# NEURAL NETWORK APPROACH TO THE EXTRACTION OF INFORMATION ABOUT CONDUCTING CYLINDERS FROM AMPLITUDE-ONLY DATA

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*Key words: Inverse scattering, neural networks, amplitude-only data, microwave imaging*

## ABSTRACT

**In this study, radial basis function neural network (RBF-NN) with amplitude-only data input for the estimation of the geometric characterization of conducting cylindrical scatterers is presented. The effects of this technique on the performance of the network is investigated. The results obtained by this technique are compared with the estimation performance of RBF neural network that makes use of the complex values of the scattered field.**

## I. INTRODUCTION

The application of electromagnetic scattering to retrieve the shape, location, size, and the internal property of an object embedded in a homogeneous space or buried underground has gained increasing interest in many areas such as non-destructive evaluation, geophysics, biomedical applications, material engineering, remote sensing, and environmental investigations, just to name a few. In general the solution to these problems are inherently ill-posed and nonunique, and consequently requires the time consuming iterative algorithms. These techniques are computationally intensive, and are not suitable for real-time applications. An interesting alternative to these methods are neural networks, together with an acceptable accuracy of the results.

Recently, neural network based methodologies are applied to the electromagnetic inverse problems [1]. Neural network models, multilayer perceptron (MLP) [2-3] and radial basis function neural networks (RBF-NN) [4-5], have been proposed for the extraction of general information about the geometric and electromagnetic properties of the scatterer under investigation. All these techniques are using the complex values of the scattered electric field as input data for the invesion procedure. The use of amplitudes of the scattered electric field has been proposed in [6] for the localization and the dielectric characterization of physically inaccessible cylindrical objects by means of MLP neural network. These methodologies significantly reduced computation time and computer resources when compared to traditional iterative inverse-scattering techniques.

In this paper, RBF -NNs with amplitude-only data input and the complex data input are applied to the estimation of the position and radius of a conducting cylindrical scatterer illuminated by transverse-magnetic plane waves. The training algorithm of the RBF neural network is the orthogonal least squares (OLS) algorithm. The back-propagation algorithm, which is the training process of MLP neural network, includes forward and backward propagation, with desired output used to generate error values for back propagation to iteratively improve the output. Back propagation algorithm is limited by the slow training performance. In contrast, the parameters of the network are computed in a straightforward manner by the OLS algorithm, which provides an optimal network size, and much faster than the back propagation. In OLS algorithm, no trail and error approach is required to define the architecture of the network.

In this study, specific emphasis is placed on the comparison of the performance of RBF neural network which has the complex values of scattered fields as input with RBF network which has the amplitude-only data as input. The effect of data reduction on the network performance is also investigated. Data reduction is achieved using the amplitude component of scattered electric field.

## II. NEURAL NETWORKS

A neural network is a computing system simulating the human nervous system. Neural networks consists of densely interconnected computing elements or nodes called neurons, each performing simple computational operations. A group of neurons is called a layer. The connections between the neurons are known as links. Every link has a weight parameter associated with it. One of the most important characteristics of the neural networks is the ability to learn input-output relationship from examples. They learn tasks by adjusting the weights of the links between the neurons. The values of the weights are defined during the training phase. A set of input patterns is granted to the network and corresponding output is calculated. By minimizing with respect to weights, the difference between the output of the neural network and the expected target, the strength of each connection is evaluated and the neural network is specialized to the solution of the given problem. Once the NN has been trained for a particular class of problems, it instantaneously produces an output to a given input.

There are different ways in which information can be processed by a neuron, and different ways of connecting the neurons to one another. Different neural network structures can be constructed by using different processing elements and by the specific manner in which they are connected.

Neural network models, especially multilayer layer perceptron (MLP) and Radial Basis Function (RBF) neural networks have been successfully used for function approximation. Since solving the inverse problem is equivalent to approximating an inverse mapping, it is logical to consider using neural networks.

RBF networks belong to a general class of structures called feed forward neural networks. The architecture of a two layer feed forward neural network used for the estimation of geometric characteristic of the scatterers is shown in Figure 1.

A radial basis function (RBF) network is a two-layer network whose output nodes form a linear combination of the basis functions computed by the hidden layer nodes. Commonly used radial basis activation functions are Gaussian and multiquadratic. A common learning strategy is to randomly select some network input vectors as the RBF centers, effectively fixing the network hidden layer. The weight in the output layer can then be derived by using the least-squares method. However the performance of an RBF network critically depends upon the chosen centers, which may require an unnecessarily large RBF network to obtain a given level of accuracy and cause numerical ill-conditioning. The orthogonal least squares (OLS) method can be employed to choose appropriate RBF centers one-by-one from the training data until a satisfactory network is obtained by reducing the network size greatly. This approach provides an efficient learning algorithm for fitting adequate RBF networks. The implementation and benefits of the OLS algorithm are described in [7].

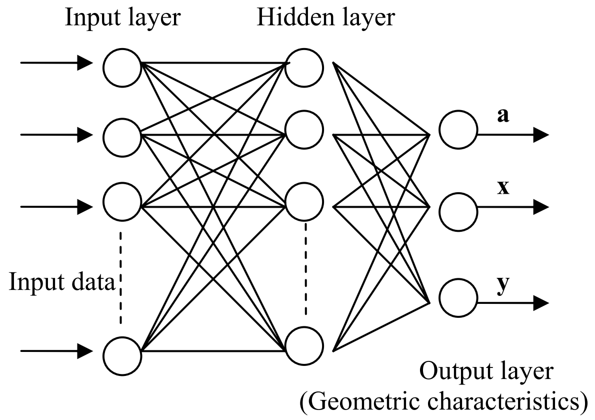



Figure 1.Two layer feed forward neural network structure.

## III. THEORY

The geometry of the problem is shown in Figure 2. The object to be analyzed is a conducting, infinitely long, cylindrical scatterer of circular cross section, which is embedded in free space. The position of cylinder is represented by the coordinates (x, y), and its radius is represented by a. A square investigation domain is illuminated by transverse magnetic plane wave that travels along x-axis. The scattered electric far field is given by [4, 8]

$$E^s(\rho,\varphi) = -E_0\left(\frac{2}{\pi k_0 \rho}\right)^{1/2} \exp\left[j(\pi/4 - k_0\rho)\right]\sum_{n=0}^{\infty} e_n \frac{J_n(k_0 a)}{H_n^{(2)}(k_0 a)}\cos(n\varphi) z_0 \tag{1}$$

where $e_n$ ={1 for n=0; 2 for n > 0}, $k_0$ is the wavenumber in free space, $J_n$ is the Bessel function of nth order, and $H_n^{(2)}$ is the Hankel function of second kind and nth order.

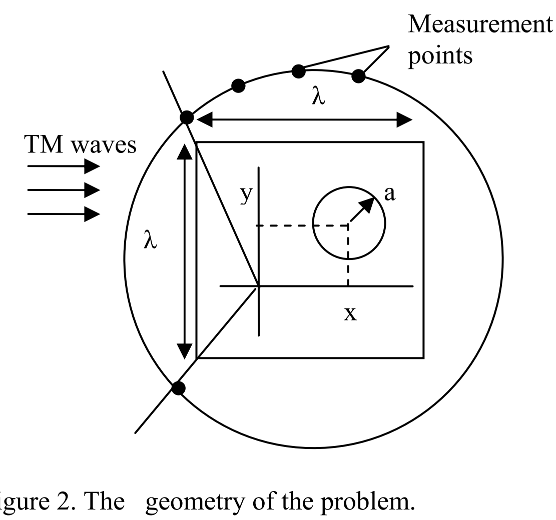



Figure 2. The geometry of the problem.

## IV. RESULTS

Sixteen equally spaced observation points are used to simulate the scattered electric far field. They are located in the (x, y) plane, all around the investigation region distributed along the arc defined by R = 10λ ($\lambda$ is the wavelength in free space), and $-3\pi/4 \leq \varphi \leq 3\pi/4$. The search interval for the radius a and the coordinates of the position (x, y) of the object have been chosen as $0.05\lambda < a < 0.5\lambda$, $-0.4\lambda + a < x < 0.4\lambda - a$, $-0.4\lambda + a < y < 0.4\lambda - a$ respectively.

In the first example, the input values for the neural network are the scattered electric field values that are available at a number of observation points out of the investigation region. The coordinates of the position (x, y) and the radius (a) of the scatterer form the output of the RBF neural networks. All values have been normalized with respect to the wavelength. A 32-32-3 network structure is obtained after the training set composed of 400 input-output vectors.

The generalization ability of the network have been examined by testing a new set of data composed of 1000 input-output vectors . The results for the first example are given in Table 1.

Table 1. Absolute errors for the geometric characteristics of the scatterer estimated by the RBF neural network with complex values of scattered electric as input .

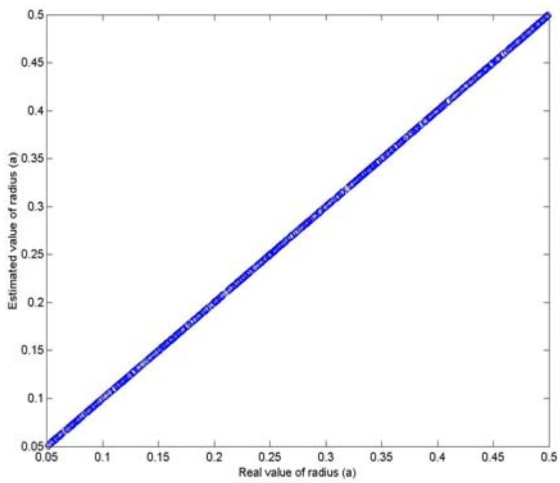
| Geometric characteristics | Absolute mean Error | Standard deviation |
|---|---|---|
| $a / \lambda$ | 0.0011 | 0.0015 |
| $x / \lambda$ | 0.0061 | 0.0111 |
| $x / \lambda$ | 0.0051 | 0.0078 |

In the second example, the input values for the neural network is the amplitudes of the scattered field. The geometric characteristics (a, x, y) are the output of the neural networks. A 16-15-3 network structure is obtained after the training set of 400 input-output vectors. The number of the epoch (15) is equal to the number of hidden layer neurons. The generalization ability of the network has been examined by testing a new set of data composed of 1000 input-output vectors. The results for the second example are given in Table 2.

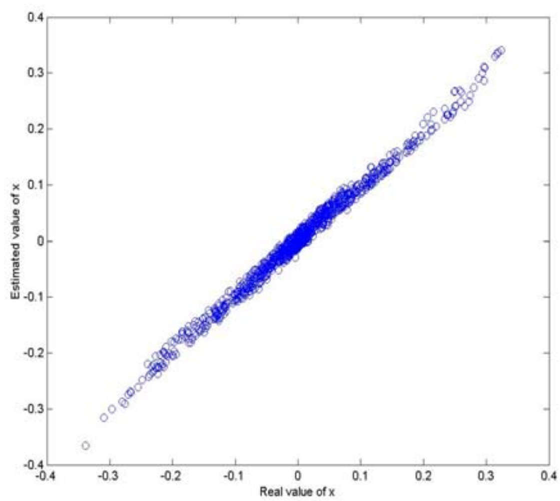
Table 2. Absolute errors for the geometric characteristics of the scatterer estimated by the RBF neural network with the amplitudes of scattered electric field as input.

| Geometric characteristics | Absolute mean Error | Standard deviation |
|---|---|---|
| $a / \lambda$ | $7.10^{-5}$ | $9.10^{-5}$ |
| $x / \lambda$ | 0.0084 | 0.01 |
| $y / \lambda$ | 0.0017 | 0.0028 |

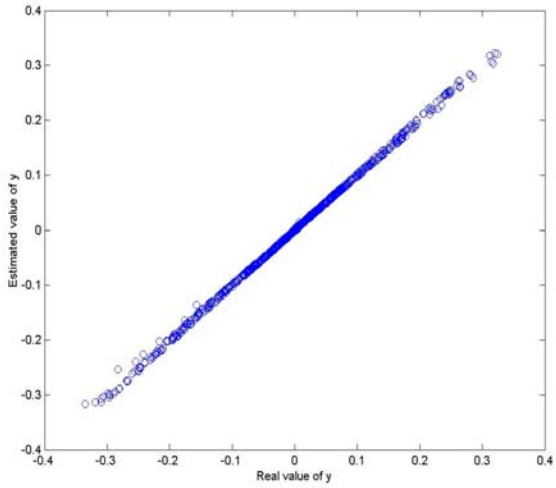
Results in all tables show that the estimation of the geometric characteristics of the scatterer by the neural network structures is very successful. Using amplitude-only data as input without compromising the accuracy of the estimation process., the number of input parameters for the RBF-NN is reduced to the half of the input parameters for the RBF-NN which uses the complex values of scattered fields as input. The number of neurons of the hidden layer is also reduced to the half of the first example. The architecture of the network is also simplified by decreasing the number of input parameters. Thus, training RBF-NN for the second example is much faster than the first one. The training time of the first network is three times much than that of the second network.




(a)




(b)




(c)

Figure 3. Estimated values of the normalized scatterer properties (a) a/λ, (b) x/λ, and (c) y/λ versus the actual ones for a test set of 1000 input-output pairs.

The estimation of the radius of the scatterers and the coordinates (x, y) of their centers are illustrated in Fig. 3(a), (b) and (c), respectively. Figure 3 proves the reliability of the network which uses the amplitude of the scattered electric field.

## V. CONCLUSION

In this paper, we have proposed inverse-scattering technique, based on the RBF neural networks and amplitude-only data for the estimation of geometric characteristics of conducting cylindrical scatterers. The efficiency of the proposed technique was illustrated by comparing with the technique which is based on the whole information of the scattered electric field. As a result, the use of RBF neural networks and amplitude-only data is a promising technique for the microwave detection and characterization of different objects

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