Random noise attenuation from GPR data using the Radial Basis Function neural network

Leila Aliouane, LABOPHYT, FHC, UMBB, Sid-Ali Ouadfeul, Algerian Petroleum Institute*

Summary

The main goal of this paper is to use the Radial Basis Function (RBF) neural network for random 2D Ground Penetrating Radar (GPR) noise attenuation. The RBF machine is trained in a supervised mode, 2D GPR data free of noise recorded in Algeria are used as an output, while the same data with white noise are used as an input. The training of this machine provides weights of connection that can be used to filter other noisy GPR data. Obtained results demonstrate the power of the RBF neural network model to attenuate random noise from GPR data.

Keywords: Radial basis function, 2D GPR, filter, random noise.

Introduction

The Ground Penetrating Radar (GPR) method has becoming a very useful method in geophysics. One of the major problems of GPR data interpretation is the random noise, since the presence of the random noise in GPR data can affect the interpretation and hide important near surface anomalies. Many techniques have been proposed to improve the S/N ratio and to attenuate noise in GPR data. Ouadfeul and Aliouane (2012) have suggested the application of low pass filter to the wavelet transform coefficients to decrease the effect the random noise on the wavelet transform (Ouadfeul and Aliouane, 2012). Loopera et al (2007) have published a paper on the filtering soil surface and antenna effects from GPR data to enhance landmine detection. Kim et al (2007) have shown a removal of ringing noise in GPR data by signal processing. In this paper, we use the Radial Basis Function (RBF) neural network neural network to attenuate the random noise in 2D GPR data recorded in the Algerian Sahara. These profiles show the altimetry versus the abscissa. We start the paper by talking about the radial basis function neural network, and then the 2D GPR data and the processing algorithm are described. We end the paper interpretation of the obtained results and conclusions.

Radial basis function neural network model

In the field of mathematical modeling, a radial basis function network is an artificial neural network that uses radial basis functions as activation functions. The output of the network is a linear combination of radial basis functions of the inputs and neuron parameters. Radial basis function networks have many uses, including function approximation, time series prediction, classification, and system control. They were first formulated in a 1988 by Broomhead and Lowe. Radial basis function (RBF) networks typically have three layers: an input layer, a hidden layer with a non-linear RBF activation function and a linear output layer. The input can be modeled as a vector of real numbers $X \in R^n$. Figure 01 shows an example of a radial basis function neural network with three neurons in the input layer, one neuron in the output layer and four neurons in the hidden layer. For more details about the RBF neural network model we invite readers to the paper Broomhead and Lowe(1998) or Moody and Darken (1989).

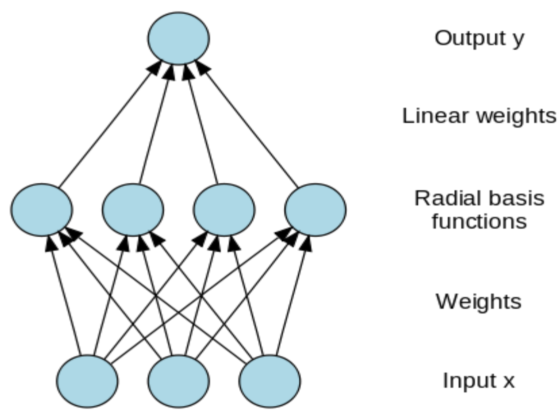

Figure 01 An example of a RBF neural network with three inputs and one output

Application to real data

The proposed idea is applied to two GPR profiles recorded in the Algerian Sahara; these profiles show the altimetry in meter versus the abscissa. The GPR data are recorded with an antenna of 50HZ, the distance between two points of measurements is 50m, figure 2 shows the first profile. The first step consists to add a 05 percent of white noise to the data of the first profile; figure 03 shows the noisy data. Each GPR profile is divided in 33 sets, each set contains 10 measurements. Each couple of sets (noisy GPR data-GPR data free of noise) is used for the training of the radial basis function neural network machine shown in figure 04. The

GPR data filtering using RBF neural network

RBF machine is composed of three layers, an input layer with ten neurons, an output layer with ten neurons and a hidden layer with ten neurons. The number of neurons in the hidden layer is obtained after many numerical experiences with different number of neurons. The RBF machine is trained in a supervised mode, using the couple input-desired output for the whole GPR data. For each iteration, the root mean square error is calculated. Figure 05 shows the root mean square error between the desired and calculated outputs versus the iteration number. This figure shows very low values of the RMS error at the end of the learning stage, which proves the good learning of the RBF neural machine. The input (noisy data) is propagated through the neural network machine an output is calculated (see figure 06).
To show the efficiency of this RBF neural machine another 2D GPR profile recorded with the same parameters in the same area is used. Figure 07 shows the graph of this profile with 05 percent of white noise. The data of this profile are sub-divided into sets, each set contains ten measurements. These sets of data are propagated in the implemented RBF machine and many sets of outputs are calculated. These outputs are the denoised GPR data (see figure 08). Figure 09 shows the GPR profile free of noise (original) and figure 10 is the comparison between the intial GPR data free of noise and the denoised data.

Results interpretation and conclusions

We can observe in figure 10 that the implemented machine is able to attenuate a big part of the random noise, some spikes are always remaining (see the red graph in figure 10), for example the peak at abscise 410000m. To resolve this problem we suggest to propagate again the denoised data through the RBF machine, we expect a more denoised output. This operation is not always recommended since it can remove very important high frequency components in the GPR signal which can generate a big uncertainty in GPR data interpretation.
We have tested an implemented Radial Basis Function (RBF) neural network machine to attenuate the random GPR noise of two GPR profiles recorded in the Algerian Sahara. Obtained results show that the RBF machine is not able to remove all the random noise; however a big part is attenuated. We suggest application of the Radial Basis Function neural network to denoise other GPR data or to resolve other problems in the field of Ground Penetrating Radar data processing and interpretation.

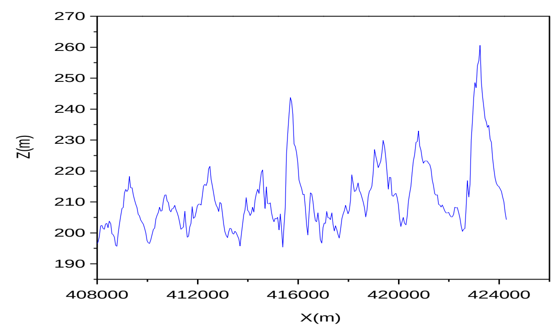

Figure 2 A 2D GPRP profile of the altimetry with 50m as spacing between two measurements

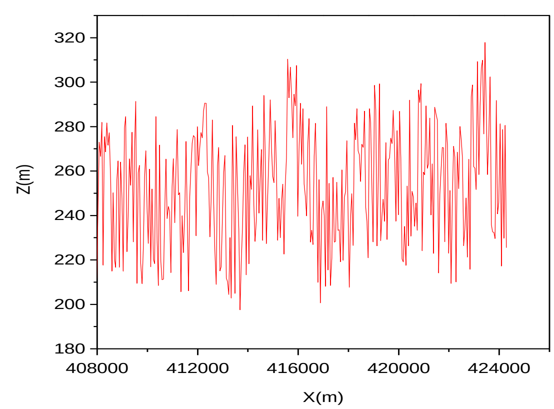

Figure 3 Noisy GPR profile to be used as an input of the Radial basis function neural network

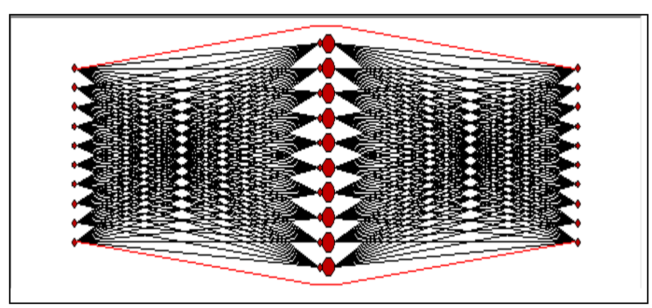

Figure 4 Architecture of the Radial basis function neural machine to be used for GPR data filtering

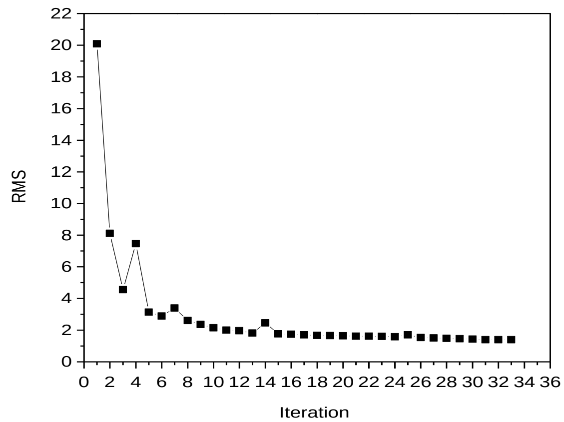

Figure 5 Root Mean square error calculated during the RBF learning

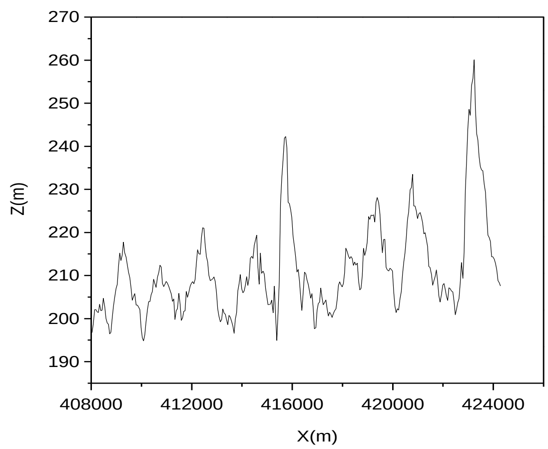

Figure 6 Calculated output using the radial basis function neural network for the first GPR profile used for the RBF learning

References

Broomhead, D. S., David, L., 1998, Multivariable functional interpolation and adaptive networks, Complex Systems 2: 321–355, 1998.

Kim, J-H., Cho, S.-J., Yi, M-J., 2007, Removal of ringing noise in GPR data by signal processing, Geosciences Journal, Volume 11, Issue 1, pp 75-81, 2007.

Lopera, O., C.Slob, E., Milisavljevic, N., Lambot, S., 2007, Filtering Soil Surface and Antenna Effects From GPR Data to Enhance Landmine Detection, Geoscience and Remote Sensing, IEEE Transactions on , vol.45, no.3.

Moody, J., and Darken, J., 1989, Fast learning in networks of locally tuned processing units, Neural Computation, 1, 281-294.

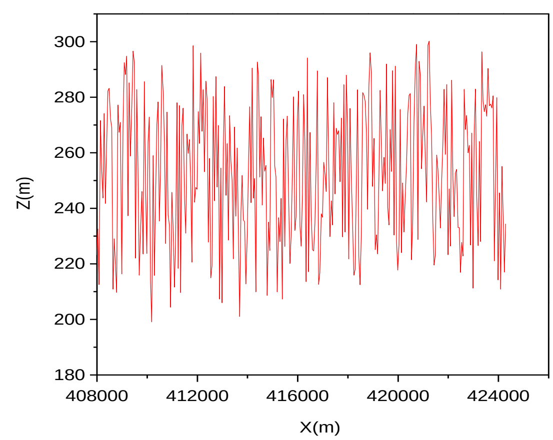

Figure 7 Noisy GPR profile that will be denoised by the implanted RBF machine

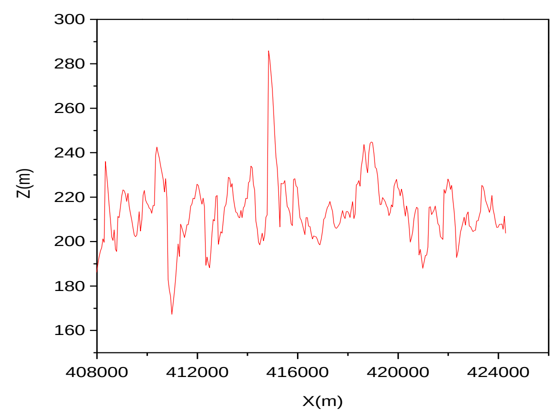

Figure 8 Denoised GPR profile using the implanted RBF machine

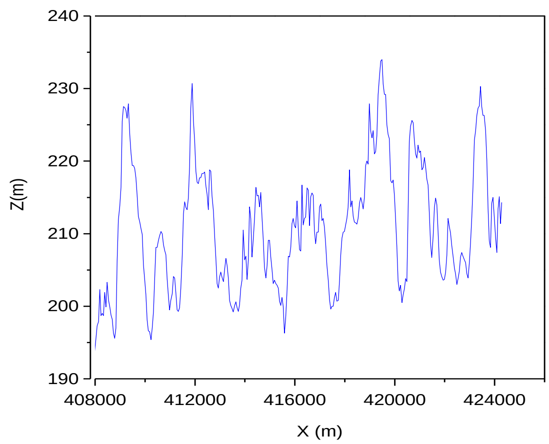

Figure 9 Second 2D GPR profile without noise

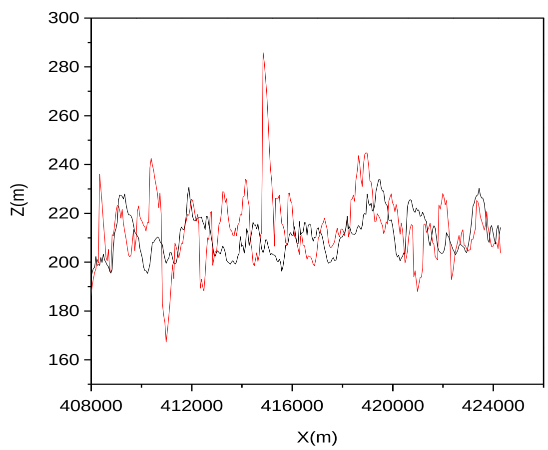

Figure 10 Denoised GPR profile (red color) compared with the same profile free of noise (black color)