Optimized Sequential Sampling Algorithm for EMI Near-Field Scanning

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Abstract—**In this paper, a recently proposed automatic and sequential sampling and modeling algorithm for near-field scanning of printed circuit boards and/or integrated circuits is further optimized in two ways. The main goal of this optimization is to reduce the total measurement time needed to come to a complete model of the near-field distribution over the full scan area. The first optimization is that the new adaptive sampling algorithm in every step proposes a batch of *N* locations in which to measure the near-field while the original algorithm gave in every step exactly one location. The second optimization is that one tries to minimize the total distance that one needs to go through these *N* locations. These two optimization result in a significant reduction of the total measurements because the time needed to move the probe around is reduced and because much less models of the near-field distribution have to made. The performance and effectiveness of the proposed sampling algorithm is tested in practice on a simple printed circuit board. The time reduction that is achieved when increasing the batch size *N* is discussed. In the end a trade-off needs to be made. Choosing the bath size *N* larger means a reduction of the measurement time for the same total number of sampling points. However, a larger batch size *N* also means that for the same quality of the near-field scan, a larger total number of samples is needed.**

Keywords – near-field scanning, surrogate modeling, sequential sampling, Kriging

I. INTRODUCTION

Near-field scanning for Electro-Magnetic Compatibility (EMC) purposes has become a very active area of research during the last few years [1]. As Printed Circuit Boards (PCBs) and integrated circuits (ICs) are integrating more and more functionalities working at high frequencies in an ever more confined space, detailed knowledge of the electromagnetic behavior of these PCBs and ICs early in the design process is therefore essential. Compared to standardized EMC measurements at 3 or 10 m from the device-under-test (DUT), near-field scanning has the advantage that it can give a very detailed picture of the fields caused by the DUT, leading to more insight and allowing a lot of post-processing.

Unfortunately, one of the main draw-backs of NF scanning is the time that is typically needed to scan the complete DUT with a sufficient resolution to capture all relevant phenomena. In many cases, one even needs this information at different frequencies. The most common way to measure is to sample the near-fields on a regular Cartesian grid where the distance between the sampling points is chosen relatively small in order to capture all details. However, it is not known before the end of the measurements how small this distance actually needs to be. To be on the safe side, most often the near-fields are measured in much more points than is really necessary.

A few possible solutions to tackle this problem have been proposed in recent literature. In [2], the use of neural networks is proposed to interpolate the near-field data, but a uniform Cartesian grid is still used. Nevertheless, the technique of [2] allows to choose the distance between the sampling points larger, thereby reducing the total measurement time. However, it is still not known a priori how dense this measurement uniform grid has to be to get in the end accurate data with all details.

In [3] and [4], a sequential sampling and modeling algorithm for the near-field analysis of electronic devices was proposed. This technique combines a sequential sampling algorithm based on a balanced trade-off between 'exploration' (*Voronoi Tesselations*) and 'exploitation' (*Local Linear Approximations*) with analytical approximation models based on Kriging. The main advantages of this technique are that (*i*) it minimizes the number of sampling points required to capture the NF pattern with a given accuracy and (*ii*) it allows to check at every moment the convergence of the measured NF data allowing to implement an automatic stopping criterion. In [3] and [4] it was shown with both simulations and practical measurements, that with this technique the total number of sampling points can be significantly reduced compared to using a uniform Cartesian grid and this for the same quality of the final data. It was shown in [3] and [4] that the sequential sampling and modeling algorithm could reach with about 350 samples the same accuracy and detail as the uniform sampling with more than 3000 samples.

Unfortunately, the total measurement time does not reduce with the same factor. There are two reasons for this. The first reason is that the locations in which the near-field has to be measured and that are proposed in every step of the algorithm seem to be randomly distributed. This means that the NF scanner has to move the probe over quite a large distance which makes that the time that is spent just moving around the probe can be significant compared to the total measurement

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time. The second reason is that after measuring every new sample a new Kriging model of the total near-field distribution has to be made. In this paper, the above is addressed in two ways. First, the sampling algorithm doesn't give only one location to measure the near-field but a batch of *N* locations. Second, a simple algorithm is used to go through these *N* locations in an quasi-optimal way.

This paper is organized as follows. Section II gives some more details about the near-field scanner, the near-field probe and the PCB under test. Section III describes the sequential sampling and modeling algorithm. Section IV discusses the efficiency and accuracy when increasing the batch size *N*. Finally, Section VI draws concluding remarks.

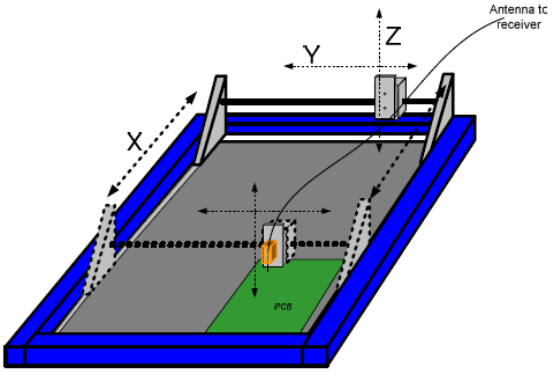

Figure 1: Near-field scanning system

II. MEASUREMENT SET-UP

A. Near-field scanning system and probe

Figure 1 shows the NF scanning system available at the ReMI research group of KU Leuven, campus Ostend. It comprises a CNC milling machine that was rebuilt into a near-field scanning system. To do this, the miller and its suspension were removed and replaced by a head to which a near-field probe can be attached. The head can be moved automatically in three dimensions above the device under test to make a NF measurement.

The near-field probe used for the measurements is a magnetic near-field probe from Langer EMV-Technik (RF-U 2.5-2) specified for the frequency range of 30 MHz up to 3 GHz. This probe is connected to a Rohde&Schwarz EMI receiver. Only the magnitude (and not the phase) of the tangential magnetic fields is measured and this at a height of 2 mm above the PCB under test. All measurements are done at 200 MHz.

B. PCBs under test

In order to test the performance of the proposed sampling algorithm, a simple PCB was used. This PCB (Fig. 2) comprises a 50 Ohm microstrip with two 90 degree bends on a 12 cm by 10 cm two-sided FR4 substrate of 1.5 mm thickness. To create sufficient radiation, some basic EMC rules were violated on the test PCB. More specifically, the microstrip was routed over a slot in the ground-plane

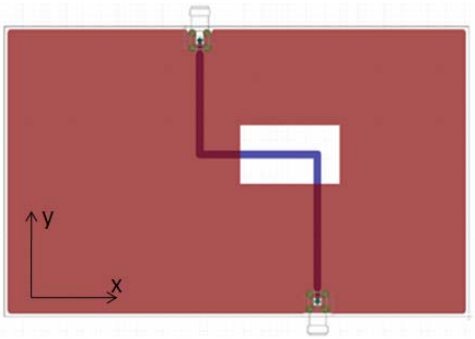

Figure 2: PCBs under test (50 Ohm microstrip with two 90 degree bends route over a slot in the ground-plane)

III. OPTIMIZED SEQUENTIAL SAMPLING ALGORITHM

The sequential sampling algorithm proposed in [3] and [4] starts by computing a small number of initial scan points (typically 24) according to a Latin hypercube design [5]. In successive steps, additional sampling points are selected one by one in a sequential way until the overall variation of the NF pattern is characterized. In order to sample the NF pattern as efficiently as possible, the robust sampling strategy from [6]-[8] is applied to determine the optimal coordinates of the sampling points in a sequential way. The sampling algorithm makes a balanced trade-off between exploration and exploitation criteria :

- *Exploration* is the act of exploring the design space in order to detect key regions that have not yet been identified before. It does not involve the actual pattern of the near-fields, but only the coordinates of the sampling points and their coverage of the design space. It ensures that all the scan points are spread as evenly as possible.
- *Exploitation* ensures that additional scans are performed in regions of the design space where the amplitude of the near-field component that is being measured is changing more rapidly. These regions often require a finer sampling density than regions with little variation.

Both criteria are combined into a unified metric that can be used to identify under-sampled regions of the design space, and to determine the optimal location of additional sample points.

Once a set of data samples is obtained from the sequential sampling algorithm, an analytic approximation model can be computed by Kriging. Kriging, also known as Gaussian Process regression, is a geostatistical modeling technique that originates from geology and mining [9]. In the original model, building a Kriging approximation model is done after every sample that is measured.

As mentioned before, the two main problems of this algorithm is that (*i*) compared to the uniform sampling the distance over which the probe has to be moved is much larger because of the seemingly random distribution of the sampling locations and (*ii*) the large number of Kriging models that need to be built during the complete measurement.

These two problems can be overcome by changing the sampling and modeling algorithm such that the sampling

locations are not given one by one but in batches of N locations. In that case, a new Kriging model only needs to be built after every N samples instead of after every sample. Moreover, for every new batch of N sampling locations one can optimize the way one can go through these N locations in order to reduce the total distance over which the probe has to be moved. This problem is similar to the "Hamiltonian path problem", which is known to be NP-complete. Hence, solving this problem is again a costly process. Therefore, it was decided to apply a greedy algorithmic approach in order to find a (possibly non-optimal) path that visits each scanning point exactly once. The algorithm that was used simply looks at the remaining locations and moves the probe to the sampling location that is closest to the current location of the probe (Fig. 3).

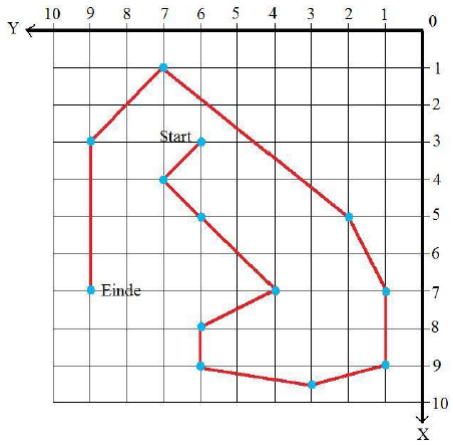

Figure 3: Greedy solution for the Hamiltonian path problem

IV. PRACTICAL EXAMPLE

In this Section, the new optimized algorithm is applied to the PCB shown in Fig. 2. The batch size N is gradually increased for 1 to 5, 10 and 15. The total number of sampling points was kept to 350 for all batch sizes. Table I compares the total number of Kriging models, the time needed to build the Kriging models, the total distance over which the probe moves, the time needed to move the probe, and the total measurement time. It is seen that the main reduction of the total measurement time is due to the reduction of the number of Kriging models that need to be built.

Figures 4 to 7 show the measured x-component of the tangential magnetic field at a height of 2 mm above the PCB under test and this after 350 sample points for the different batch sizes. In this case a very good agreement between all batch size is observed despites the significant difference in measurement time.

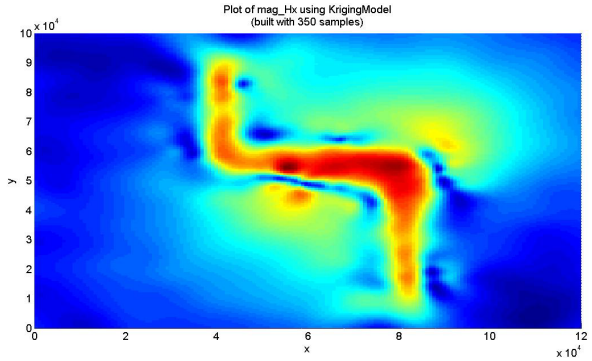

Figure 4: $|H_x|$ for a bent microstrip over a slot, batch size $N = 1$, 350 samples

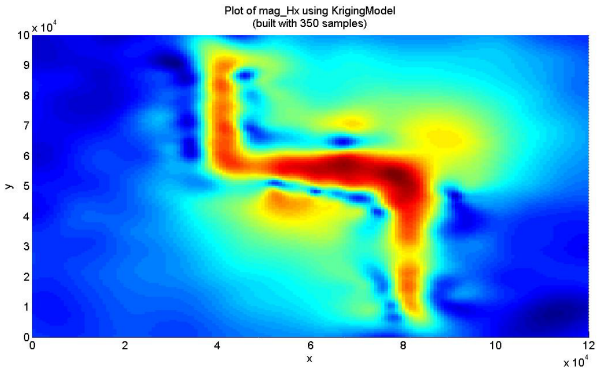

Figure 5: $|H_x|$ for a bent microstrip over a slot, batch size $N = 5$, 350 samples

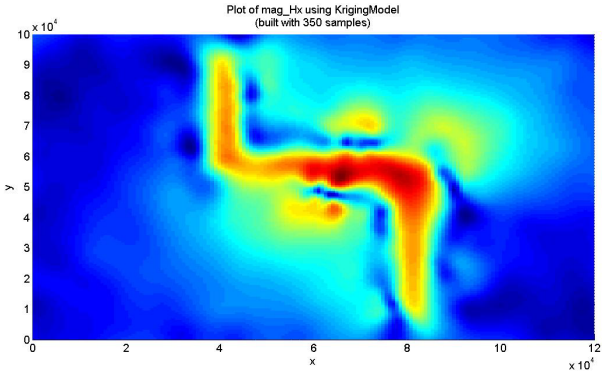

Figure 6: $|H_x|$ for a bent microstrip over a slot, batch size $N = 10$, 350 samples

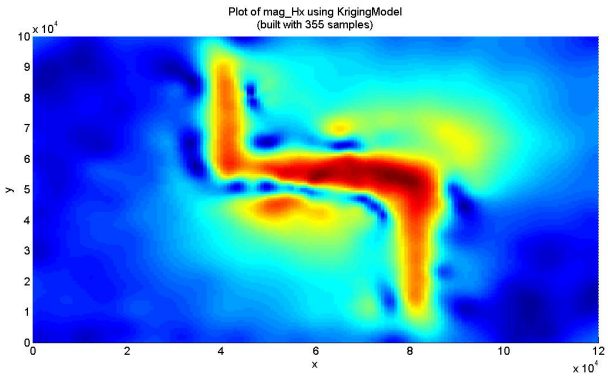

Figure 7: $|H_x|$ for a bent microstrip over a slot, batch size $N = 15$, 350 samples

Batch Size *N*	**Number of Kriging models**	**Time for building Kriging models**	**Total distance probe**	**Time for moving probe**	**Total measurement time**
1	251	7 min 41 s	13.0 m	9 min 52 s	17 min 33 s
5	51	1 min 30	11.4 m	8 min 24 s	9 min 54 s
10	26	51 s	9.2 m	7 min 0 s	7 min 51 s
15	18	31 s	7.7 m	6 min 4 s	6 min 35 s

Table I: Measurement time and distance probe versus batch size (in all cases the total number of sampling points was 350, the first Kriging model is only built after 100 samples)

Of course, one cannot keep on increasing and increasing the batch size *N*. A tradeoff needs to be made as increasing the batch size *N* will make that the accuracy of the modeled near-field distribution will be lower than for a smaller batch size *N*. This will be shown in more detail during the presentation on the conference.

V. CONCLUSIONS

The sequential sampling algorithm proposed in [3] and [4] was optimized in order to reduce the number of Kriging models that needs to be build and to reduce the distance that the probes has to move. This was achieved by generating a batch size of *N* locations instead of generating the sampling points one by one. The performance of the algorithm was tested on a simple PCB. A trade-off needs to be made between the batch size *N* which reduces the number of Kriging models and the accuracy that one gets after a given number of sampling points compared to the case where one uses a smaller batch size.

An open source MATLAB implementation of the modeling techniques in Section III is made publicly available for non-commercial, personal and academic use (AGPLv3 license) [10]. It can be downloaded as "SUMO Toolbox"from [11].

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