# Characterization of inclusions in a non-homogeneous GPR problem by neural networks

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***Abstract*— This paper addresses the problem of inverting Ground Penetrating Radar (GPR) data, to find the buried inclusions characteristics $depth$ and $radii$ considering a non-homogenous host media by using neural networks (NN). The aim is the detection and characterization of inclusions in concrete structures. A novel asynchronous model is proposed to the NN arrangement. The model is shown to outperform the traditional approaches of using one NN with two outputs or two parallel independent NN. Results are included to show the performance of the new model.**

***Index Terms*— Ground Penetrating Radar, Inverse Scattering Problem, Neural Networks.**

## I. Introduction

GROUND Penetrating Radar (GPR) is currently one of the most commonly used methods to investigate concrete structures due to its noninvasive nature and possibility of using electromagnetic waves covering a wide-frequency spectrum. However, the operation of GPR tools and the interpretation of data often require trained personnel. Therefore, the use of electromagnetic inversion techniques becomes important to decrease the interpretation time for a fully effective maintenance and/or repair [1].

Over the past decade, various imaging or inversion techniques have been developed to refocus the scattered signals back to their true spatial location. Among them the Neural Networks (NN) have proved to be a promising tehcnique [2].

The use of NN in the inverse scattering problem using parallel networks and networks with multiple outputs for an homogenous host medium was presented in [3] and [4]. In [4] it is shown that both configurations could deliver reasonable and very similar results. In this paper we considered the case when the host media is non-homogenous and, surprisingly, using a network with multiple outputs and parallel networks were not adequate to estimate the $radii$ of the inclusion. Thus, to increase the prediction accuracy, we propose the use of an asynchronous configuration for the neural networks. The training is then done in two steps: (i) training one network with the scattered wave to predict the $depth$ of the inclusion, (ii) training one network with the scattered wave and the predicted $depth$ to define the inclusion $radii$. Even though it is a very simple modification in the training procedure a significant improvement in the predictions of the $radii$ was observed.

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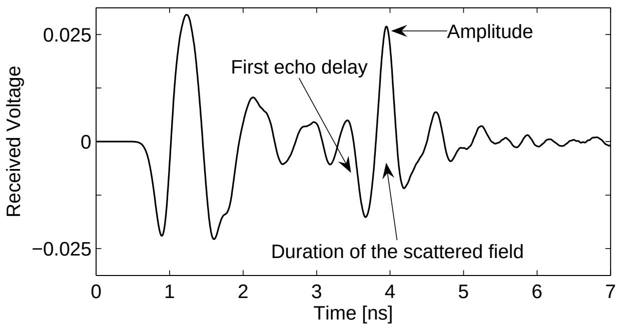


Fig. 1. Reflected wavefield from a buried target.

## II. The inverse scattering problem

Inverse scattering from buried objects is a subject of interest in many applications related to ground penetrating radar (GPR) prospecting, such as archaeological applications, police inquiries, civil engineering and demining [1].

The problem can be stated as the determination of the spatial map of the dielectric and/or conductive properties of a probed region embedded in the soil starting from the measurement of scattered field data gathered close to the air-soil interface. This has the purpose to detect, locate and determine the extent of the buried objects [5].

From the scattered wave, following the recommendations of [4], the following input parameters were defined (see Fig. 1): 1) the peak amplitude of the reflected field ($d_1$); 2) the delay of the first reflected echo, calculated with respect to the time of arrival, at the receiving point, of the direct field ($d_2$); 3) a measure of the duration of the scattered field ($d_3$).

These variables alone have proven sufficient for the homogenous inverse scattering problem but they were insufficient for the non-homogenous problem (in order to simulate a more realistic concrete model, we randomly created subsurface heterogeneities) treated in this paper.

## III. The neural network

In this paper we employ a Parallel Layer Perceptron (PLP) [6][7], but, Multi-Layer Perceptrons and Adaptive Neuro Fuzzy Inference Systems (ANFIS) have achieved similar results in our experiments.

In [4] were discussed two different configurations to solve this inverse problem, a network with multiple outputs, Fig. 2(a), and independent networks in parallel, Fig. 2(b). The

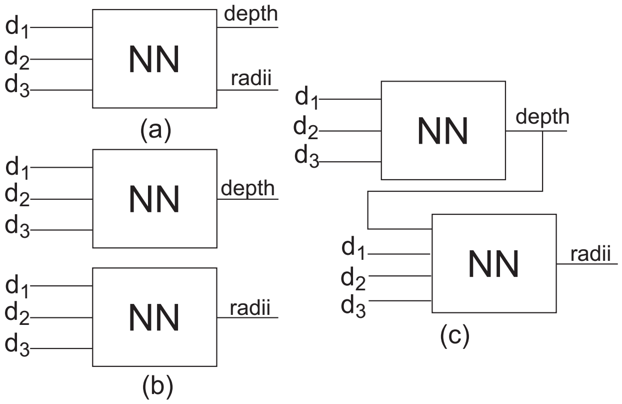


Fig. 2. Three neural network configurations employed in this paper. (a) One network used to calculate simultaneously the $depth$ and $radii$ given $d_1$, $d_2$ and $d_3$, called here Configuration $C1$. (b) Two networks ($C2$) applied in parallel to calculate independently the $depth$ and $radii$ given $d_1$, $d_2$ and $d_3$. (c) The configuration proposed in this paper ($C3$) in which, the $depth$ is calculated using $d_1$, $d_2$ and $d_3$ and the $radii$ are calculated in a second step (asynchronously) using also the calculated $depth$.

network with multiple outputs, called here $C1$, calculates simultaneously the $depth$ and $radii$ given $d_1$, $d_2$ and $d_3$. The parallel networks, called here $C2$, calculate independently each output given the measured variables $d_1$, $d_2$ and $d_3$. In our experiments it was noticed that having the information of the $depth$, the prediction of the $radii$ was substantially improved. Considering this fact, in this paper we propose to use an asynchronous training as presented in Fig. 2(c). This configuration, called here $C3$, first calculates the depth using the measured variables $d_1$, $d_2$ and $d_3$ and then calculates $radii$ using $d_1$, $d_2$ and $d_3$ and the predicted $depth$.

## IV. RESULTS

A typical two-dimensional GPR data is simulated using two antennas located above the dielectric slab. The FDTD scenario used for the NN trainning consisted of one buried inclusion in concrete that was modeled with a mean relative electrical permittivity value of 6 and standard deviation (sd) 0.15 according to the equation:

$$\epsilon_r = 6 + sd \cdot (random). \tag{1}$$

The source type is a differentiated gaussian pulse with a center frequency of F = 900 MHz and significant energy between 0.3 and 2 GHz. In order to control the numerical dispersion and provide a good discretization for the inclusions the spatial steps were chosen as $\Delta x = \Delta y = 6mm$.

The NN has been trained with a set of different inclusions examples, constructed by varying the $radii$ in the range $[0.02 \div 0.1]$ m according to the rule $radii = 0.02 + i \times 0.001$, $i = 0, .., 80$, with $\epsilon_r$ in the range $[1 \div 10]$, according to the rule $\epsilon_r = 1 + i \times 1$, $i = 0, ..., 9$, $\sigma$ in the range $[0 \div 4000]$ $S/m$ according to the rule $\sigma = 0 + i \times 500$, $i = 0, ..., 8$ and $depth$ in the range $[0.05 \div 0.25]$ m according to the rule $depth = 0.05 + i \times 0.025$, $i = 0, ..., 9$ where $75\%$ of these samples were used as a training set and $25\%$ to validate the methodology.

The training of the NN took only 2.9 s on a AMD Atlhon 64 processor with 2.22 GHz, while the processing of the entire test set took 17 ms.

To evaluate the performance of the techniques studied the following error figure is used:

$$Err(p) = \frac{|p_t - p_r|}{p_r}, \tag{2}$$

where $p$ is the unknown variable ($depth$ or $radii$), the subscript $t$ indicates the real value of the variable, and subscript $r$ indicates the value reconstructed by the neural network. The results for the configuration $C1$, $C2$ and $C3$ are presented on Table I. As all the techniques apply similar mechanism to reconstruct the $depth$ their error are also very similar, as indicated in the second column of Table I. The main difference is in the reconstruction of the $radii$ for which the technique proposed in this paper has shown an improvement of at least $7.1\%$ when compared with $C1$ and $C2$.

TABLE I

RESULTS CONSIDERING THE THREE CONFIGURATIONS OF THE NEURAL NETWORKS STUDIED IN THIS PAPER.

| Configuration | $Err(depth)$ | $Err(radii)$ |
|---|---|---|
| $C1$ | $5.8\%$ | $12.9\%$ |
| $C2$ | $5.7\%$ | $13.4\%$ |
| $C3$ | $5.7\%$ | $5.8\%$ |

## V. CONCLUSIONS

This paper has presented a simple structure to improve the characterization of inclusions using neural networks. An asynchronous model was applied to train the network used to reconstruct the $radii$ and it has delivered much better outcomes when compared with the standard techniques. We believe that this asynchronous model can be extended to a recursive one, in such a way that the predicted $radii$ can be used to improve the prediction of the $depth$ and so on.

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