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FAST METHODS FOR EVALUATING THE ELECTRIC FIELD LEVEL IN 2D-INDOOR ENVIRONMENTS

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Abstract—When estimating the electric field level in an indoor environment, the usual complexity of the geometry and its large electric size make it necessary to deal with asymptotic assumptions, also known as high frequency techniques. But, even with these assumptions, the computational complexity, and the CPU-time cost, can be very high. Considering this drawback, this paper proposes the implementation of a "Neural Networks System" for fast calculations of the Electric field in 2D-indoor environments.

1. INTRODUCTION

When dealing with an indoor environment, the computational complexity when using deterministic methods even if frequency techniques are considered to calculate the field level in a given area, can be extremely high. Because of it, this paper deals with the implementation of fast methods using Artificial Neural Networks, for the reduction of CPU-time and memory resources when calculating the field coverage in an indoor environment. Artificial Neural Networks (ANNs) are defined as intelligent knowledge based systems. This means that, starting from a previous knowledge or any training information, ANNs are able to solve certain complex mathematical problems. Moreover, any ANN's structures are assumed to be universal function's approximators, (as proved in [1] for Multilayer Perceptrons MLP, and in [2] for Radial Basis Function Networks RBFN). Taking into account these characteristics, it can be derived that an ANN is able to link inputs and outputs in a problem, as accurate as we want. if ANNs are Universal Approximators for known functions, why to use them in this application? One reason is that the analytical equations that describes the problems, are not known, in a general case the only information that may be available, is a set of pairs input-output. The other and most important reason in this application, is that the results using a trained ANN are obtained faster than using asymptotic techniques and of course, faster than using full-wave numerical methods. This paper is divided in five sections; description of the theoretical basis for the field level estimation in indoor propagation using high frequency techniques (GO-UTD); the theoretical and operational basis of the Artificial Neural Networks; the geometrical features to be treated; the obtained results and finally the conclusions.

2. INDOOR PROPAGATION

When dealing with a source of electromagnetic field, placed in a "free space" environment, the electric field (or the magnetic field) can be computed using integral equations which relate current densities and field magnitudes [14] derived from Maxwell's equations. However, in the case under study, with a complex environment with obstacles, the boundary conditions imposed by that environment must be taken into account, for solving the electric or magnetic field in a defined position. In essence, all the contributions due to the interactions among the elements of the environment must be considered. These interactions with electrically large obstacles are mainly described through asymptotic approximations like Physical Optics (PO) [3] or Geometrical Optics (GO) [4], by means of the reflection and the diffraction. In this paper, in order to train de ANN, all the electromagnetic interactions will be modeled through the Geometrical Optics, and its improvement for dealing with the diffraction phenomenon, the Geometrical Theory of Diffraction (GTD) [5] and its correction, the Uniform Theory of Diffraction (UTD) [6]. Originally, the GO was developed for analyzing light propagation, that is, at a frequency high enough that the electromagnetic waves can be considered as a ray that propagates in the shortest direction between two points (Fermat's principle). From this, the well known Snell's laws, which define the light behavior when it collides with an obstacle, can be demonstrated. Taking into account this ray nature assumption into the Maxwell's equations, the equations for the reflection (1) and the diffraction (2) due a flat surface and a wedge structure [14], respectively, can be derived:

For reflection:

$$E^r(s) = E_0^r \cdot \bar{R} \cdot \sqrt{\frac{\rho_1 \cdot \rho_2}{(\rho_1 + s) \cdot (\rho_2 + s)}} \cdot e^{-j\beta s} \tag{1}$$

where E_0^r is the incident electric field at the reflection point, ρ_1 and ρ_2 are the spatial attenuation factors that depend on the initial source, $\bar{R}$ is the Fresnell's reflection coefficient, s is the distance from the reflection point to the receiver and β is wavenumber.

For diffraction:

$$E^r(s) = E_0^r \cdot \bar{D} \cdot A(\rho_c,\, s) \cdot e^{-j\beta s} \tag{2}$$

where E_0^r is the incident electric field at the reflection point, $A(\rho_c,\, s)$ is the spatial attenuation factor that depends on the type of obstacle, on the position where the field is calculated, s, and on the original source, ρ_c, and $\bar{D}$ is the diffraction coefficient of the obstacle.

3. RADIAL BASIS FUNCTIONS NETWORKS

When dealing with an indoor propagation problem, it is necessary to compute non linear functions (in this case, those of the analysis by using Geometrical Optics). These non linear functions must be approximated by means of Artificial Neural Networks which work as universal approximators, such as those architectures whose discriminant functions are Volterra expansions, Splines, or Polynomial Functions [15]. In this paper, Radial Basis Function Networks (RBFN), which use symmetric functions as discriminant functions, have been used. It is possible to demonstrate, starting from the Stone-Weierstrass theorem, that an ANN, which uses these symmetric discriminant functions, is a universal function's approximator [2]. In the RBFNs, these polynomial symmetric discriminant functions, have the shape of Equation (3), and so, they are called Gaussian functions. Moreover, these Gaussian discriminant functions are local, that is, their effect on the approximation is only significant in the near environment of the application point, so one discriminant function can be modified in the expansion without producing any considerable effect on the rest of the approximation. From a theoretical point of view, RBFNs comply with the Chebyshev's concept of best uniform approximation (i.e., there is always a RBFN that provides the minimum desired error when estimating a given function) [16]

$$G(x) = \exp\left(-\frac{x^2}{2\sigma^2}\right) \tag{3}$$

Therefore, when approximating a non linear function, the procedure is based on establishing a collection of Gaussian functions, with means, variances and locations, dependent on the ANN's input parameters. A graphical example is showed in Fig. 1, where a non linear function is approximated by an addition of Gaussian functions.

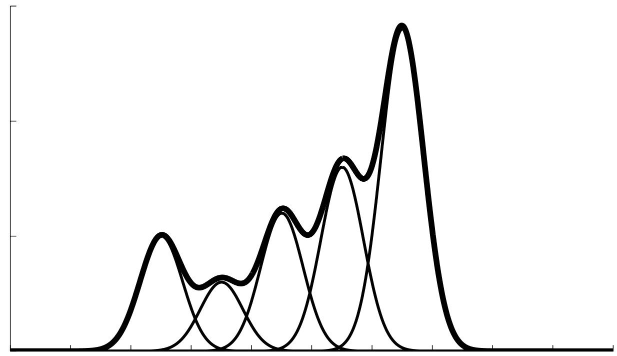

Figure 1. Function approximation by combination of Gaussians.

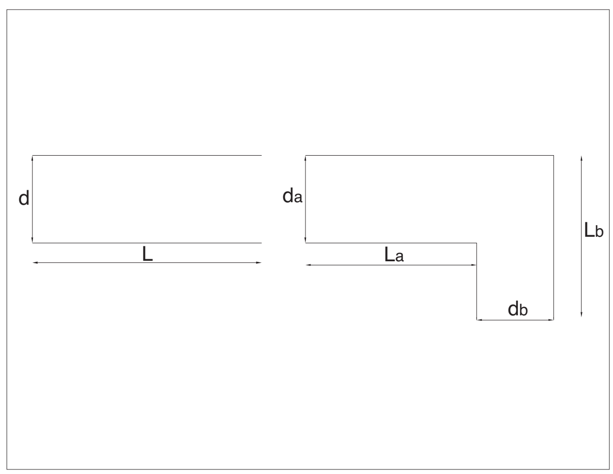

Figure 2. Analyzed rooms.

4. TRAINING'S PROCEDURE

In the development of this work, two different canonical scenarios have been tested. The first one is a simple corridor in a two dimensional space, with two walls, one opposite to the other, and a constant distance between them. In the second scenario, a corridor with a ninety degrees' corner is considered (Fig. 2). The geometrical parameters of these two different structures and the position of the transmitter which generates the electric field in the structure will be ANN's input parameters. For simplicity in the computations, the transmitter is considered to be an elemental dipole (Hertz dipole) of magnetic current density. Moreover, any other arbitrary radiating source could be modeled using a set of this type of elementary dipoles, according to the surface equivalence theorem, known as Huygens's principle [7]. By means of such principle, actual electromagnetic sources, such as an antenna, are replaced by equivalent sources, and as defined in the Love's principle [8], these sources can be magnetic currents. For the ANN's trainings, a set of points in a plane transversal to the corridor will be selected, and the electric field will be computed on, using the Geometrical Optics routines. These points will work as ANN's input parameters, and another set of points in another plane transversal to the corridor will be considered as the output parameters. This sort of training, imply a very expensive training's procedure (in terms of CPU-time and memory cost), but it is only necessary to run it once, making worth the overall improvement.

5. RESULTS

First of all, the field level inside all the domain of the proposed scenarios has been computed using the GO techniques as a reference result for the goal of later comparisons. The whole set of trainings and final results have been developed in 2.4 GHZ, the frequency used in wireless computer's networks, WIFI. These results are shown in Fig. 3 and Fig. 4. For the ANN's trainings, the variation of the geometrical

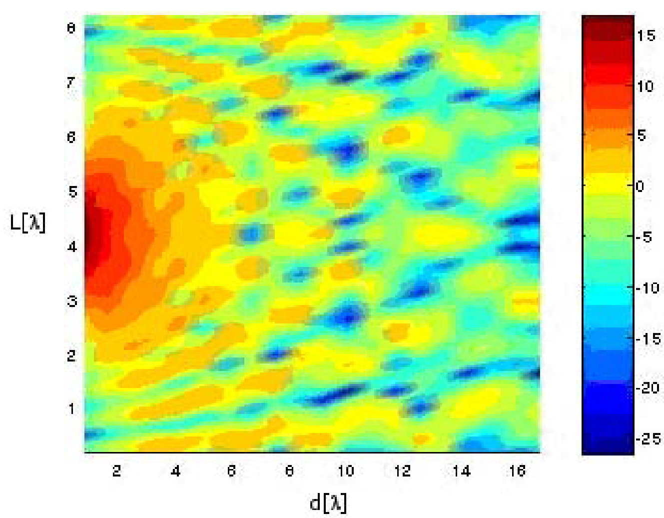

Figure 3. Field level in a straight corridor, computed using GO [dBμV/m].

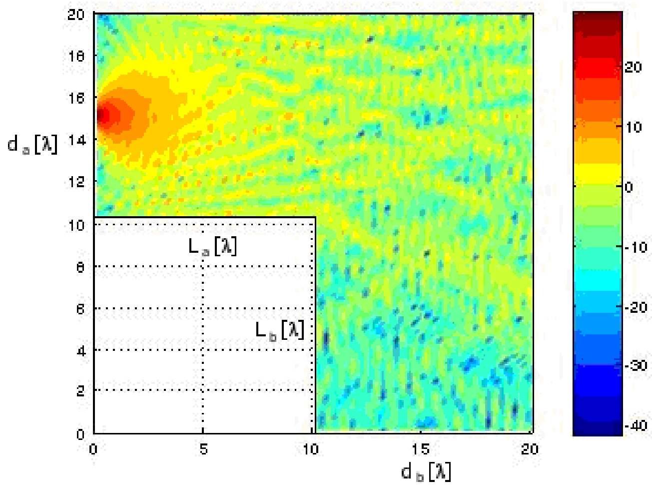

Figure 4. Field level in a corridor with a corner, computed using GO [dBμV/m].

parameters of the scenarios, such as the separation between walls (d), or the walls' length (L) has been considered. In the case of the corridor scenario the separation between walls (d) has been varied between 8 and 24 wavelengths (λ) with a fixed length (L) of 17 λ.

For this case, the original source has been centered between walls. For the second scenario, the separation between walls before the corner (da) has been varied from 8 to 24 λ for a fixed length (La) of 10 λ, and the separation between walls after the corner (Lb) has been varied from 8 to 24 λ, for a fixed length (Lb) of 10 λ. Along the training process, the separation between field points and the step for the variation of the geometrical parameters of the scenario, have been varied in order to minimize the error parameters, those are, the Electric field level difference between that obtained by GO and that obtained by the trained ANN. Once the ANN has been trained, the ANN's response at other points than those of the training, but in between the parameters rank has been evaluated (Fig. 5 and Fig. 6). As it can be seen, the complementary figures are extremely similar. Indeed, the differences between the GO results and the ANN results keep under 1 dBμV/m (E_{GO} [dBμV/m]$-E_{ANN}$ [dBμV/m] $\leq \pm 1$ dB) when the maximum variations for the separation between field points and step for the variation of the geometrical parameters of the scenario are $\lambda/5$ and $\lambda/4$ respectively. One last result, probably the most important one, is that the CPU-time spent in the evaluation of field level along the

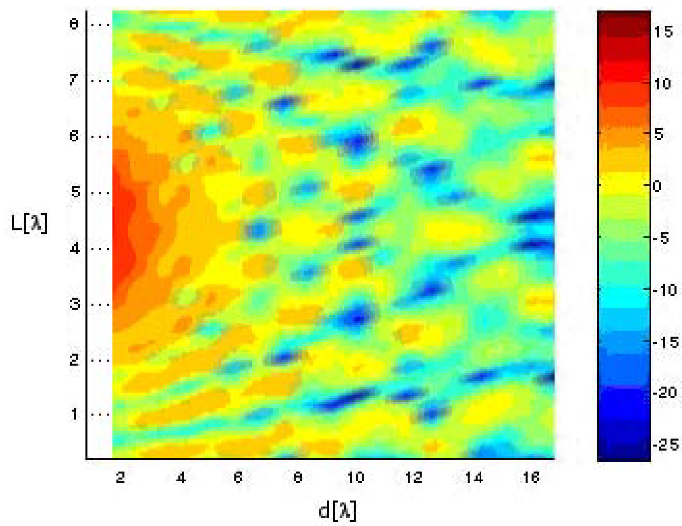

Figure 5. Field level in a straight corridor, using a trained ANN [dBμV/m].

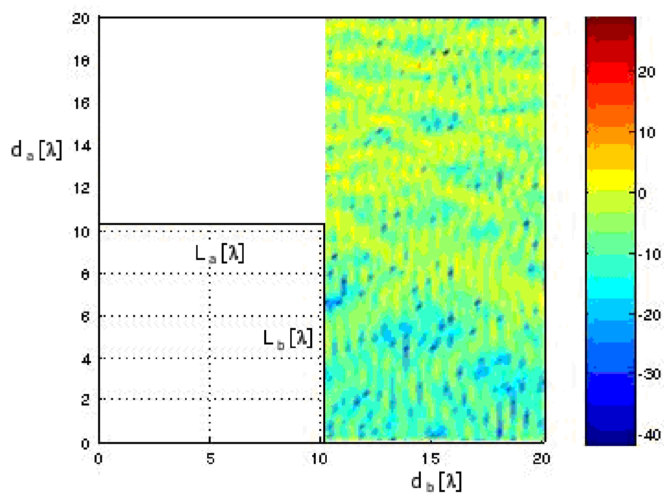

Figure 6. Field level in a straight corridor, using a trained ANN [dBμV/m].

simple corridor (scenario 1) using ANN proposed method, is less than ten percent of that spent when GO techniques is used. This result has been obtained averaging the execution time's costs over a lot of different executions. Time consumption's reduction is bigger than one magnitude's order for the presented examples.

6. CONCLUSIONS

From the obtained results with the proposed ANN method and their comparison with standard GO technique results, it can be stated that using ANNs in this kind of problems, the computations of the electric field in a complex environment can be accelerated of the order of ten times for the proposed scenarios. On the other hand, it is necessary a very hard training procedure, with a very high computational cost if simulations are the base of the training procedure. However, the use of ANNs leaves it opened to other interesting options such as the use of measurements for the training procedure. In such case, the ANN's results would be as accurate as measurements could be.

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