

WAVEGUIDE MICROWAVE IMAGING: GEOMETRICAL PARAMETERS OF A SPHERICAL INHOMOGENEITY

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Introduction

Microwave (MW) imaging is currently under extensive development as a promising NDE/NDT technique [1]. While, e.g., X-Rays, ultrasound, and MRI are very popular in medical applications, MW imaging has a potential for overcoming their major drawbacks and becoming safer, more accurate, and more cost-effective technology. It can also be used for NDT of defects/cracks in construction materials [2], composite panels [3], wood slabs [4], reconstruction of material properties [5]-[6], and in other applications.

The work reported in this paper continues a series of our earlier studies that demonstrated feasibility of using modeling (instead of experimental) data in imaging conducted in closed cavities [5-7]. The reason for this is that, in contrast to the implementation in open space, EM processes inside waveguides and resonators are now accessible for virtual experimentation based on advanced numerical techniques. We present the development of a computational procedure, which, by using data of a single elementary measurement of reflection and transmission in the MW system, reconstructs parameters of an internal spherical inhomogeneity of a dielectric sample. Three spatial coordinates and radius of the sphere are determined for the sample placed inside a four-port closed system, and highly accurate reconstruction takes place without moving or rotating the sample. The proposed modeling-based method of MW imaging is made fully operational with a forthcoming experimental implementation.

Technique

Expanding upon our earlier work [7], we introduce an advanced computational procedure utilizing an artificial neural network (ANN) performing numerical inversion and reconstructing geometrical parameters of a spherical inclusion in a dielectric sample situated inside a closed microwave system. Instead of rotating or moving the sample [7], we use a multiport structure to increase amount of data (complex S -parameters) which is produced for the ANN by an FDTD model of the system

Our technique is implemented with a standard four-port microwave component – a combination of four waveguides that is known as a Magic Tees Junction (MTJ) (Fig. 1). The records of responses to the fields in all four ports (i.e., the elements of the full matrix

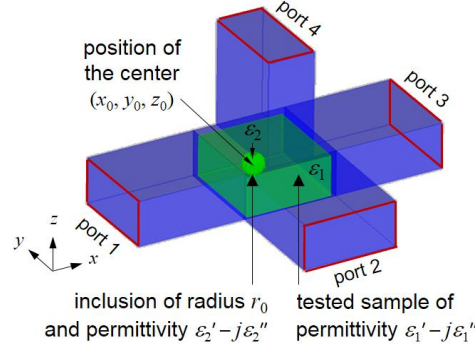


Fig. 1. A MTJ-based system for reconstruction of spatial coordinate and radius of a spherical inclusion inside a dielectric sample.

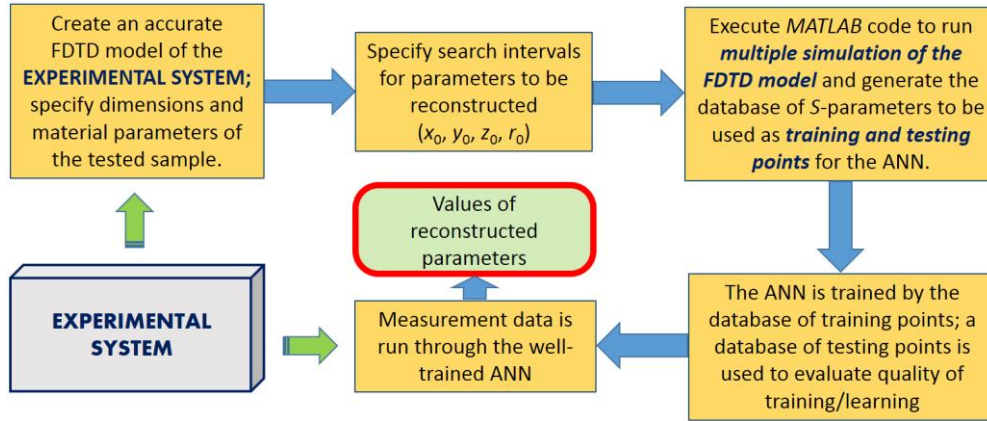


Fig. 2. Mechanism of FDTD-backed ANN-based reconstruction of the position and radius of a spherical inclusion in the tested sample.

of S -parameters) are hypothesized to be sufficient for reconstruction of the sought parameters. Also, in contrast to [7], for further enhancing reconstruction capabilities, amount of data available for the ANN inversion is expanded by using data corresponding to the reflection/transmission coefficients at two additional frequencies.

Functionality of the technique can be conceptually described with the help of the flow-chart in Fig. 2. The model reproduces the four-port waveguide system, the tested sample (with complex permittivity ϵ_1) in the center of the MTJ, and a spherical inclusion of radius r_0 and complex permittivity ϵ_2 that is located in an arbitrary position within the tested sample. An FDTD model computes frequency characteristics of the real and imaginary parts of the S -parameters. Input data and output results of the model (at three frequencies) form the output and the input of the ANN, respectively.

Multiple simulations performed for random values of the reconstructed parameters (taken in certain intervals) produce a database for training and testing the ANN. When the network is sufficiently well trained, it is given the experimental set of S -parameters corresponding to the unknown coordinates of the center of the inclusion (x_0, y_0, z_0 ,) and its radius (r_0). The ANN then reconstructs the values of all these parameters.

Computational Results

Performance of the ANN inversion procedure was illustrated by its operation with a dielectric and metal sphere hidden in a rectangular Teflon sample inside a MTJ. In both cases, computation was made for the following geometrical and material parameters:

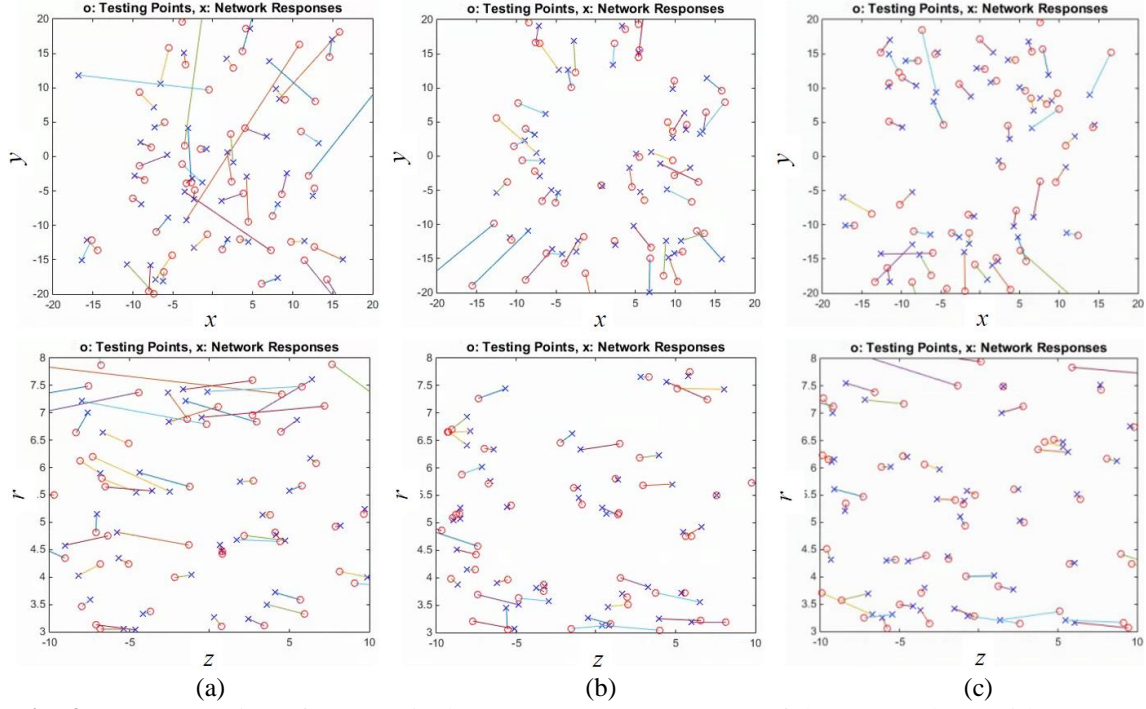


Fig. 3. Reconstruction of geometrical parameters ((x_0, y_0, z_0, r_0)) of the ZrO_2 sphere with 500 (a), 1000 (b), and 1500 (c) training points; number of testing points: 50.

- WR340 MTJ (waveguide cross-section 86×43 mm)
- Rectangular tested sample ($60 \times 60 \times 40$ mm)
- Complex permittivity: Teflon $\epsilon_1 = 2.04 - j0.004$; silicon carbide (SiC): $\epsilon_2 = 10.4 - j0.9$; zirconia (ZrO_2): $\epsilon_2 = 6.69 - j0.1$

The reconstructed parameters were sought within the following integrals: $-20 \leq x \leq 20$ mm, $-20 \leq y \leq 20$ mm, $-10 \leq z \leq 10$ mm, and $3 \leq r \leq 8$ mm.

A series of special diagrams showing the quality of reconstruction of the coordinates and the radius was generated for zirconia, silicon carbide, and metal; a typical set of those diagrams is shown in Fig. 3. The disagreement between the two positions is highlighted by a straight line between them. For all materials of the inclusion, the accuracy of reconstruction improves with the number of training points, and the performance is better for ZrO_2 and SiC than for metal.

For each parameter, the error was calculated using a formula that takes into account the bounds of the randomly generated values of the input parameters:

$$Error (\%) = \frac{|P_a - P_r|}{CI} 100, \quad (1)$$

where P_a and P_r are the actual and reconstructed values and CI stands for a “conditional interval” which is specified in accordance with physical constraints for a particular parameter in the considered scenario. For the coordinates of the center of the inclusion, we define CI as the physical dimensions of the sample, i.e., $CI_x = CI_y = 60$ mm, and $CI_z = 40$ mm. For the radius, the CI is defined by the interval in which variation of the size of the sphere is assumed to be possible, i.e., $CI_r = 5$ mm.

In Fig. 4, the average percent error is shown as the function of number of training points. One can see an excellent convergence: the error drops below 4% when the number of training points is larger than 500. The average percent errors in reconstruction, as seen

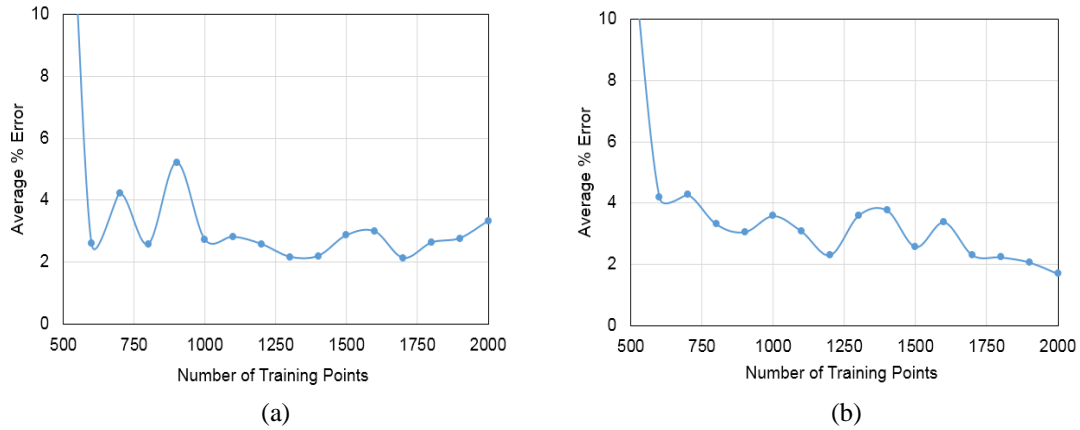


Fig. 4. Convergence of the computational procedure for the spheres made of ZrO₂ (a) and SiC (b).

Table 1. Average percent error in reconstruction of geometrical parameters*)

	Material	x_0	y_0	z_0	r_0	Overall
Dielectric (mineral)	Zirconium dioxide (ZrO ₂) $\varepsilon = 6.69 - i0.1896$	1.10	2.18	2.13	1.35	1.7
Dielectric (ceramics)	Silicon carbide (SiC) $\varepsilon = 10.4 - i0.9$	3.84	4.72	3.06	1.66	3.3
Metal	Stainless steel $\sigma = 10^7$ (S/m)	12.76	7.3	7.21	2.82	7.5

*) ANN training points: 2000; average over 15 testing points

from Table 1, is high: computed for the 15 points from the testing set, the errors are as low as 1.7% and 3.3% for dielectric inclusions, but a bit higher for a metal sphere (7.5%).

Conclusions

A series of computational experiments for a four-port closed system (a waveguide Magic Tees Junction) have shown excellent (not worse than 4% error) results in reconstruction of geometrical parameters of a spherical dielectric inhomogeneity inside a rectangular Teflon sample. The developed FDTD-backed ANN-based procedure working with a multiple (at least four) ports and collecting data on complex S -parameters at multiple (at least three) frequencies is operational without rotating/moving the tested sample. The procedure is ready for working with corresponding experimental systems.

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