Human RF-EMF Exposure Assessment for an indoor 5G Access Point with Beamforming Capability using Stochastic Dosimetry

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Abstract

Among the novel technologies that 5th Generation (5G) networks will introduce to fulfill the ambitious goals that promise, there are the antenna arrays with three-dimensional (3D) beamforming capabilities. This technology does the RF-EMF exposure scenario evolve with the particular radiation pattern that the Access Point, in an indoor environment, generates in an adaptive way. The problem of setting up an assessment to evaluate the human exposure levels in such a scenario becomes challenging. In this paper, by the jointly use of deterministic and stochastic methods, it was possible to consider up to 1000 different 3D beamforming patterns of the AP with low computational costs. The work allowed to highlight the conditions of major exposure and to prove the validity of stochastic methods, facing the variability and heterogeneity that will characterized 5G scenarios.

1 Introduction

The interest in evaluating the human RF-EMF exposure levels is continuously growing in recent years primarily because of the deployment of the incoming 5G networks. Although the 5G networks will bring great improvements in terms of services and utilities to the whole world, developing the concept of Internet of Things world [1], it is undeniable that the new involved technologies will drastically change the RF-EMF population exposure levels [2]. To satisfy the ambitious requirements in terms of enhanced broad band communications, new frequency ranges have been licensed, in Italy the first licensed frequency ranges are 3.7 GHz and 27 GHz, that is in the mm-wave spectrum. In particular, the use of mm-wave frequencies will need the adoption of countermeasures for combatting the high path loss that signals suffer when propagate at such frequencies, as the deployments with dense micro cells’ coverage, massive multiple-input-multiple-output (MIMO) base station antenna [2, 3] and antennas with 3D beamforming capabilities [4]. The RF-EMF exposure scenario consequently evolves and it becomes urgent to estimate in advance how the exposure levels will behave.

One of the peculiarities of these new scenarios is their variability, let’s just think to a 3D beamforming antenna able to direct its main beam in the 3D space, changing adaptively its radiation pattern. In this work we afford just the problem of setting up an exposure assessment to evaluate the exposure levels of a single-user in an indoor scenario with an access point that uses a uniform planar array (UPA) with 64 patch elements at 3.7 GHz.

Starting from the conclusion of our previous work [5], where the 64 element UPA antenna array had a fixed configuration of the radiation pattern, here we consider the overall capability of 3D beamforming technique, evaluating the exposure levels for 1000 different configurations of the 3D antenna pattern, through a novel approach of stochastic dosimetry that combines traditional deterministic computational methods with stochastic ones.

The method of stochastic dosimetry was successfully applied previously for both low and high frequencies exposure scenarios [6, 7], where metamodeling allowed to enormously reduce the associated computational costs.

The exposure levels were evaluated in terms of the Specific Absorption Rate (SAR) in different tissues, following the ICNIRP guidelines [8]. Among the novel technologies that 5th Generation (5G) networks will introduce to fulfill the ambitious goals that promise, there are the antenna arrays with three-dimensional (3D) beamforming capabilities. This technology does the RF-EMF exposure scenario evolve with the particular radiation pattern that the Access Point, in an indoor environment, generates in an adaptive way. The problem of setting up an assessment to evaluate the human exposure levels in such a scenario becomes challenging. In this paper, by the jointly use of deterministic and stochastic methods, it was possible to consider up to 1000 different 3D beamforming patterns of the AP with low computational costs. The work allowed to highlight the conditions of major exposure and to prove the validity of stochastic methods, facing the variability and heterogeneity that will characterized 5G scenarios.

2 Materials and Methods

Despite the progress in high performance computing, the traditional computational methods still require highly time-consuming simulations. For this reason, their applicability is limited only to worst-case exposure scenario, providing no information about how the exposure changes in realistic and highly variable scenarios.

To overcome this problem, stochastic dosimetry has been proposed recently as a method to face variability and heterogeneity that characterize the realistic exposure scenarios [6, 7]. Stochastic dosimetry, starting from a limited number N of simulations obtained by deterministic dosimetry, approximates the deterministic dosimetry model, that would require expensive computational cost, with a metamodel, with similar statistical properties but at significantly lower computational cost w.r.t. deterministic dosimetry. After the surrogate models’ validation, based on iteratively techniques, it is possible not only to estimate with low computational effort the exposure level for a high number of scenario configurations, but also to provide different types of statistical analysis on the results.

Here the stochastic dosimetry was applied to face the exposure variability due to the 3D beamforming capability of the 5G AP.
The deterministic dosimetry results were used to build and then validate the surrogate models obtained with stochastic dosimetry. The SAR averaged on tissue mass was evaluated for the whole body, the whole head and the whole brain of the model.

2.2 Surrogate Modelling and Validation

Among the different stochastic approaches presented in the literature, in the present work the Polynomial Chaos Kriging technique (PC-Kriging) was applied [15]. The PC-Kriging allows to combine the advantages of polynomial chaos expansions (PCE) techniques with those of Gaussian process modelling (Kriging). Details of PCE and Kriging techniques separately can be found in [16, 17], whereas PC-Kriging can be summarized by the following expression:

$$\hat{y} = \hat{\mathcal{M}}(x) = \sum_{i=1}^{p} \alpha_i \psi_i(x) + Z(x),$$

where the first term $\sum_{i=1}^{p} \alpha_i \psi_i(x)$ represents the trend of the model, equal to the PCE solution, whereas the second term is a calibration term, characterized by the stationary Gaussian process $Z(x)$.

To jointly optimize the two parts, we chose the Optimal Polynomial Chaos Kriging (OPCK) method. In OPCK method the optimal set of polynomials necessary for PCE solution is individuated by Least Angle Regression Selection (LARS) algorithm [18]. LARS detects a sparse set of polynomials basis and their corresponding coefficients in decreasing order according to their correlation to the current residual at each iteration. The trend of the surrogate model is then calculated adding each polynomial one by one and calibrating for each iteration the new PC-Kriging model. The surrogate models obtained were then validated with the Leave-One-Out Cross-Validation (LOO-CV) error, previously tested in other works [6, 7]. The technique consists in (i) building the surrogate model using all the deterministic dosimetry results except one, (ii) using the surrogate model to predict the value of the excluded deterministic dosimetry result and (iii) comparing the result obtained by the surrogate model with that obtained with deterministic dosimetry. The procedure is repeated for all the results obtained by computational method resulting in a LOO-CV error with the following form:

$$\epsilon_{\text{LOO-CV}} = \frac{1}{N} \sum_{i=1}^{N} \frac{(M(x_i) - \hat{M}_{\text{CV}}(x_i))^2}{\text{Var}[Y]},$$

where $M(x_i)$ is the model output in $x_i$ obtained with computational methods, $\hat{M}_{\text{CV}}(x_i)$ represents the output of PC-Kriging metamodel in $x_i$ obtained using all the points of the experimental design except $x_i$. $\text{Var}[Y]$ is the variance of the output data obtained with traditional deterministic dosimetry and N is the number of the results of the deterministic dosimetry simulations.

We verified that $N = 60$ simulations were an adequate number to minimize the input design while guaranteeing an acceptable LOO-CV error.
The surrogate models’ construction and validation were obtained with the use of the software “UQLab: The Framework for Uncertainty Quantification” [19].

2.3 Exposure Assessment

Once the surrogate models were validated for the tissue mass averaged SAR (namely for the whole body, the whole head and the whole brain), it was possible to conduct an exposure assessment calculating the levels of SAR for different beamforming patterns considering 1000 combinations of the two input angles in the azimuth and in the elevation planes. The Quartile Dispersion Coefficient (QDC) for each examined distribution of SAR was also calculated in the following form:

\[ QDC = \frac{Q_3 - Q_1}{Q_3 + Q_1} \]

where, \( Q_1 \) and \( Q_3 \) are respectively the first and third quartiles of the analyzed SAR distributions.

At last, an analysis of the input ranges causing SAR levels higher that the 70% of their maximum value was conducted, in order to identify the scan angles ranges that might cause the highest exposure levels.

3 Results

In this section the preliminary results on the exposure levels are presented, considering 1000 different beamforming patterns of a 5G indoor 64 element UPA antenna with an input power of 1W. Regarding the validation of the surrogate models, the minimum LOO-CV error resulted equal to 0.27% for the whole head SAR distribution, followed by a 0.31% value for the whole body, while the highest error, i.e. 0.94%, occurred for the whole brain, anyway remaining an acceptable value to validate the model.

In Figure 2, the boxplots of the three SAR distributions are reported. The highest exposure levels are obtained in the whole head, with a maximum value of 0.08 W/kg, followed by 0.04 W/kg in the whole brain, till to 0.0015 W/kg for the whole body, that is really low.

The QDC values of the SAR distributions were 75% in the whole brain, 74% in the whole head and 72% in the whole body: they underline that the exposure scenario is characterized by high variability, depending on the input values of the two scan angles.

Moreover, only a small percentage of values of the SAR distributions resulted higher than the 70% of their maximum values (7.2 % for the whole-body, 4.7% for the whole head and only 3.3% for the whole brain).

Interestingly, the antenna patterns that caused the highest exposure levels have the main beam focused on the azimuth plane in a symmetric narrow range (about 14°) around 0° (i.e. the alignment direction between the human model and the UPA antenna in the azimuth lane).

On the other hand, in the elevation plane the beam directions that cause the highest exposure levels vary depending on the part of the body. In particular, for the whole body the beam directions are in the range [-22°, 7°], covering also the shoulder of the model, instead narrower ranges of beam directions, respectively [-10°, 7°] and [0.6°, 7°], generated the highest SAR levels in the whole head and the whole brain.

4 Conclusions

The aim of the paper was to verify the applicability of the PC Kriging stochastic method to assess the EMF exposure levels due to antennas with 3D beamforming capability, and it was reached out. In particular, we showed that the stochastic methodology is able to evaluate the SAR distributions for any beamforming patterns of an antenna array, so detecting the beam directions that cause the maximum exposure.

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6 References


