b_l (l = 1,…, R) of the surrogate model, a greedy algorithm, based on Alternated Least-Squares (ALS) minimization [11-12]. The employed algorithm involves a sequence of pairs of "correction step" and "updating step". In the r-th "correction step", the rank-one tensor w_r is built, while in the r-th "updating step" the set of normalizing coefficients $\{b_1,..., b_r\}$ is determined. In order to obtain sparse low rank approximations, the approach described by [14] has been integrated by solving all the minimization problems using the hybrid least angle regression method [13]. The approach proposed here allowed obtaining sparsity both for each rank-one tensor w_r, discarding non-significant polynomials, and for the complete Y_{LRA} model, discarding non-significant rank-one tensors. For more details about the algorithm to obtain sparse LRA models, see [14].

To apply the ALS algorithm and obtain a proper surrogate model, we need a set of observations of the quantity (i.e. the SAR level) that has to be modelled. Therefore, 150 positions of the femtocell and the child in the room were selected using Latin Hypercube Sampling (LHS) [13], and the corresponding SAR level was estimated by means of deterministic dosimetry. Because of the possible proximity of the femtocell to the child, the field emitted could not be assessed with the plane wave hypothesis, thus a procedure based on the combined use of Spherical Wave Expansion and Finite-Difference-Time-Domain method was applied [15-16]. The simulations were carried out using a high resolution 8-years child model "Eartha" from the Virtual Classroom [17]; the dielectric properties in each tissue of the child were assigned according to the data available in literature [18]. The input power of the femtocell was set equal to 100 mW.

The LRA surrogate models were used to estimate the values of WB SAR in 10^7 randomly selected positions of the femtocell and the child, i.e. 10^7 set of input parameters. A statistical analysis has been performed to assess the variability of the exposure due to the position of the femtocell and the child, in terms of Quartile Coefficient of Dispersion (QCD).

3. Results

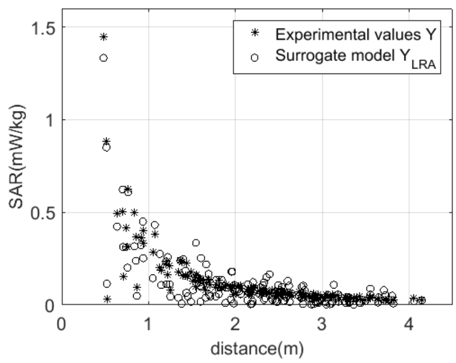

Figure 2. SAR values obtained by LRA model vs. experimental values obtained by deterministic dosimetry.

Fig. 2 shows the WB SAR values obtained by LRA model plotted versus the experimental values obtained through deterministic dosimetry. The LRA model was efficient in predicting SAR values: for smaller SAR values (i.e. higher distances between the femtocell and the child), the estimated points appeared to be more scattered in the neighborhood of the straight line, compared to the higher SAR values, in which the points estimated by LRA model were almost identical to those obtained by deterministic dosimetry. A 3-fold cross validation procedure was performed: the experimental design was divided into three subsets and three LRA models were built iteratively considering two among the three subsets as training set. Then the root mean square error between the values estimated by the LRA model and those of the respective testing set was evaluated. The root mean square error estimated with this procedure was found to be equal to 32.1 μW/kg.

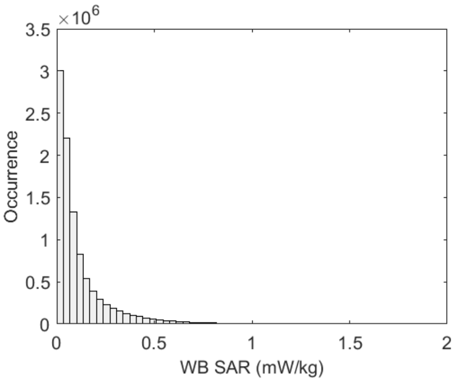

Figure 3. WB SAR values obtained in 10^7 random positions of the femtocell and the child.

Fig. 3 represents the histogram of the SAR values obtained in 10^7 random positions of the femtocell and the child in the room. The WB SAR values were in the $1.4*10^{-7}$-1.71 mW/kg range, with mean and median values equal to 0.12 mW/kg and 0.06 mW/kg, respectively. The variability of the exposure in terms of SAR due to the positions of the femtocell and the child was high, resulting in QCD values equal to 67%.

4. Discussion and Conclusions

In this study the exposure of an 8-years child to a 4G LTE femtocell (at its maximum power output of 100 mW), located randomly in a representative indoor environment has been addressed using a stochastic dosimetry approach based on the Low Rank tensor Approximations method. The LRA method in its sparse form minimizes the number of unknowns, thus obtaining a complete description of the exposure for any positions of the femtocell and the child in the room, with limited computational effort.

Preliminary results confirmed that the deployment of a 4G LTE femtocell in indoor environments generates extremely low levels of SAR in children. The histogram of the WB SAR values obtained by the LRA model showed highly asymmetric profiles, with positive-skewed shapes, meaning that, considering any position of the femtocell and the child in the room, the probability of having a level of WB SAR higher than the mean values was extremely low.

All the observed values for WB SAR were significantly below the ICNIRP guidelines for general public exposure [19]. This finding is in according with results by previous studies about femtocell exposure [7].

Although extremely low, the exposure levels change consistently as a function of the distance between child and the source. This was confirmed by the QCD value equal to 67%, meaning that the variation of the positions of the femtocell and the child influenced greatly the exposure level. This is probably due to extremely wide range of variation of the relative position of the femtocell and the child. This is in agreement with previous findings by other authors (see, e.g. [8], [20]) who analyzed different types of RF-EMF sources, finding that the source location is very influential on the induced SAR in human tissues.

In conclusion, stochastic exposure assessment by LRA method has been found to be capable in providing a complete description of the EMF exposure for all the possible positions of the femtocell and the child in a realistic indoor environment, with a negligible computational effort.

5. Acknowledgements

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