Neural Networks for Scattering Signal Based Object Recognition

Hristomir Yordanov and Irina Topalova

Faculty of German Engineering Education and Industrial Management
Technical University of Sofia, Sofia, Bulgaria
Emails: yordanov@fdiba.tu-sofia.bg, itopalova@abv.bg

***Abstract*—Radar based imaging techniques can be used to collect 3D information about objects, which in turn can be used to identify and measure specific parameters of these objects. Such measurements need to correlate specific radar signals with the object properties. This can be done using neural networks, as they are designed to search for patterns, which are difficult to find using analytic methods. This work presents a first step towards a neural network based radar signal processing system for object identification by attempting to identify an object placed in a rectangular waveguide.**

Keywords–Scattering signals; Object identification; Neural Networks

I. Introduction

Radars find many applications as imaging tools. Using the property of electromagnetic waves to partially penetrate and partially reflect from dielectric materials, they can provide 3D images of a large set of objects. The development of easily available high-frequency components up in the microwave, millimetre wave and even THz regions allows for high spatial resolution of the obtained images. This technique finds multiple applications in security systems, the medical systems and in agriculture.

We can consider as an example the sensor described in [1]. The system consists of a 24 GHz Frequency Modulated Continuous Wave (FMCW) radar used to make 3D images of grapevine plants in order to estimate the volume of grapes in a given plant. The radar is equipped with a high gain antenna and is mounted on a pan-tilt platform, which allows for performing azimuthal and elevation scans. The radar bandwidth is 2 GHz. This setup allows for a 7.5 cm depth resolution (that is the precision of the measurement of the distance between the object and the radar) and transverse resolution of 1.5 cm. Of course, using higher signal frequencies and bandwidths and more directive antennas, resolutions in the millimetre range can be achieved [2].

The processing of the radar signal in order to obtain information about the object parameters of interest can be a challenging task. The measurement system described in [1] relies on statistical analysis in order to obtain the grapes volume. Neural networks are optimised for pattern search in complex data. Therefore, they can be used in radar based measurement systems as they can extract the data of interest from the clutter and simultaneously estimate the value of the parameter of interest. In the grapevines radar example, the parameter of interest is the volume of the produced grapes and the clutter is the signals from the plant's trunk and leaves.

In order to develop a full intelligent 3D image processing system, we need to start by implementing simple 1D solutions. In this paper, we present a neural network for shape recognition based on the scattered signal as a benchmark case study.

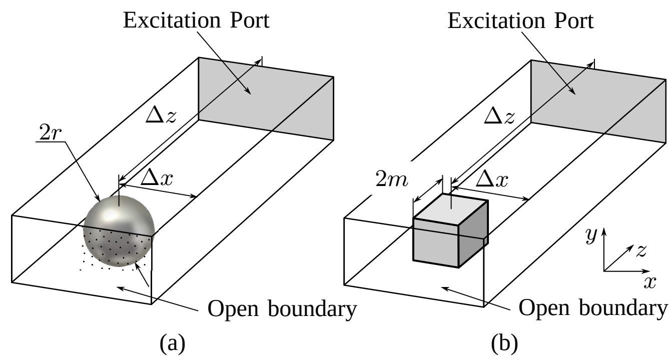

Figure 1. Positioning of a ball of a diameter $2r$ (a) and a cube with edge $2m$ (b) in a WG-12 rectangular waveguide.

The investigated object is an obstacle of perfectly conducting material placed in a rectangular hollow waveguide. This limits the neural network input signal to the spectral representation of a single point reflection signal. The setup has been modelled numerically and the results have been obtained using computer simulation.

Section II describes the setup of the performed simulation and shows the computed reflected signals from the two types of objects in a waveguide. Section III details the neural network based signal processing used to identify the objects based on the reflected signal. Section IV summarises the results and sketches the future work.

II. Experimental Setup

The experimental setup consists of a hollow rectangular WG12 waveguide with an object placed at distance Δz form the excitation port, as shown in Figure 1. The cross-sectional dimensions of the waveguide are $a = 47.5$ mm and $b = 22.1$ mm. The scattering objects are a sphere of radius r (Figure 1a) and a cube of length $2m$ (Figure 1b). Both objects are made of a perfect electric conductor and are placed at a distance of Δx from the short wall of the conductor. The objects were placed in the middle of the waveguide in the vertical y direction. The excitation port has been placed at the $-z$ end of the waveguide. The opposite end has been terminated with an open boundary in order to model an infinitely extended waveguide and thus eliminate the reflections from that boundary. The model has been simulated for the frequency range of 4 to 6 GHz, which corresponds to the full single mode range of the waveguide. We measure the reflection coefficient at the excitation port. The used simulation tool is CST Microwave studio.

Two families of results have been generated. First, we varied the dimensions of the objects—correspondingly the sphere radius r and the cube edge $2m$—while keeping both

 ISBN: 978-1-61208-634-7

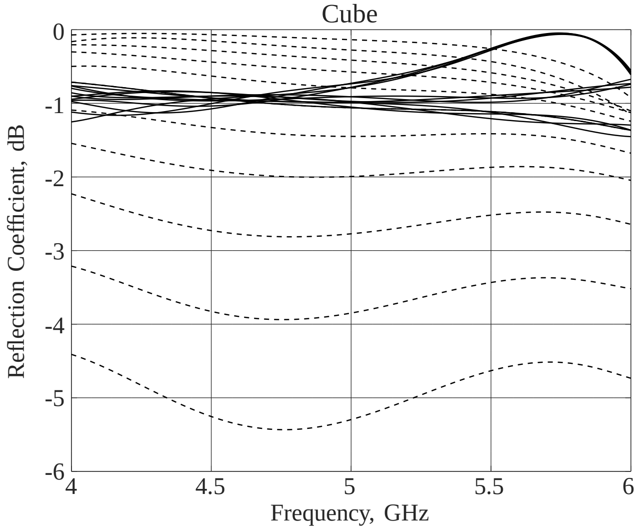

Figure 2. Family of curves showing the magnitude of the reflection coefficient of a waveguide with a conducting cube inside. The solid lines and the dotted lines represent varying position and size of the cube correspondingly.

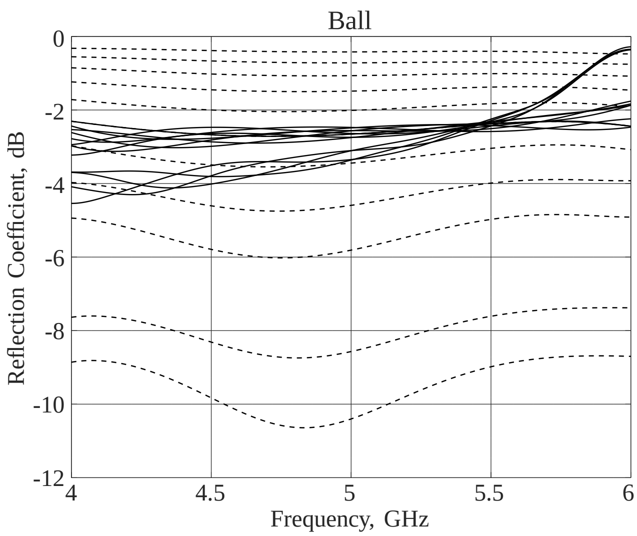

Figure 3. Family of curves showing the magnitude of the reflection coefficient of a waveguide with a spherical object inside. The solid lines and the dotted lines represent varying position and size of the sphere correspondingly.

objects at fixed position $\Delta z = 100\,\mathrm{mm}$ and $\Delta x = a/2$, that is 100 mm from the excitation port and in the middle along the x direction. The size parameters r and m varied from 4 to 10 mm in 0.6 mm steps. Then, we held the object dimensions fixed at $r, m = 7\,\mathrm{mm}$ and varied the offset dimension as follows:

$$\Delta z = 0 \text{ to } -30\,\mathrm{mm} \text{ in } 10\,\mathrm{mm} \text{ steps,}$$
$$\Delta x = 0 \text{ to } 10\,\mathrm{mm} \text{ in } 5\,\mathrm{mm} \text{ steps.}$$

The full combination of offset coefficients has been modelled.

The results for a cube and a ball are presented in Figures 2 and 3, correspondingly, where the dotted lines show the family of curves for varying object size, while the position is held fixed, and the solid lines show the results for fixed size and varying offset. The dotted lines show a greater reflection coefficient ans the object dimensions r and m increase, which can be expected as larger objects create larger echo.

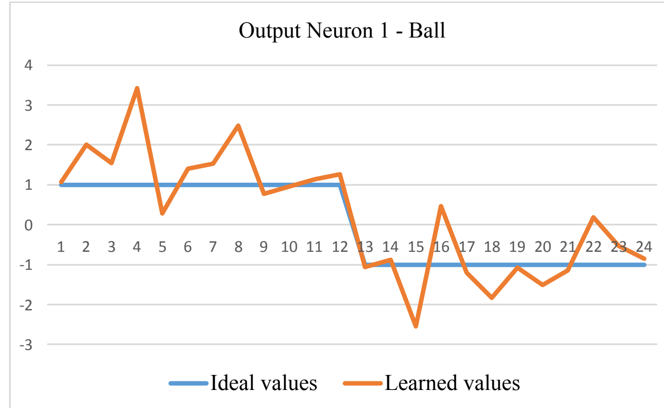

Figure 4. MLP NN (11-8-5-2) output results for Output neuron 1 when recognizing the 12 exemplars of objects *ball* and *cube*.

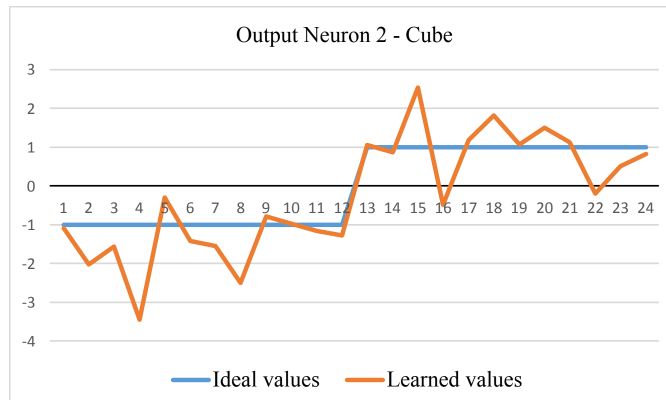

Figure 5. MLP NN (11-8-5-2) output results for Output neuron 2 when recognizing the 12 exemplars of objects *ball* and *cube*.

The frequency distribution of the reflection coefficients have been used to train a neural network to recognise between the two types of objects - a ball and a cube. We have used only 11 points from each curve, as the frequency response varies slowly and using this representation we lose no information. The network has been trained with 10 curves from each object, including curves with varying offset and varying object size, and has been tested with the rest of the curves.

III. Neural Network Signal Processing

As the two 3D objects have similar shapes, it is necessary to use an adaptive and precise method for recognition and classification of the two objects. The Deep Learning method using LP (Multi-Layered-Perceptron) feed forward Neural Network (NN), trained by the BP (Backpropagation) algorithm, gives satisfactory results in these cases [3]. This allows precise placement of boundaries between object classes with overlapping parametric descriptions – in our case very similar reflection signals.

To meet the requirement for fast real-time neural network performance, we need to run small MLP NN structures. Thereafter, the structure may be changed by increasing the number of hidden neurons and /or the number of hidden layers, in order to improve the proportion between response time and the recognition accuracy. The software package NeuroSystem

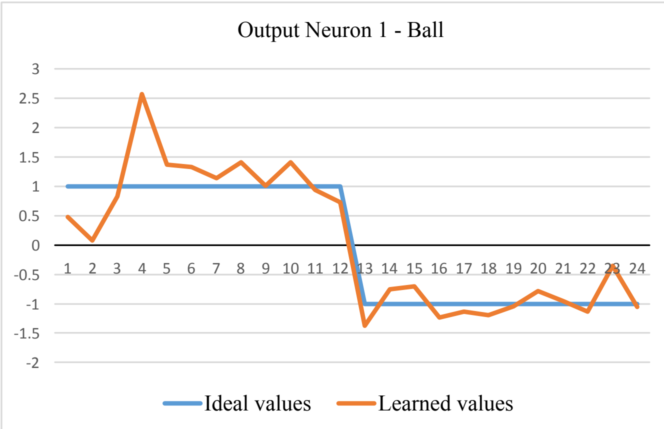

Figure 6. MLP NN (11-10-8-2) output results for Output neuron 1 when recognizing the 12 exemplars of objects *ball* and *cube*.

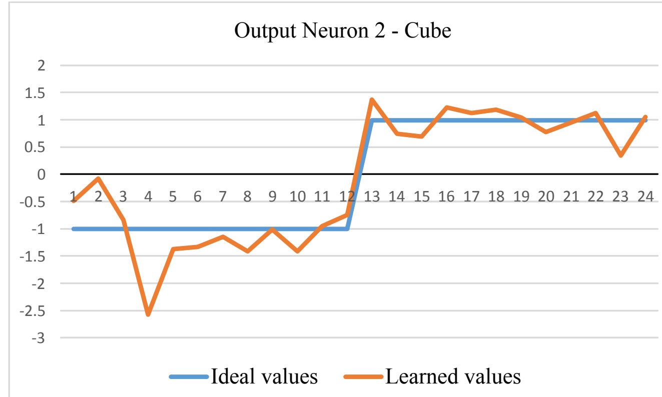

Figure 7. MLP NN (11-10-8-2) output results for Output neuron 2 when recognizing the 12 exemplars of objects *ball* and *cube*.

by Siemens [4] was used for running the experimental simulations.

We have trained the NN with only 11 points from each curve, as they vary slowly in frequency. For each of the two objects, the training set contains 10 curves with varying offset and object size. The test set contains 12 specimens, representing the two types of objects, whose reflected signals have not participated in the training set.

We have designed the NN by adding two hidden layers and increasing the number of neurons in each layer until satisfactory recognition was achieved. The first 100 % recognition accuracy was obtained for object ball when training a 11-8-5-2 MLP NN structure (with two hidden layers, having 8 and 5 neurons and 2 output neurons, representing the two recognizable objects). The MLP NN (11-8-5-2) output results for Output neuron 1 when recognizing the first 12 exemplars of object ball and the second 12 exemplars of object cube are given in Figure 4. The training iterations were stopped when the Mean Square Error (MSE – ε) has reached 5 %. In this case, the obtained recognition accuracy for object cube was 83.3 % (two of twelve tested objects are misrecognized), with results shown in Figure 5. It can be noted that objects 16 and 22 (both are cubes) are incorrectly recognized.

In order to put more precise boundaries between the object classes and to improve the accuracy of recognition, it is necessary to increase the number of neurons in the two hidden layers of the MLP NN. Thus, the next attempt is made with a MLP 11-10-8-2 structure. The training iterations were stopped when the MSE has reached 2 %. In this case the obtained recognition accuracy for both objects was 100 % when tested with the same test set. The obtained results for Output neurons 1 and 2 are given in Figure 6 and Figure 7 respectively. It is good recognizable that the approximation of ideal/ desired values is much better. The summary of the experimental results is shown in Table I.

TABLE I. SUMMARY OF THE EXPERIMENTAL RESULTS.

MLP Structure	Recognition Accuracy, [%]		
	Ball	Cube	MSE – (ε)
11-8-5-2	100 %	83.3 %	5 %
11-10-8-2	100 %	100 %	2 %

IV. CONCLUSIONS AND FUTURE WORK

This paper shows the initial work on identifying suitable neural network signal processing tools for radar based shape recognition techniques. The achieved recognition results show that it is very appropriate to implement MLP NN for 3D object recognition, when using radar reflection signals. The good approximation abilities of the MLP NNs make it possible to recognize even objects of very similar shapes.

As future work, we intend to test the method for a larger number of objects with similar 3D object shapes. Also, to generalize the method, the test sample set will be increased. Additional calculations of approximation error are also foreseen. The presented results provide shape recognition by a single point wideband reflected signal, which is a model of a pulse radar. We intend to expand these results towards scanning pulsed and scanning frequency modulated continuous wave (FMCW) radars.

REFERENCES

[1] D. Henry, H. Aubert, T. Veronese, and E. Serrano, “Remote estimation of intra-parcel grape quantity from three-dimensional imagery technique using ground-based microwave fmcw radar,” IEEE Instrumentation Measurement Magazine, vol. 20, no. 3, June 2017, pp. 20–24.

[2] K. B. Cooper *et al.*, “Penetrating 3-d imaging at 4- and 25-m range using a submillimeter-wave radar,” IEEE Transactions on Microwave Theory and Techniques, vol. 56, no. 12, Dec 2008, pp. 2771–2778.

[3] J. Schmidhuber, “Deep learning in neural networks: An overview,” Neural Networks, vol. 61, 2015, pp. 85 – 117. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0893608014002135, [retrieved March 2018].

[4] NeuroSystems V4.0 Manuall. Germany: Siemens GmbH, 2016.

 ISBN: 978-1-61208-634-7