Surrogate-based fast peak mass-averaged SAR assessment

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SHORT ABSTRACT

We propose a fast peak mass-averaged SAR assessment methodology based on surrogate modeling techniques. This method reduces the number of measurement points for the 3D zoom scan in a compliance test. The sampling algorithm is crucial to solving the problem at hand. For the measurements in a plane, we used a generalized Probability of Improvement criterion, while for the zoom scan we selected the LOLA-Voronoi algorithm. We applied this method to determine the peak mass-averaged SAR in 10 g induced by a dipole antenna in the flat phantom. The total number of measurement points for both surface and zoom scan was 80 with a root relative squared error (RRSE) of less than 0.3 for both scans. Current measurement standards specify a zoom scan which consists of at least 5x5x7 or 175 measurement points.

INTRODUCTION

Surrogate modeling techniques, also known as metamodeling, are increasingly becoming popular in the engineering community to speed up complex, computationally expensive design problems [1, 2]. Surrogate models, or meta models, are mathematical approximation models that mimic the behavior of computationally expensive simulation codes such as mechanical or electrical finite element simulations, or computational fluid dynamic simulations, etc. While several types of surrogate modeling use-cases can be identified, this work is concerned with the integration of surrogate models into the specific absorption rate (SAR) compliance testing process. Surrogate-based methods are mostly used to solve expensive optimization problems, and typically generate surrogate models on the fly that are only accurate in certain regions of the input space, e.g., around potentially optimal regions. The generated surrogate models can then be used to intelligently guide the optimization process to the global optimum. Since performing measurements is a time-consuming process, it is desirable to minimize the number of measurements to perform in order to test SAR compliance of a system under consideration. Surrogate modeling can help achieve this goal by carefully selecting locations where measurements should be performed using adaptive sampling techniques as explained below.

MATERIALS AND METHODS

A typical surrogate modeling flowchart can be seen in Figure 1. The process begins with an "Initial Design" of k points, which is here an arrangement of locations. The initial design is usually space-filling, so as to cover as much of the input space as possible. This helps in maximizing information gain initially, when nothing is known about the system under consideration. Measurements are performed at these locations and the data is used as a training set to construct a model. The model is validated (e.g., using cross-validation), and if the stopping criteria (model accuracy, sampling/measurement budget, time limit, etc.) are met, the process stops. If not, then a cycle of sample selection or adaptive sampling and model building is iterated over. The adaptive sampling algorithm selects additional samples iteratively at intelligently chosen locations where measurements are performed to obtain output values. The samples and output values are added to the training set, and the model is rebuilt. This cycle continues till one of the stopping criteria are met.



Figure 1: Surrogate modeling flowchart.

The sampling algorithm is crucial to solving the problem at hand. For SAR compliance testing using surrogates, a two-stage scheme is followed according to the two-step compliance procedure: surface scan followed by a zoom scan at the location of maximum SAR. For the surface scan a generalized Probability of Improvement criterion [3] is used, whereas for the zoom scan (in a cube) the LOLA-Voronoi algorithm is applied [4].

RESULTS

We have determined the peak mass-averaged SAR induced by a half-wavelength dipole antenna at 2450 MHz in the flat phantom. The phantom was filled with head simulating liquid. The initial design used in both stages was a Latin Hypercube of 30 samples (in addition to the corner points). A DASY 3 mini system (SPEAG, Switzerland) was used to perform the measurements. Thus, a total of 34 samples were present in the initial design in Stage 1, and 38 samples were present in stage 2. Additional samples were selected in batches of 5 by the sampling algorithm. Both stages had a total budget of 80 measurements, which is more than half the number of points specified for the zoom scan by current measurement standards (at least 5x5x7 points) (IEC 62209-1 and IEC 62209-2). The experiments were performed using the SUMO Toolbox [5]. The final model obtained after completion of the first stage can be seen in Figure 2. As desired and expected, the majority of selected samples (black dots) lie in the region corresponding of the peak SAR. The root relative squared error (RRSE) of Kriging model used for the surface scan was 1.9E-01, which indicates that the model is very accurate. The RRSE Kriging model for the zoom scan was 1.04.



Figure 2: The SAR distribution of the surface scan obtained using the Kriging model.

CONCLUSIONS

The proposed method of SAR compliance testing using surrogate models allows for approximating average SAR values using fewer measurements as compared to existing methods. This speeds up the compliance testing process, and saves valuable time of practitioners.

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