Adaptive classification algorithm for EMC-compliance testing of electronic devices

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A novel technique that facilitates near-field (NF) scanning for electromagnetic compatibility-compliance testing is described. It performs measurements in a sequential way with the aim of discovering multiple, possibly disjoint regions where the amplitudes of an NF component belong to certain output ranges. The measured data samples are used to train a classification model where each NF range is represented by a given class (e.g. low/medium/high NF amplitudes). The outcome of the algorithm is a visual map that clearly characterises and pinpoints the exact location and boundaries of each class. Such maps are useful, for example, to detect hotspots or regions that are prone to electromagnetic compatibility issues. The technique has been validated on a measured microstrip bend discontinuity.

Introduction: The detection of electromagnetic compatibility (EMC) issues for electronic devices is becoming important as an increasing number of components are operating at higher clock frequencies. A popular method to examine the EMC behaviour of such electronic (sub)systems is based on electromagnetic near-field (NF) scanning [1], as it facilitates the assessment of both the intra-system and inter-system EMC behaviour of the device under test. To reduce the overall NF scanning time, an automated algorithm was proposed in [2] that builds a high-resolution cartography model of the NF pattern by performing a minimum number of measurements and fitting the data with a Kriging-based interpolation model. Such models are highly accurate in the sense that they capture all the variations in the NF pattern. For EMC pre-compliance testing, however, one is usually interested in identifying only those regions of interest that belong to a certain class (e.g. regions with low/medium/high NF amplitudes). The early detection of such regions during the design-phase yields an insight into the EMC behaviour of the device and can be exploited to reduce development costs and design effort while increasing the performance. This Letter presents a novel classification-based scanning algorithm that sequentially performs batches of measurements with the aim of detecting only the regions of interest and outlining their boundaries. Numerical results confirm that the number of measurements can be reduced significantly as compared with a full device scan proposed in [2].

Goal statement: The goal of the algorithm is to identify all the NF regions of the device that correspond to a given class, while minimising the number of measurements (data samples) needed. Each data sample, k, is conveniently represented as a tuple $(x_k, L(x_k))$ where x_k is a scan point that contains the horizontal, vertical and height coordinates of the probe and $L(x_k)$ is the resulting class label. Note that this label is assigned by inspecting the output range of the amplitude of the electric or magnetic field component and by mapping it onto the corresponding class (e.g. low, medium or high).

Adaptive classification algorithm: The adaptive algorithm starts from a small initial set of scan points that is chosen according to an optimised Latin Hypercube design. In each sequential step, optimal coordinates for an additional batch of NF scan points are calculated and the corresponding measurements are performed. This process is repeated iteratively until all the regions of interest are well characterised. The resulting data samples are used to train a classification model (e.g. least-squares support vector machine (LS-SVM), artificial neural network) that predicts the class label at arbitrary coordinates in the scanning plane. The predictions of the model can be used to calculate a visual map that accurately pinpoints the location and the boundaries of each class region.

Sequential sampling scheme: When choosing the scan points, it is important that the exploration and exploitation criteria are combined in a balanced way. Both criteria are quantified by normalised metrics $V(x)$ and $W(x) \in [0, 1]$ for exploration and exploitation, respectively, as described below:

• Exploration makes sure that the scanning plane is sampled as evenly as possible, to ensure that no important regions are missed. Given a set of K scan points, a Voronoi tessellation is computed that divides the plane into cells C_k. Cells with a larger relative volume correspond to sparse areas and are assigned a higher score $V(x_k)$ (see Section III-A in [2]):

$$V(x_k) = \frac{\mathrm{Vol}(C_k)}{\mathrm{Vol}(C_1) + \cdots + \mathrm{Vol}(C_K)} \tag{1}$$

• Exploitation makes sure that the boundaries between different classes are sampled more densely, because these are the areas where the uncertainty of the classification model is the largest. For each scan point x_k, a neighbourhood $\{x_k^n\}_{n=1}^{N}$ of N scan points is calculated (see Section 4.2 in [3]). These neighbours should satisfy the properties of cohesion and adhesion. Cohesion implies that the neighbours are located as close to the scan point as possible, whereas at the same time adhesion implies that the neighbours must be as far apart from each other as possible. These properties ensure that all the directions around the scan point are well covered. Once the neighbourhood is constructed, the class labels $L(x_k^n)$ of all the neighbours are compared. A higher score $W(x_k)$ is assigned to the Voronoi cells, where the class labels of the neighbours have a mismatch, because this corresponds to the areas where the boundaries are located:

$$W(x_k) = \begin{cases} 1 \Leftrightarrow \forall 1 \le i, \quad j \le N \colon L(x_k^i) = L(x_k^j) \\ 0 \Leftrightarrow \exists 1 \le i, \quad j \le N \colon L(x_k^i) \neq L(x_k^j) \end{cases} \tag{2}$$

Once these metrics are computed for each Voronoi cell, all the cells are ranked according to a global metric $G(x)$ that combines both criteria:

$$G(x) = V(x) + W(x) \tag{3}$$

Optimal scan coordinates for the next batch of scan points are then chosen inside the highest ranked cells, and in such a way that the distance from the neighbours is maximised. The iterative process of measuring additional scan points is repeated until all the class regions are well characterised.

Experiment: The algorithm was applied to scan the NF pattern of a double bended microstrip line (see Fig. 1) that was measured by using an NF scanning system. The printed circuit board (PCB) comprised a 50 Ω microstrip on a 15 cm × 9 cm FR4 substrate with a thickness of 1.5 mm. To create sufficient radiation, some basic EMC rules were violated on the test PCB (e.g. routing the microstrip over a slot in the ground plane). The microstrip was excited at one end with a generator set at an available power of 0 dBm and terminated in 50 Ω at the other end. The amplitude of a field component, e.g. $|H_y|$, was measured with an NF scanner that was built from a computer numerical control milling machine. To do this, the miller and its suspension were removed and replaced by a head to which an NF probe is attached. The head can be moved automatically in three dimensions above the device under test to perform measurements. The probe was a magnetic NF probe from Langer EMV-Technik (RF-U 2.5-2) that was specified for the frequency range [30 MHz–3 GHz]. It was connected to a Rohde & Schwarz EMI receiver and all the measurements were performed at a fixed height of 2 mm above the PCB under test at a frequency of 200 MHz.
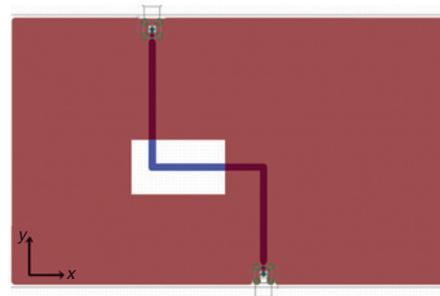
Fig. 1 *Layout of bent microstrip*

The algorithm is used to detect three regions in the scanning plane where the amplitude of the NF component $|H_y|$ is split into three NF ranges. As an example, the ranges are chosen as defined in the following table:

Class label	NF range (dBμV)	Colour
Low	[0–30[	blue
Medium	[30–40[	green
High	[40–∞[	red
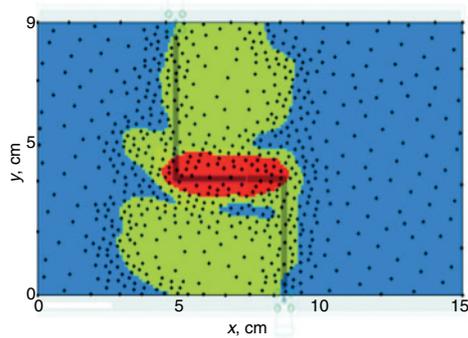
Fig. 2 *Map of classification model with 700 scan points marked as black dots*

It starts from an initial set of 80 measurements that are chosen according to an optimised Latin Hypercube. The sampling algorithm iteratively computes the optimal coordinates of a batch of 20 additional scan points and the measurements are performed. This process is repeated until a total amount of 700 samples are available and an LS-SVM classification model is calculated whose output is visualised as a map in Fig. 2. It is seen that the algorithm focuses on the location of selected scan points (black dots) near the class boundaries where the classifier is rather prone to uncertainty, and at the same time covering the overall region in a space-filling way [4].

Table 1: Validation of classification models

Number of Measurements	Precision	Recall	Accuracy (%)
100	0.5702	0.6191	89
150	0.9523	0.9023	95
200	0.9676	0.9245	96.6
250	0.9679	0.9154	96.8
300	0.9622	0.9460	96
700	0.9865	0.9865	98.4

The same experiment was repeated for varying numbers of scan points, and the resulting models were validated on a separate test set of 500 measurements that were uniformly distributed in the scanning plane. Table 1 shows that the resulting models perform very well in terms of the precision, recall and accuracy metrics [5], even with a limited number of scan points (150 or above). This is a significant reduction when compared to a full device scan that requires at least 350 measurements (see Fig. 22 in [2]).

Conclusion: A novel algorithm is proposed for EMC-compliance testing of electronic devices by means of NF scanning. It combines the adaptive classification and sequential sampling algorithms to iteratively identify the regions of interest where the amplitude of the NF pattern has prespecified characteristics. Numerical results show that it can significantly reduce the number of measurements needed when compared with a full device scan.

One or more of the Figures in this Letter are available in colour online.

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