APPLICATION OF NEURAL NETWORKS IN THE ESTIMATION OF TWO-DIMENSIONAL TARGET ORIENTATION

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Abstract

A new method for the robust estimation of target orientation using measured radar cross section is proposed. The method is based on a Generalized Regression Neural Network (GRNN) scheme. The network is trained by the FFT modulus of bistatic radar cross section data sampled at the receiver positions. The target value to be trained is the angle between a defined target orientation and the incident wave. Results based on actual measurements are presented.

INTRODUCTION

Accurate estimation of target orientation is essential in range profiling schemes [1-4]. In such cases, the knowledge of target orientation can yield information about the target-structure. The range profile itself, however, is quite sensitive to variations in target orientation and cannot be the basis for such estimation. A detailed tracking of object orientation is therefore necessary.

Attempts have been made to use artificial neural networks (ANNs) for solving the inverse problem. However, the proposed methods have not been able to exploit the fundamental advantages of neural systems, which are their speed and robustness. In many instances, the problem formulation was fitted into previously developed algorithms for network training [5, 6]. Nevertheless, successful methods were developed for cases where a priori knowledge of the target geometry is available [7]. Neural networks have proven to do well in target classification area. A spectral approach to radar target classification using ANNs was proposed in [8].

The Generalized Regression Neural Network (GRNN) [9] is among radial basis networks and has found applications in regression and function estimation processes. It has been shown that given a sufficient number of neurons in the hidden layer, a GRNN can approximate a continuous function to an arbitrary precision [10].

In this paper, the orientation of a cylindrical conducting target is estimated with a GRNN network using radar cross section data. The definition of the problem is shown in Figure 1, where a target is illuminated by a number of transmitters/receivers at different angles of incidence. The orientation angle is defined as the angle between a preferred direction specified on the target geometry and the incident wave. The task is to find the orientation angle by using a number of bistatic radar measurements.

THE FORWARD PROBLEM

Consider a perfectly conducting cylinder of arbitrary cross section shape, as shown in Figure 2, illuminated by a plane wave in free space. The cylindrical contour is denoted by *C*. For the TM^z polarization, the electric field integral equation (EFIE) is given by

$$E_z^i(\boldsymbol{\rho}) = \frac{k_0 Z_0}{4} \oint_C K_z(\boldsymbol{\rho}') H_0^{(2)}(k_0|\boldsymbol{\rho} - \boldsymbol{\rho}'|) d\ell' \quad (1)$$

where $\boldsymbol{\rho}$ and $\boldsymbol{\rho}'$ are the field and source points, respectively, and $H_0^{(2)}$ is the zeroth order Hankel function of the second kind.

The above integral equations are solved numerically by the method of moments. Once the induced current is calculated, the scattering echo width is given by

$$\sigma^{TM} = \frac{k_0 Z_0}{4} \left| \oint_C K_z(\boldsymbol{\rho}') e^{jk_0(x'\cos\phi + y'\sin\phi)} d\ell' \right|^2 \quad (2)$$

THE GRNN

The Generalized Regression Neural Network belongs to the family of radial basis neural networks. Radial basis networks require more neurons than standard feed-forward backpropagation networks, but they can often be designed in a fraction of the time it takes to train standard feed-forward networks. They work best when many training vectors are available.

Radial basis networks were previously used in field estimation processes. It is shown that given a sufficient number of neurons in the hidden layer, a GRNN can approximate a continuous function to an arbitrary precision. The GRNN is a memory based network, which provides estimates of continuous variables and converges to the underlying optimal linear or nonlinear regression surface. The network requires no prior knowledge of a specific functional from between input and output. The appropriate form is expressed as a probability density function that is empirically determined from observed data using Parzen window estimation [11]. For this reason, it works very well with sparse data. The network is a one-pass learning algorithm and can generalize from examples as soon as they are stored. The structure of the Network is depicted in Figure 3.

Let $\boldsymbol{x}$ be a vector random variable of dimension p, and y be a scalar random variable. Then $f(\boldsymbol{x},y)$ is the joint continuous probability density function of $\boldsymbol{x}$ and y. Let $\boldsymbol{X}$ be a particular value of the random variable $\boldsymbol{x}$. The conditional mean of y given $\boldsymbol{X}$ (regression of y on $\boldsymbol{X}$) is given by

$$E[y \mid \mathbf{X}] = \frac{\int_{-\infty}^{\infty} y f(\mathbf{X}, y)\, dy}{\int_{-\infty}^{\infty} f(\mathbf{X}, y)\, dy} \tag{3}$$

But the probability density function $f(\boldsymbol{x},y)$ is not known a priori. It may be estimated from a sample of observations of $\boldsymbol{x}$ and y as proposed by Parzen as [9]

$$E[y \mid \mathbf{X}] \cong \frac{\sum_{i=1}^{n} Y^i \exp\left(-\frac{C_i}{\sigma}\right)}{\sum_{i=1}^{n} \exp\left(-\frac{C_i}{\sigma}\right)} \tag{4}$$

where

$$C_i = \sum_{j=1}^{p} | X_j - X_j^i | \tag{5}$$

is the city block distance. Note that in (4), σ is the spread parameter of the density estimator, and should not be confused with the echo-width defined in (2). The estimate (4) can be considered as a weighted average of all the observed values, each being weighted exponentially according to its distance from X. It can be shown that this density estimator used in estimating (3) asymptotically converges to the underlying probability density function $f(x,y)$ at all points (x,y) at which the density function is continuous, provided that the spread parameter $\sigma = \sigma(n)$ is chosen as a decreasing function of n. When σ is large, the estimated density function approaches a multivariate Gaussian function. For intermediate values of σ, all values of Y^i are taken into account, but those corresponding to points closer to $\mathbf{X}$ are weighted heavier. The estimate cannot converge to poor solutions corresponding to local minima of the error criterion.

TRAINING

The sensors are assumed to be fixed with respect to the wave direction. The target is impinged upon by transverse magnetic plane waves from different directions. To prepare the training data, a total of 10 equally spaced receivers are used.

It was found that the FFT modulus of the echo-width patterns sampled at the receiver positions for angles of incidence provided better generalization capabilities for the network, compared with the case when the network was trained with the echo-width vector (amplitude and phase). Simulated bistatic echo-width was used for the training of the network. The forward problem was solved using the method of moments. These calculations formed a 10 element input vector at every receiver for the network.

Some noisy data created by displacing the receivers, were added to the training data set to let the system face small sensor position drifts. These vectors were used in training the network. The spread parameter σ was manipulated so that the network angular estimation was sufficiently robust. The target value to be trained was the angle between the target orientation and the incident wave.

RESULTS

In this section, the performance of the network will be examined.

The network was trained using the data described in the previous section for the triangular shaped target shown in Figure 1. To check the generalization power of the network, a set of 40 new input data was produced, this time by angles not previously encountered by the network with all other parameters held unchanged. Figure 4 shows the cumulative error for estimating the target orientation for trained and untrained data. The network clearly displays a very good level of generalization of its estimates based on the training data set and more than 99% of the cases have less than one-degree error.

The triangular cylindrical target shown in Figure 5 was considered next. This is the Ipswich target IPS-009. The network was trained using the simulated echo-width data. Then the network was presented with the RCS data collected at Ipswich bistatic RCS range. Only the bistatic echo-width data on 180 degree range was used (that is, one side of the cylinder was examined). The performance of the network in estimating the orientation of the target is shown in Figure 6. It is observed that the error is less than one degree in more than 98% of the cases.

Next, the performance of the network was examined for the case when the target size is not exactly known a priori, but rather the geometry of its shape is known. The system was tested in facing an elliptical cylinder when the electrical size of the cross-section was rescaled from –7% to +5%. The cumulative error is shown in Figure 7 for three different frequency scaling factors in the above range.

CONCLUDING REMARKS

The problem of estimation of two-dimensional conducting target orientation was efficiently handled by a Generalized Regression Neural Network. The training data set consisted of the calculated bistatic echo-width data when the target was exposed by an incident single frequency TM plane wave. The performance of the network does not change if the frequency of the plane wave is altered. Currently, The network performance against sensor misplacements, sensor noise (correlated and uncorrelated), are under study.

It is believed that time domain schemes such as range profiling techniques can utilize this method to overcome difficulties in estimating the orientation of the target.

ACKNOWLEDGEMENTS

The authors are indebted to Dr. Robert McGahan for facilitating access to the Ipswich scattering data provided by Electromagnetics Technology Division, AFRL/SNH, 31 Grenier Street, Hanscom AFB, MA 01731-3010.

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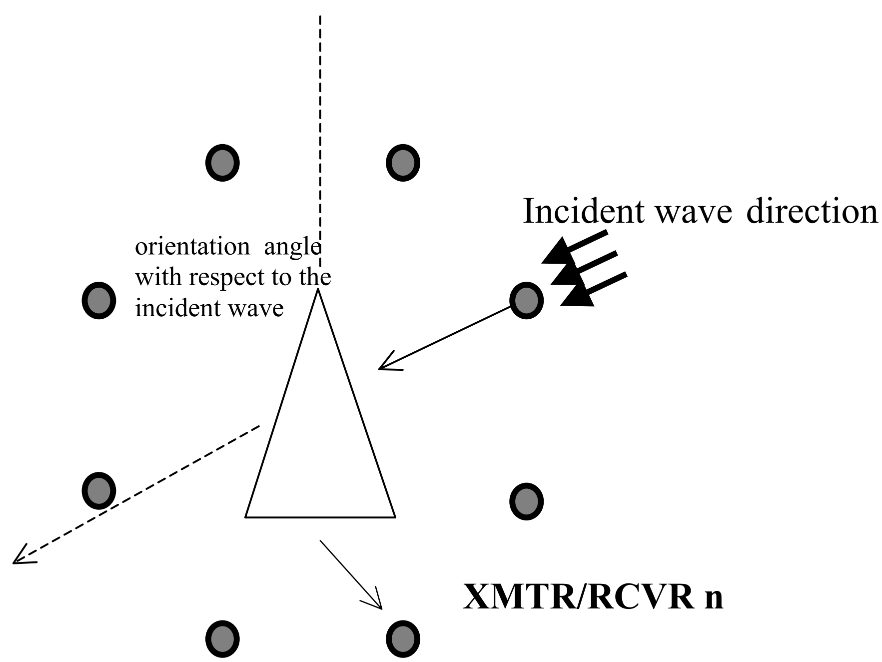

Figure 1- Problem set-up.

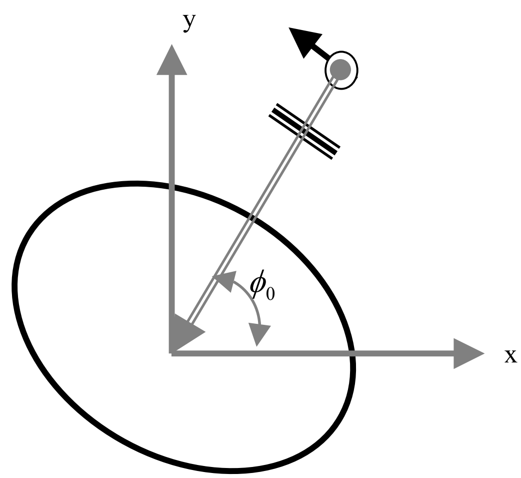

Figure 2- A uniform plane wave impinging upon a perfectly conducting cylinder.

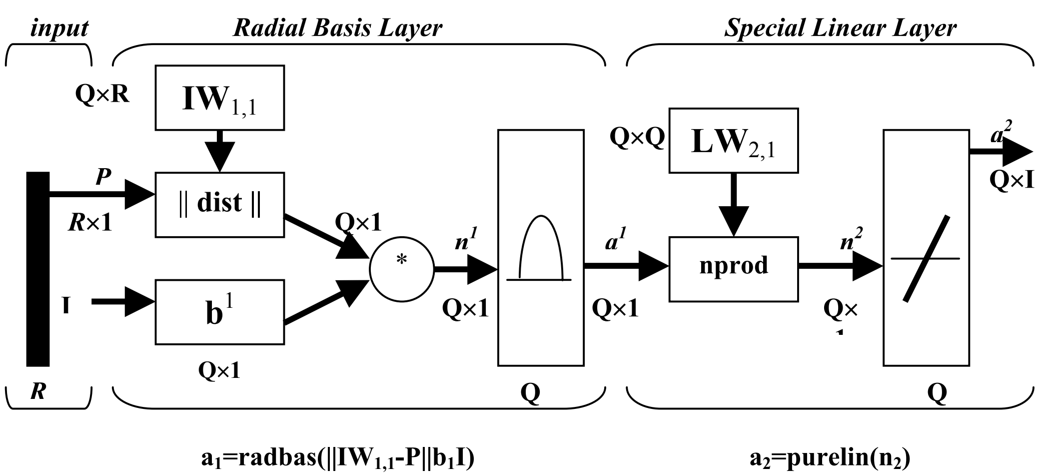

Figure 3- The structure of GRNN.

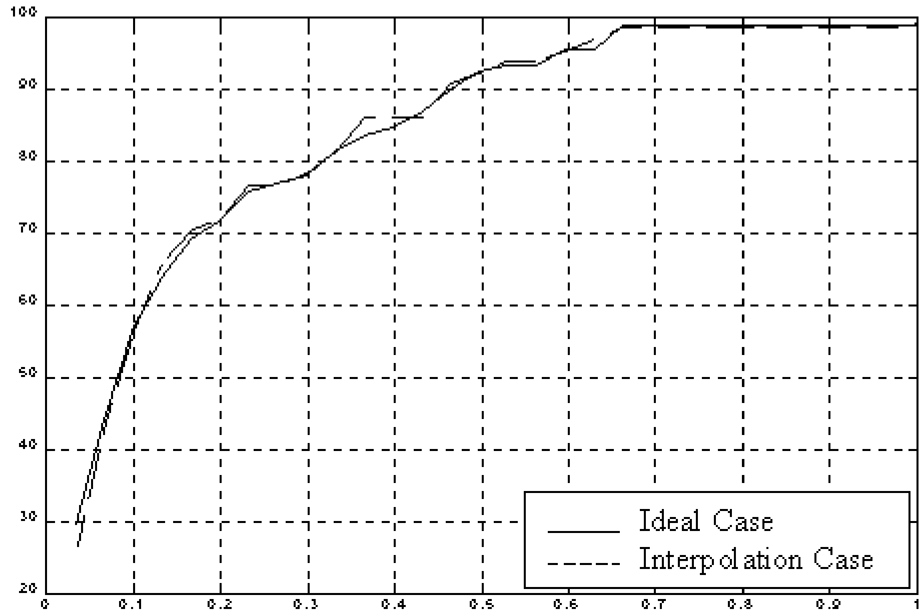

Figure 4- The GRNN estimates the orientation of the target shown in Figure 1 by the concept of generalization.

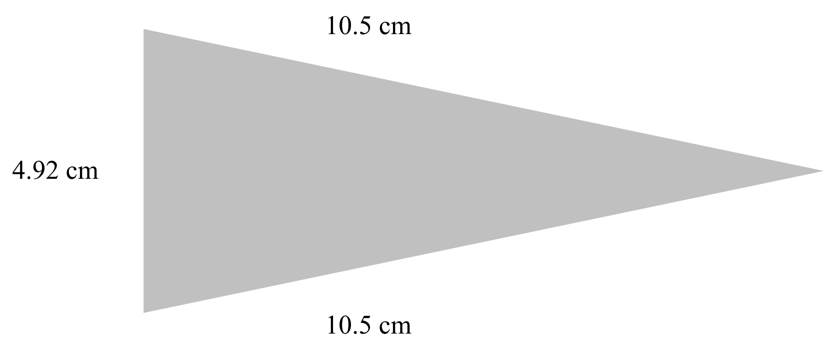

Figure 5- A triangular cylinder of sides $10.5cm \times 4.92cm \times 10.5cm$ illuminated by a 10 GHz TM^z plane wave. The height of the cylinder is 40.8 cm.

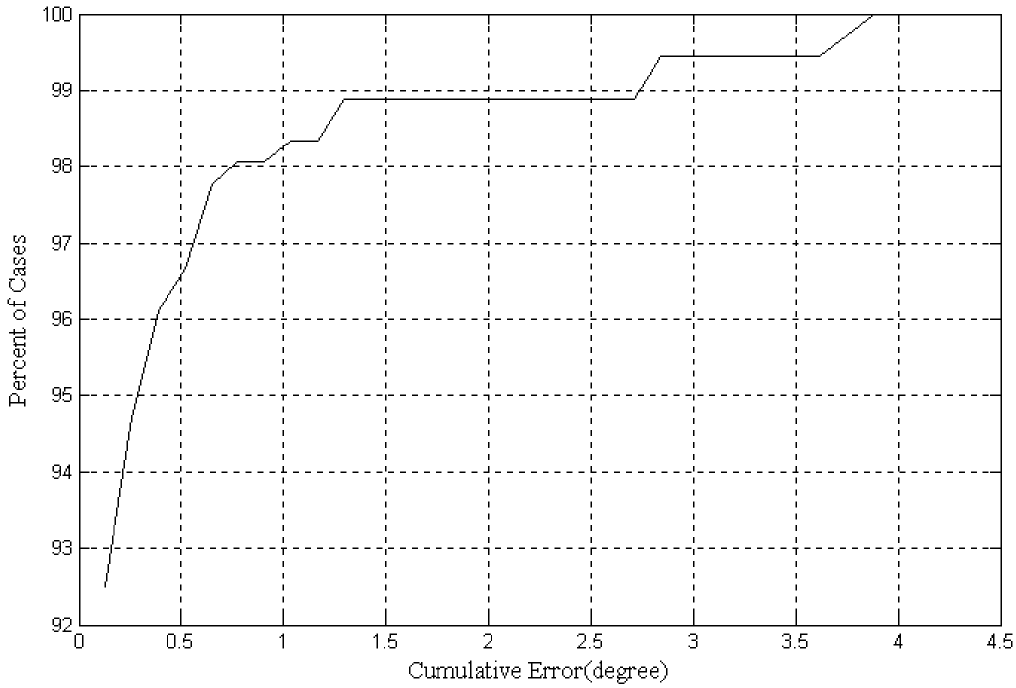

Figure 6- Error diagram for the network response for the target shown in Figure 5.

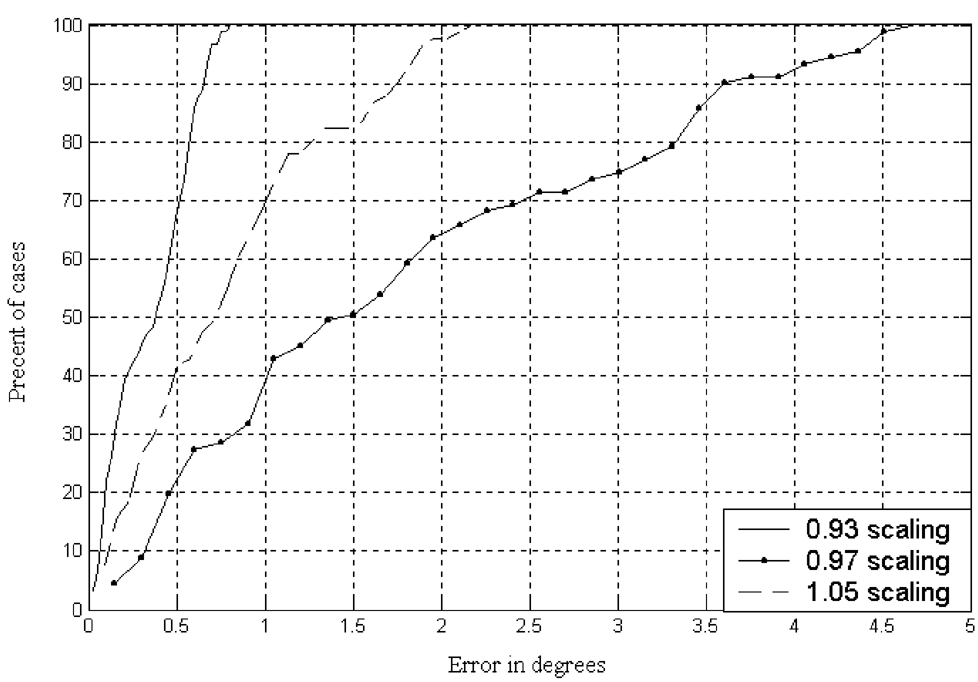

Figure 7- Cumulative error at various levels of frequency scaling.