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ONE DIMENSIONAL PROFILE RECONSTRUCTION OF DIELECTRIC CYLINDER BY USING NEURAL NETWORK

Necmi Serkan TEZEL

Istanbul Technical University
Electronics and Communication Engineering Department
34469, Maslak, Istanbul, Turkey

E-mail: tezeln@itu.edu.tr

ABSTRACT

In this paper, Neural Network (NN) is used for profile reconstruction of dielectric constant of the cylinder. The region is assumed to be filled with dielectric medium of which dielectric constant changes along the radial direction. Radial variation of dielectric constant is represented by Fourier series. Scattered fields, which are obtained by numerically Method of Moments (MoM) technique, and Fourier coefficients are used for training the NN as inputs and outputs respectively. In numerical examples, Scattered fields are applied trained NN, outputs of NN are compared the exact profiles and good reconstructions are observed.

Key words: *Neural network, inverse medium scattering*

1. INTRODUCTION

Direct and Inverse Scattering of electromagnetic waves is one of the main objects of electromagnetic theory and have considerable application such as radar remote sensing, nondestructive testing. Object of direct scattering problems investigate to find scattering fields for given object and exciter fields. However, Aim of inverse scattering problems to find object information, such as shape, electromagnetic parameters, position for given scattered fields. Because of the fact that scattered fields can only be measured in the limited region of the space, solution of the inverse scattering problems is inherently ill-posed and non-unique, consequently, it requires regularization and time consuming iterative algorithms [1]. Therefore, these techniques are not suitable for real time application. On the other hand, if direct scattering problem is solved using any analytical or numerical methods for plenty of different situations, obtained data can be used for training the neural network. Therefore, neural network can be used for solving inverse scattering problems.

Recently, neural network based approaches have been applied to electromagnetic inverse problems for finding geometric and electromagnetic parameters of the scatterer under investigation [2-9]. Determination of position and radius of the conducting cylinder is investigated by using radial-basis function NN that are constructed by using orthogonal least square algorithm in [10], same problem is also

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solved by using Wavelet based radial basis function NN in [11].

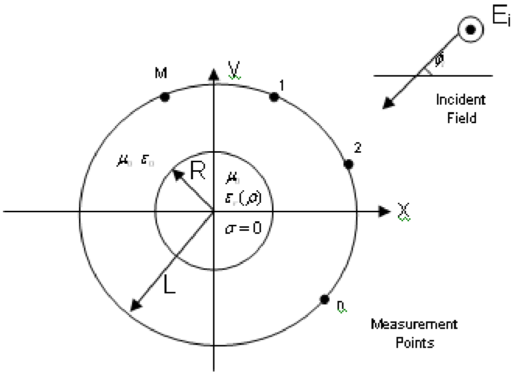

Figure 1. Geometry of the considered inverse scattering problem.

In this study, NN is applied to reconstruct the profile of dielectric constant of the cylinder. Considered problem is depicted in Fig.1. Dielectric constant is expressed by using Fourier series, then, scattered fields are obtained by using numerically MoM technique [12] for plenty of different dielectric constant variations. Scattered data and Fourier coefficients are used for training NN as inputs and outputs respectively. Once feed forward NN is educated, it instantaneously produce an output for given input which is different from data used for training. Therefore, NN is good solution for online scattering, where rapid solution of inverse problem is demanded.

2. RECONSTRUCTION BY NN

In order to solve inverse problem, one needs to solve direct scattering problem for training NN. Scattering from 2-D inhomogeneous lossless dielectric cylinder is solved by using point matching MoM method. Because of fact that solution of this problem is well known and straightforward, it is not mentioned in this study. Interested readers can refer to [12].

Dielectric constant variation of cylinder is represented by using Fourier series as,

$$\varepsilon_r(\rho) = a_0 + \sum_{n=1}^{N}\left[a_n \cos(\frac{2\pi n\rho}{R}) + b_n \sin(\frac{2\pi n\rho}{R})\right] \quad (1)$$

This unknown profile can be reconstructed by using NN from a sufficient number of scattered field measurements obtained on the circle which contains the cylinder as depicted in Fig.1. Scattered field measurements which is unknown function of Fourier coefficients of dielectric constant variation can be given as,

$$E_z^s(L,\phi_m) = f_m(a_0, a_1, ...a_N, b_1, b_2, ..b_N),\ m=1,2,...,M \quad (2)$$

where L is radius of measurement circle, M is number of the measurement points NN are trained by using the M calculated scattered fields as inputs and 2N+1 real Fourier coefficients of the profile as outputs as depicted Fig.2. For testing, scattered fields, which are not in training set, are applied to NN, and profiles obtained by NN outputs are compared to exact profiles which produce scattered fields. Effect of the noise on the performance of the NN can also be investigated by adding Gaussian noise to scattered field measurements. In this case, signal to noise ratio (SNR) is given by

$$SNR = 10\log \frac{\sum_{m=1}^{M}\left|E_z^s(L,\phi_m)\right|^2}{2M\sigma^2} \quad (3)$$

where σ^2 is variance of Gaussian noise.

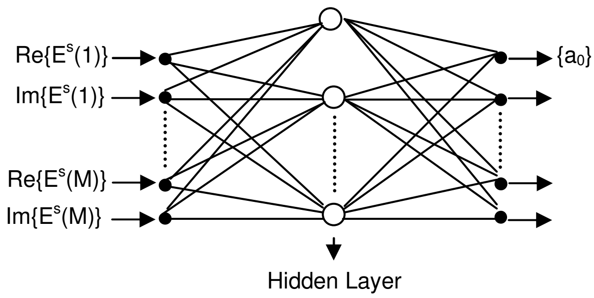

Figure 2. Architecture of the feed forward neural network (FF-NN).

3. NUMERICAL RESULTS

The proposed method has been applied to three illustrative cases. In all cases, frequency is selected as f=1GHz., angle of incidence $\phi_i = 0^0$ and radius of cylinder is R= 30cm. Direct scattering problem is solved by 500 point MoM technique.Levenberg-Marquardt back propagation algorithm [13] is used for training of NN. The scattered electric field is measured at M=60 positions on circle with L=10λ radius and equal degree intervals. Dielectric variation of the cylinder is expressed by using 11 Fourier coefficients. Thus, the architecture of NN has 120 components (60 real and 60 imaginary), while its output has 11 components. It is used 100 nodes in the hidden layer of NN architecture. 1000 input-output vector set is used to train the NN. For testing, scattering fields are applied to the input of the NN as measurements then the output vector is obtained. Substituting of outputs into (1), one gets profile of the cylinder. In order to demonstrate the performance of this approach, noiseless and noisy measurements are applied to NN. Obtained profiles are compared with the exact profiles.

In the first example, we consider the cylinder whose relative dielectric constant vary as,

$$\varepsilon_r(\rho) = 2 + \frac{\rho}{R} \tag{4}$$

Exact profile, reconstructed with noiseless data and reconstructed with SNR=30dB are depicted in Fig.3.

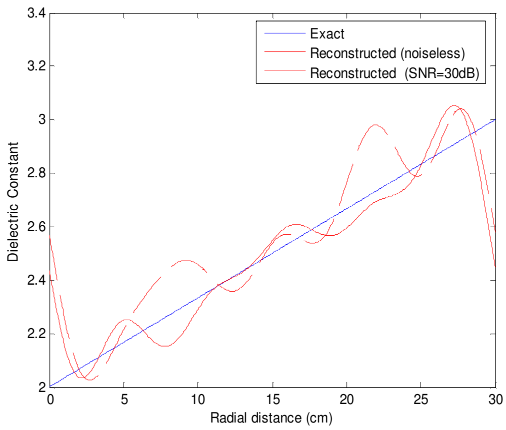

Figure 3. Exact and Reconstructed Profiles.

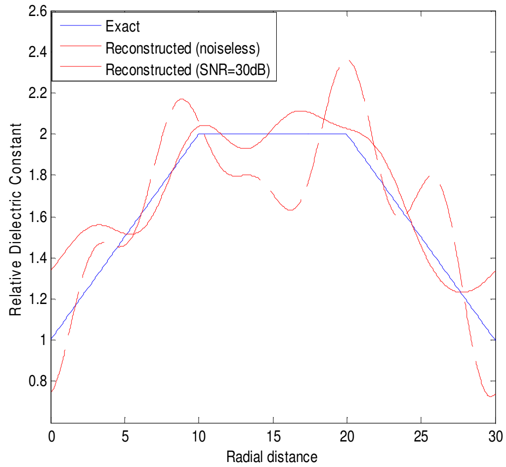

Figure 4. Exact and Reconstructed Profiles.

In the second example, we consider the cylinder whose relative dielectric constant vary as,

$$\varepsilon_r(\rho) = \begin{cases} 1 + \dfrac{3\rho}{R} & 0 \le \rho \le \dfrac{R}{3} \\ 2 & \dfrac{R}{3} < \rho \le \dfrac{2R}{3} \\ 2 - \dfrac{3(\rho - \frac{2R}{3})}{R} & \dfrac{2R}{3} < \rho \le R \end{cases} \tag{5}$$

Obtained results are depicted in Fig.4. In Fig.4, Fig.5 exact profiles are compared with reconstructed by NN for noiseless and SNR= 30dB noise level. As seen from Fig.4 and Fig.5, NN results are consistent with exact profiles.

4. CONCLUSIONS

In this study, profile reconstruction of dielectric cylinder from electromagnetic scattered fields is presented by using FF-NN. Direct scattering problem is solved by point matching MoM for different profiles, then obtained results are used for training and testing the NN to solve inverse problem. Effect of the noise on performance of NN is also investigated. More complicated profiles can be expressed by using more Fourier coefficients. In this case, in order to obtain desired accuracy, more number of training set and more measurement points must be used to train NN. Similar method can be applied to three dimensional objects and determination of conductivity of the objects as well. It can be concluded that proposed method can be applied for inverse electromagnetic scattering without involving complicated methods and time consuming algorithms.

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