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Application of Radial Basis Function Artificial Neural Networks in Seismic Data Processing

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Summary

During the last decade, the application of artificial neural networks has gained in popularity, thanks to its ability to discover input-output relationships. The aim of this work is to attempt to use the radial basis function artificial neural network (RBF-ANN) to address tow problems in seismic data processing, to recognize and remove the seismic random noise and to inverse seismic data. The proposed structure has the advantage of being easily trained by means of a back-propagation algorithm without getting stuck in local minima.

We use numerical examples, along with synthetic and field data, to demonstrate the validity of the proposed method in practice. The effects of network architectures, i.e. the number of neurons in the hidden layer, the centre and the width, on the rate of convergence and prediction accuracy of ANN models are examined. The optimum network parameters and performance were considered as a function of the testing error convergence with respect to the network training mean square error. An adequate cross-validation test is run to ensure the performance of the network on new data sets.

We have successfully used the RBF filter for the removal of the random noise and to invert the seismic data from 2D seismic land data extracted from the study field in Southern Algeria. The results are very promising and indicate the high performance of the proposed tool in seismic data processing in the processed problems.

In the rest of this chapter, we are going to give some useful background theory of ANN and specific type RBF that will be used during this chapter, then will come up time and again in inverse theory and seismic filtering, and give some examples of application for each problem.

5.1 Introduction

The Artificial neural networks (ANN) systems have been frequently used by scientists and engineers as a tool to analyse and design complex systems. Over the past decade, an increasing number of theoretical and application studies of neural networks has been considered in literature showing in the most of cases interesting and promising results. Let us mention for instance, speech and character recognition, classification and combinatorial optimisation (Chen et al., 1991; Chen and Billings 1992; Calderón-Macías et al., 2000; Castellanos et al., 2007).

The use of ANN is motivated by its good ability to extract useful information from heterogeneous or inaccurate data. ANN can approximate arbitrary complicated non-linear relationships and get good nonlinear transfer functions (Chen, T., and Chen, H., 1995). All these many tasks for which the neural network can offer a good solution, in particular where the data are noisy, or the explicit knowledge of task is not available or when unknown non-linearity between input and output may exist.

Increased demands for precise data quality have stimulated development of sophisticated methods for a seismic data processing. As a result, techniques for filtering and inverting the seismic data have been improved. In this work, we focus our attention on the filtering and inversion of seismic data by artificial neural networks of RBF type. This tool is characterized by its capacity to approximate any arbitrary non linear function (universal approximation) and their ability of learning from example of historic data. The training process allows to this model to adapt its behaviour according to the environment change. For this reason, it has been applied in many fields of Science and Engineering such as classification, approximation, pattern recognition, signal processing, prediction, feature extraction, etc. A recent application of ANN in geophysics involves the use of ANN to the seismic inversion (Calderón-Macías et al., 2000), seismic data filtering (Djarfour et al., 2008), magnetotelluric time-series analysis (Manoj and Nagarajan, 2003), deconvolution and source wavelet estimation (Wang and Mendel, 1992) and for many other problems where rigorous, analytical solutions do not exist. The use of RBFANN in geophysical processing problems is a relatively recent development and offers many advantages in dealing with the nonlinearity inherent in filtering and inversion. Because they were designed to work on non-linear, multi-modal, and poorly understood problems. However, in their application to specific problems, as with all algorithms, problems of implementation arise. After extensive numerical tests, we implemented a RBFANN to efficiently filter and invert several sets of synthetic and real data. The emphasis is placed on the capacity of the ANN for training and generalization.

5.2 Artificial Neural Network Principles

An ANN is an information processing systems using the concept of neuron, which is principally inspired from the biological neuron, basic element of nervous systems. This system is composed of a large number of highly interconnected neurons working together to solve specific problems. Each neuron is connected to other neurons according to the topology structure. Every neuron is considered as an elementary processor that transforms all its inputs signals into one output signal, which is propagated to other neurons, capable to process it again, in this manner propagates the influx nervous in biologics neurons.

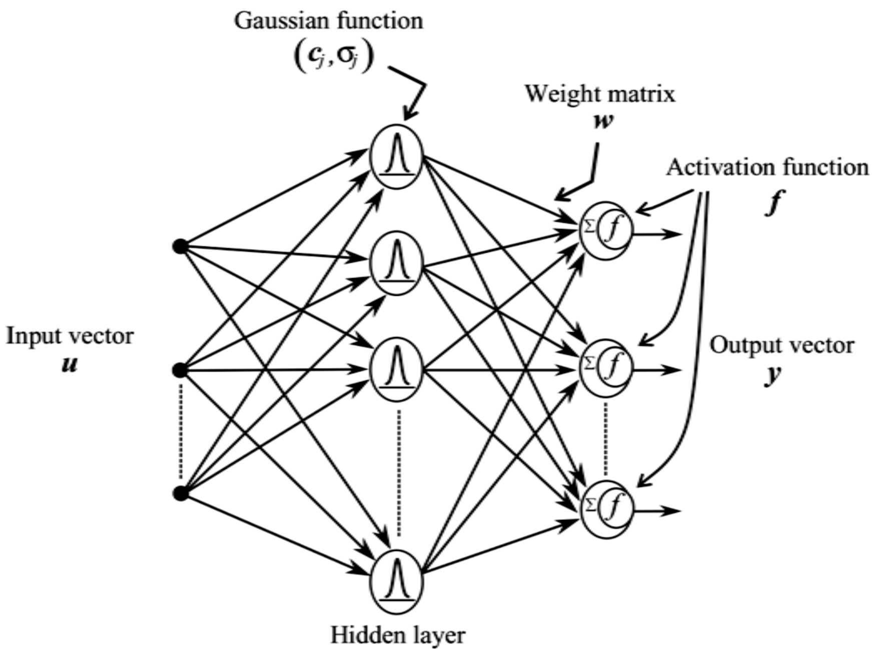


Figure 1. *Radial Basis Function Artificial Neural Networks Architecture.*

Neurons are grouped into layers, and several layers constitute a neural network. In a multi-layer network, there are usually an input layer, one or more hidden layers and an output layer (Figure 1). The layer that receives the inputs is called the input layer; it typically performs no function on the input signal. It will be used to receive the information from the environment. The network outputs are generated from the output layer and its role is to communicate the result of the processing to the user. Any other layers are called hidden layers because they are internal to the network and have no direct contact with the external environment, and constitute the centre of processing in the network system. The 'topology' or structure of a network defines how the neurons in different layers are connected. That constitutes the mode of how the neurons will exchange the information during its application. The choice of the topology to be used closely depends on the properties and the requirements of the application.

The RBFANN belong to artificial neural network feedforward structure. The specificity of this topology is that its hidden layer uses the Gaussian transfer function instead of the sigmoid one. This suitable activation function for the hidden neurons is essential to produce a localized response to the input and introduce non-linearity into the network, which allows this system to model the behaviour of the nonlinear relationship between input and output of the complex system. The activation functions in the hidden layer are calculated by the following function:

$$\rho_j = \Phi_j\left[\frac{\|U - C_j\|}{Q_j}\right] = \exp\left(-\frac{1}{2}(\mathbf{u} - \mathbf{c}_j)^T \mathbf{Q}_j^{-1}(\mathbf{u} - \mathbf{c}_j)\right) \qquad (1)$$

where, $U \in R^n$ is the input vector, C_j is the centre associated with the hidden unit j, and Q_j is the width coefficient for hidden unit j, which represent a measure of the spread of data. $||U - C_j||$ is a norm of $U \to C_j$ that is usually Euclidean, which presents the distance between the input vector X and C_j. Φ_j is a radial symmetry function, which achieves the unique maximum at the point of C_j. With the increase of $||U - C_j||$, Φ_j attenuates to zero rapidly. The hidden layer in RBF network consists of an array of nodes that contains a parameter vector called a 'radial centre' vector. The hidden layer performs a fixed non-linear transformation with non-adjustable parameters. The approximation of the input-output relation is derived by obtaining a suitable number of nodes in the hidden layer and by positioning them in the input space where the data is mostly clustered. At each iteration, the position of the radial centres, its width (variation) and the linear weights to each output node are modified. The learning is completed when each radial centre is brought up as close as possible to each discrete cluster centres formed from the input space and the error of the network's output is within the desired limit.

5.3 Artificial Neural Network's Training

By means of training, the ANN is capable to model a non-linear function of a certain complex system. There are two categories of training algorithms: supervised and unsupervised. Both of training modes are combined in the radial basic function design. As we did with supervised training procedure of neural network design, the data base is divided into two separate portions called training and test sets. The training data will be used as a desired network output. The second part of the data is used for the network confirmation. A neural network has to be trained such as the application of a set of inputs produces the desired set of outputs. The problem of determining the network parameters is essentially a non-linear optimisation task (Rumelhart et al., 1986; Renders, 1995).

To train the RBF network, there are three types of parameters that need to be chosen to adapt the network for a particular task: the center vectors ci, the output weights wi, and the RBF width parameters βi. During this process of training, the value of the output of the ANN is compared to the target value to determine an error, the weights of a connexion between the hidden layer and the output are then adjusted in a backward direction from the output layer to the hidden layer and a neuron in the hidden layer is added in order to minimize this error, this type of training is called incremental training. Once the error decrease until the threshold value or the number of iteration is reached, the training of the network is completed. In this case, the learning process is stopped, and the connection weights and number of neurons in the hidden layer are fixed. The network must be confirmed by testing stage. The training of this kind of networks combined the supervised and unsupervised training, since the centres and widths of the Gaussian functions in the hidden layer are obtained based on the unsupervised training, while the supervised learning is applied to adjust the connexion weight between the hidden and the output layers.

The approximation of the input-output relation is derived by obtaining a suitable number of nodes in the hidden layer and by positioning them in the input space where the data are mostly clustered. This later produces a least-square fit between the actual network output and the desired results by computing a local gradient in terms of the network weights (Djarfour et al., 2008). All the neurons that are connected to each other constitute a network. When one presents to the network a form to be learned, the neurons simultaneously enter into a state of activity which causes a slight modification of the synaptic forces. What follows is a quantitative reconfiguration of the whole of the synapses, some of them become very strong (high value of synaptic force), and the others become weak. The learned pattern is not directly memorized at an accurate location. It corresponds to a particular energy state of the network, a particular configuration of the activity of each neuron, in a very large case of possible configurations. This configuration is supported by the values of the synaptic forces.

From the analysis of the theory of RBF neural network, the transformation from the input layer space to the hidden layer space is nonlinear, while the transformation from the hidden layer space to the output space is linear. That is, the mapping between the input and output is nonlinear, and that the output of the network is linear for the adjustable parameters, then the weights of the network can be found directly by the linear equations. So, the learning speed can be quickened greatly, it can also avoid the problem of converging to local minimum.

Train the ANN with few neurons in the hidden layer and periodically measure the ability of ANN to produce accurate answers in test data, which are data that were not used in the training. If the ANN performs poorly in both the training and the test example, it is likely that having more neurons in the hidden layer will improve its ability in the test data.

The number of neurons in the hidden layer varies as per the requirement of the optimum performance, which could be decided on trial and error basis. Initial weights are assigned randomly in the suitable range for the activation function at neurons (Rumelhart et al., 1986; Renders, 1995; Calderón-Macías et al., 2000).

5.4 Universal Approximation Capacity of ANN

Since 1960, a number of results has been published showing that a multilayer neural network with only one hidden layer can approximate arbitrarily well a continuous function of *n* real variables; e.g. proofs have been given by Cybenko (Funahashi, 1989; Cybenko, 1989; Park and Sandberg, 1991; Chen T and Chen H, 1995). Since the RBF belongs to a one-pass learning algorithm with a highly parallel structure and is capable of approximating any arbitrary function from training data, these data consist of individual pairs of inputs and outputs called example pairs which are generally gathered from the process or system being modeled (Kurt et al., 1989). However, these theories do not discuss the number of neurons that should be used in the hidden layer, the type of training algorithm to be used, the activation functions, the number of examples used in the training phase, as well as the error of the approximation with a given number of neurons.

Consequently, many problems have been encountered while implementing this type of ANN for a specific task. Based on their capacity of approximation and classification, neural networks have been used in many areas that require computational techniques such as solving a problem of speech and character recognition, classification and combinatorial optimization, expert system (Leszek, 2004; Firat and Gungor, 2009; Chaofeng et al., 2011; Razavi et al., 2011). All these tasks to which the neural network can offer a good solution, in particular where the data are noisy, or the explicit knowledge of task is not available or when unknown non-linearity between input and output may exist. Besides the simplicity of their design which involves only three parameters to be determined (the center vectors c_i, the output weights w_i, and the RBF width parameters β_i), RBF are fast learners. The application of RBF in seismic filtering and inversion is very limited in the literature. Therefore this work is pioneering in applying this type of ANN in seismic data filtering and inversion.

5.5 Seismic Data Filtering

Modern seismic data, such as three dimensional (3D) seismic data, time-lapse, or four-dimensional (4D) data, multicomponent data, to name a few, are characterized by large data volumes and high resolution. In fact, 3D seismic volumes may contain several millions of traces and require a gigantic storage volume which can reach easily many terabyte (1 terabyte=1024 gigabytes!). This type of data is a gold mine for geophysicists and reservoir engineers. Indeed, it allows complex subsurface structures to be mapped in much more details than a conventional 2D seismic method, and provides a reliable tool to monitor changes in reservoir properties. However, the downside is that the data still distorted and masked by noise, particularly when the amplitude of the noise is very high compared with the signal. The use of the term noise refers to the undesirable part of the recorded reflection data as the definition of noise given by Dobrin and Savit (1988) "spurious seismic signals from ground motion not associated with reflections." This range from uncorrelated noise to multiples and include surface waves, ground roll, wind noise, man-made interferences and refractions. Basically, there are two types of noise: coherent noise, which is the predictable part of the signal and is correlated from trace to another; and random noise, which is the unpredictable part of the signal and is uncorrelated from one trace to another.

The simplest way to represent a seismic trace T(t) is to add a useful signal, in this case, the convolution of a wavelet with the reflectivity, and an additive noise n(t), that is:

$$T(t)=w(t)*r(t)+n(t), \qquad (2)$$

where (*) represents the convolution, w(t) the wavelet and r(t) the reflectivity. The additive noise in equation (1) is considered as a white Gaussian noise which is used to simulate a random signal. Note that it is also possible to model the noise throughout convolution process as in the case of multiples.

Seismic noises obscure the useful seismic signal, i.e. reflected arrivals, and have the potential to degrade the performance of some processing tasks on which interpretation depends. One way that comes immediately to mind to enhance the signal-to-noise ratio and improve the resolution is to remove noise from seismic records.

Seismic noise removal approaches can be subdivided into two categories: i) Modelling and inversion and ii) filtering. Modelling and inversion approach is based on noise prediction. It first models the noise, and then subtracts it from the original raw data (Cassano and Rocca, 1973; Tarantola, 1987, Henry, 1997; Buttkus and Bonnemann, 1999; Weglein, 1999; Guitton 2002; Voss and Hearn, 2003). On the other hand, filtering techniques can be grouped into four categories: i) domain transforms methods. Techniques in this class include frequency- wave number (F-K) method (March and Bailey, 1983); τ-p transform (Tatham et al., 1983; Tatham, 1984); Karhunen-Loève (K-L) transform (Al-Yahya, 1991; Jones and Levy, 2006), radial (R-T) transform (Claerbout, 1975, 1983, 1985; Mari et al., 2001; Henley, 2003) and F-X domain transform (Canales, 1984; Gulunay, 1986), ii) image processing-based techniques (Ristau and Moon., 1997; Fehmers and Hocker, 2003; Baddari et al., 2011; Ferahtia et al., 2010), iii) techniques based on prediction and wave separation such as the multichannel Wienner filter (Galbraith and Wiggins, 1968; Claerbout 1985) and iv) more sophisticated techniques such as methods based on fuzzy logic (Hashemi et al., 2008) and artificial neural networks (Essenreiter, 1999; Djarfour et al., 2008).

5.6 Seismic Data Inversion

The estimation of a hidden physical parameter inaccessible to experiment from an other one is well known to be the solution of the inverse problem. The seismic processing is one of the physics fields concerned by this problem. The reason is that geophysicists try to extract information about the Earth structure from observation data collected at the surface of the Earth. The inversion of seismic data can be used to constrain estimates of the acoustic impedance structure of the Earth from the seismic recorded amplitude data. The seismic inversion is currently used as a means for reservoir characterization or for confirming the presence of the hydrocarbons. The reason behind is that the acoustic impedance is a basic physical property of sediments that can be exploited in hydrocarbon assessment; it is a characteristic that is supposed to be intrinsic for each geological layer. This kind of problem is usually known to be ill-posed problem according to Hadamard definition of a well posed problem (Tarantola 1984a, 1984b). From a mathematical point of view, this problem is nonlinear, high-dimensional, with a complex search space, which may be riddled with many local minima, and result in irregular objective functions (Symes and Kern, 1994). The solution of this problem is to use a prior knowledge in a criterion optimization approach to process the ill-posed character of the problem. The simplest way to solve this problem is to use local optimization methods e.g., matrix inversion, steepest descent, and conjugate gradients. These methods can obtain a good solution with reasonable success, the efficiency of these methods strongly depend on a good starting model, if it is available, moreover, they can be made to run extremely fast. However, all these techniques are prone to trapping in local minima, and these methods need to compute first and/or second order derivatives of the cost function, that poses certain problems of implementation on the computer. In the case of non availability of good starting solution, the alternative to linear approximation and local optimization techniques that is becoming increasingly popular among geophysicists is the application of global optimization methods such as simulated annealing or genetic algorithm. These methods can find a good solution with reasonable prior information and perform a much more exhaustive search of the optimal solution in the model space.

5.7 Applications

The Gaussian-type RBF was chosen here owing to its similarity with the Euclidean distance and to its better smoothing and interpolation properties in several applications. The training algorithm for this topology uses an incremental training technique. The sum of squared error criterion function can be considered as an error to be minimized over the given training set. The hidden layer in RBF network consists of an array of nodes that contains a parameter vector called a ‘radial centre’ vector.

All further simulations and applications on synthetic and real data were performed under Matlab environment.

5.7.1 Seismic Data Filtering by RBF

As an application for the method described above, we designed a synthetic subsurface model given by the Figure 2. Since the main goal of this stage of simulation is to train the RBF-ANN to filter the seismic data, the proposed model of subsurface consists of several layers with a complex structure. Several shapes have been introduced in this model. The synthetic seismograms used for network training include only P-wave primary reflections computed at normal incidence. Using this model, a set of trace gathers was computed using convolution equation (2), the zero-offset reflectivity sequence for the suggested model have been convolved with a 35 Hz Ricker wavelet.

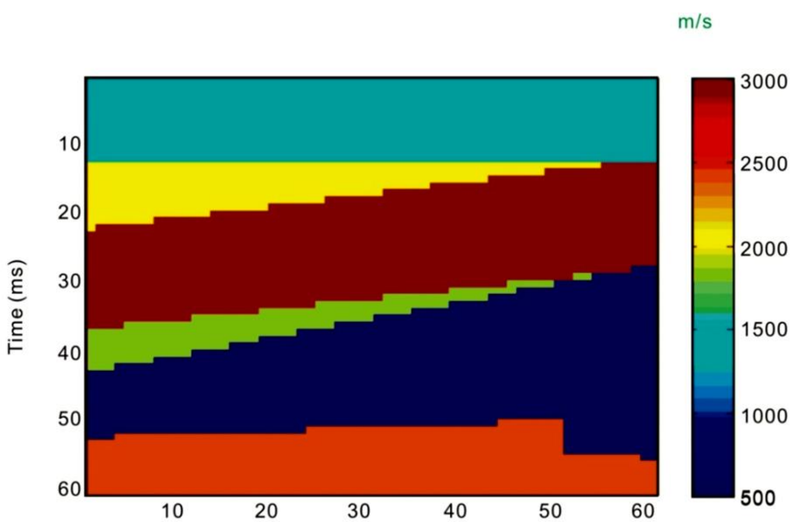
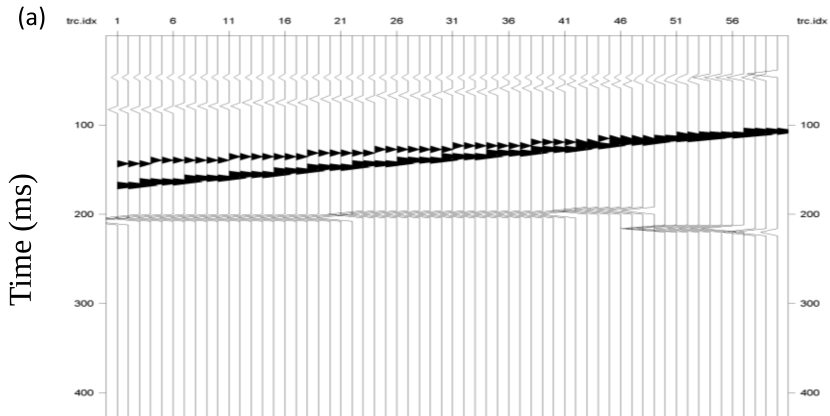


Figure 2. *Subsurface model used to create the synthetic data.*

In a typical neural data processing procedure, the data base is divided into two separate portions called training and test sets. The training set is used to develop the desired network. In this part of design, the data of the Figure 3a are used as desired output while the synthetic seismic section of the Figure 3b are used as input of ANN in the training phase. These data are obtained by adding 20% of random noise to the clean section of the Figure 3a. In test phase, we have used the synthetic seismic section of the Figure 3c, obtained by adding 50% of random noise. The random noise is normally distributed and was added using the Matlab CREWES toolbox command rnoise (Margrave 1991). The desired output in the training set is used to help the network to adjust the weights between its neurons (supervised training). Once the network has the learned information in the training set and has 'converged', the test set is applied to the network for verification. It is important to note that, in this phase of test, the user has the desired output of the test set, that it has not been used by the network in the training phase. This ensures the integrity and robustness of the trained network.

(a)



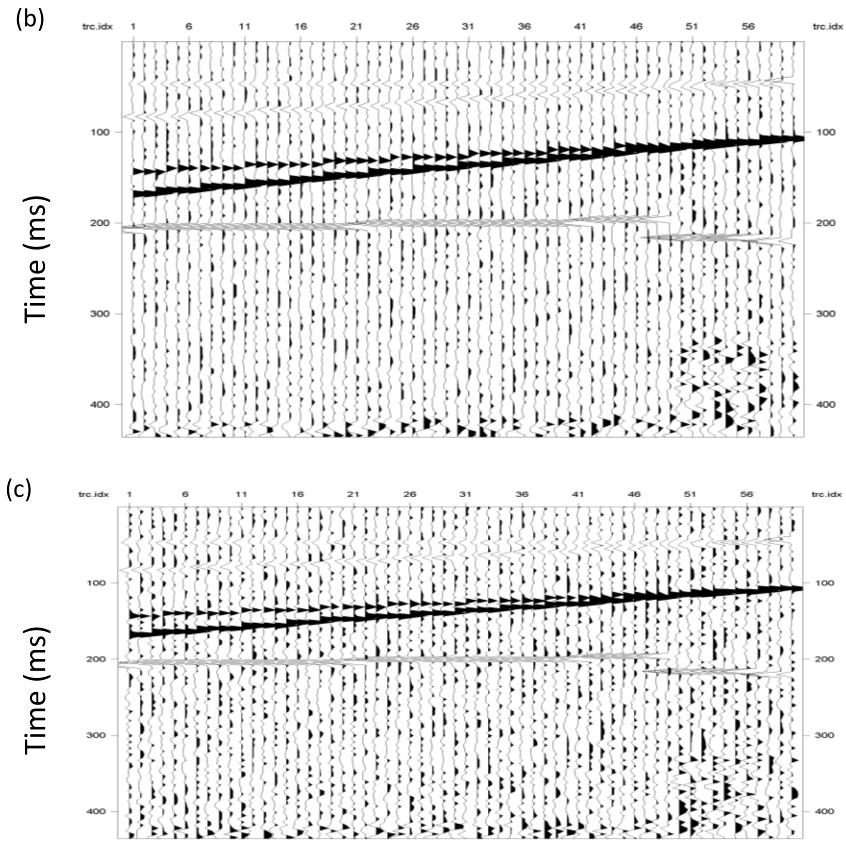


Figure 3. a) *Noise-free synthetic seismic section used during synthetic application. Noisy seismic section obtained by adding: b) 20% random noise, c) 50% random noise to the seismic section.*

The behaviour of the neural networks during the training phase is improved by the variation of the number of neurons in the hidden layer. The error at the output of the system is given by the Figure 4, the plotted error corresponds to the accumulated errors obtained from comparing the desired output with the network output. As we can see in this figure, the prediction error decreases as the number of neurons grows, that testify the simplicity of training of this ANN topology (RBF). As an example of the obtained results, we have plotted the produced result by the ANN when we use the data of the Figure 3c as an input in the generalisation phase. In the case of 30 neurons in the hidden layer (Figure 5a) and 80 then 100 neurons in the hidden layer (Figure 5b, 5c). One can notice that the quality of the obtained result for 100 neurons converges more quickly than that for 30 neurons (Figure 5a).

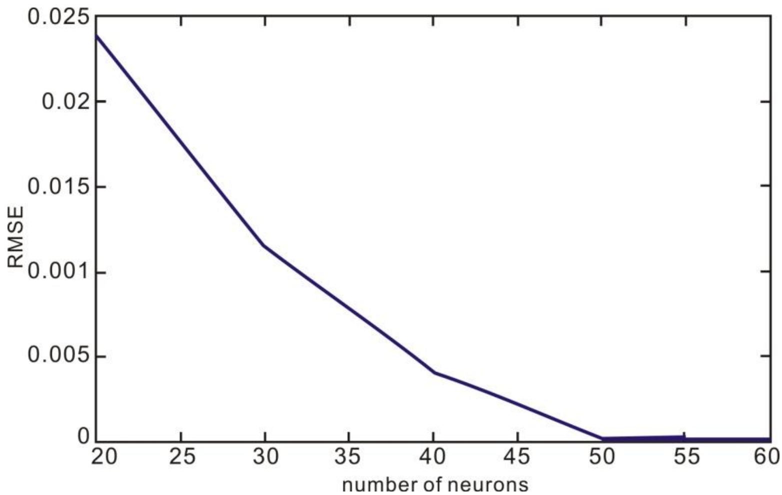
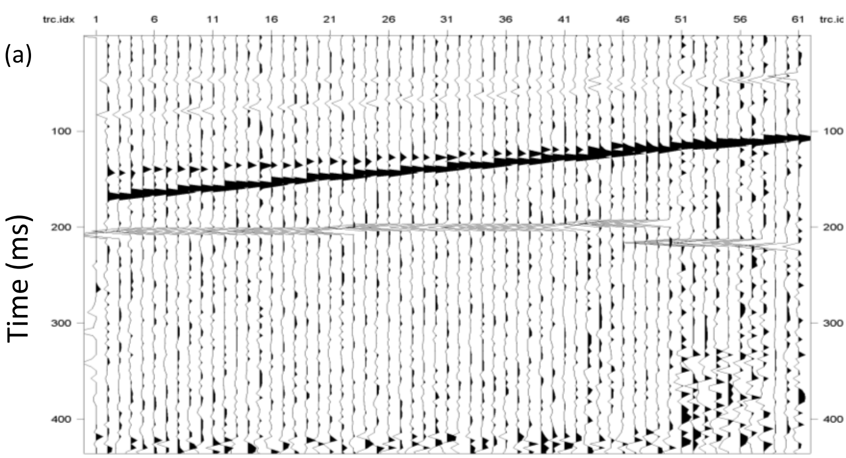


Figure 4. *Root-Mean-Squared-Error (RMSE) vs number of neurons in the hidden layer during synthetic data filtering test.*



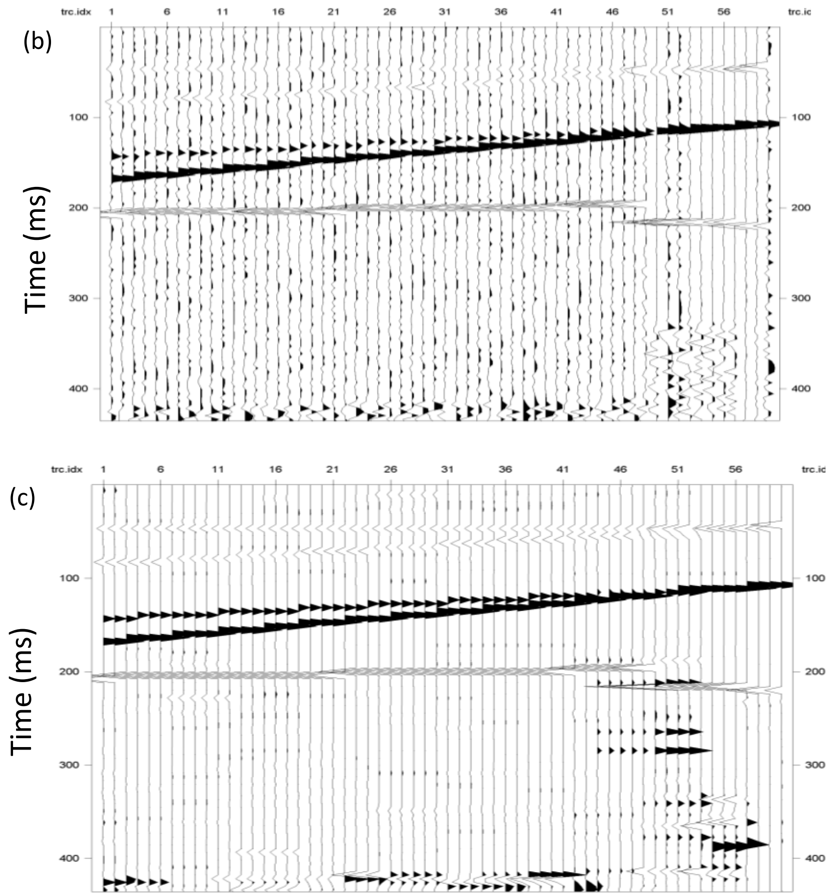


Figure 5. *Result of filtering by RBF in the generalization phase. a) case 30 neurons in the hidden layer, b) case of 80 neurons and c) case of 100 neurons.*

Here we can quantify directly how the network has performed, because we know input, output and desired output. The quality of filtering of random noise is better in the case of 100 neurons (Figure 5c). The obtained seismic section by ANN after training (Figure 5c) is compatible with the seismic model, which is also the desired output (Figure 3a). One can see that the obtained section using ANN after training (Figure 5c) is similar to the seismic model (Figure 3a).We, therefore, demonstrated that the ANN technique clearly improved the seismic section, even if some noise with reduced amplitude still remain. All the features of the desired model have been preserved by the obtained structure of RBF while a great part of random noise has been reduced.

5.7.2 Seismic Data Inversion by RBF

To prepare a set of ANN design, the acoustic impedance inversion studies were conducted on seismic data collected from a survey in Southern Algeria. The goal of the data processing is to maintain accurate amplitudes, so the processing flow is limited to the few following steps.

So the basic steps are: a compensation of the energy loss by the transmission and the spherical divergence, a deconvolution minimising the distortion of the wavelet shape, a consistent static residual surface to eliminate the surface anomalies, a precise velocity analysis, and an adequate window mute. The obtained seismic section shows a good quality, and serves as a good example to examine the application of the RBF-ANN in the inversion processes. This inversion process computes the sparse spike reflectivity from the stacked data assumed to be representative of the band limited reflectivity sequence. Constrained acoustic impedance inversion is performed using an algorithm using a linear programming approach for the estimation of the acoustic impedance. The obtained result of all these steps is the seismic section that will be used as an input of the RBF-ANN (Figure 6a), and the desired output acoustic impedance section (Figure 6b).

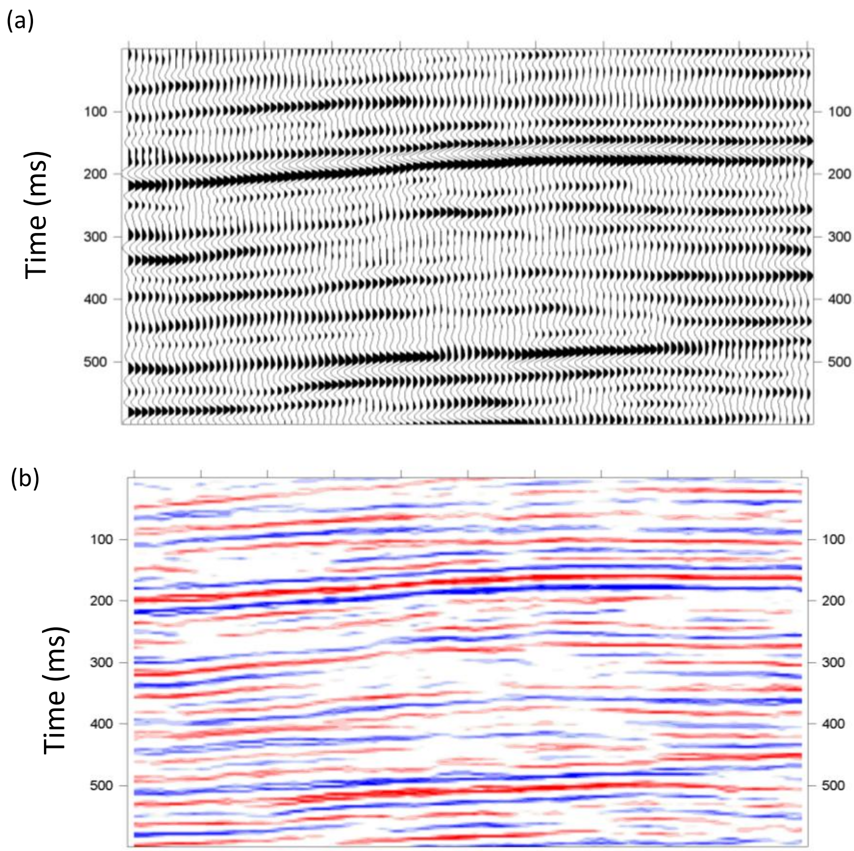


Figure 6. *Training on real seismic data. (a) ANN input seismic section. (b) ANN desired output acoustic impedance section.*

In the adopted strategy of the design of this RBF, the training is done by the 50% traces chosen randomly from the seismic section, but in the test of training and generalization, we use all the traces of the seismic section. The main goal of this part is the use of RBF-ANN type to invert the seismic data. The number of neurons in the hidden layer varies from 10 to 100. The test performance with different numbers of neurons in the hidden layer demonstrates that the prediction error decreases as the number of neurons grows (Figure 7).

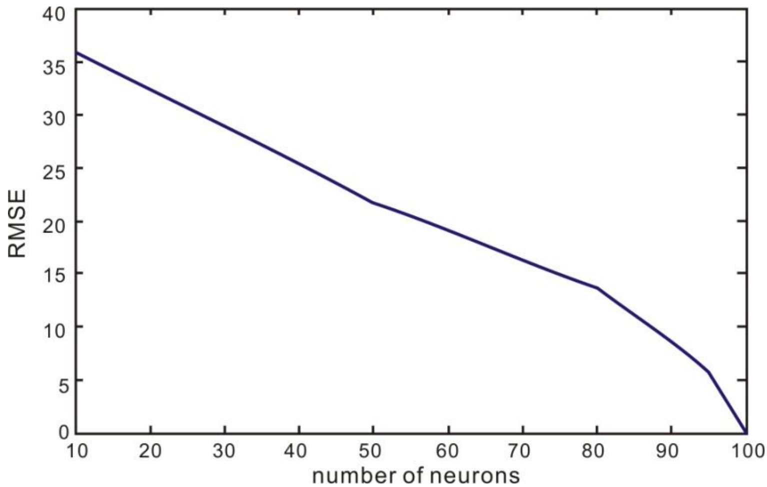


Figure 7. *Root-Mean-squared-Error (RMSE) vs number of neurons in the hidden layer during the real seismic data inversion test.*

When comparing both ANN outputs in the generalization phase (Figure 8a, b, c) (case of 10, 50 and 100 neurons in the hidden layer) with desired ANN output (Figure 6b), we can see that the behaviour of the system still improved when we increase the number of neurons in the hidden layer from 10 to 100 neurons. The traces are globally badly reproduced, all of them have the horizontal shape and are largely different with associated traces in the desired output. In short, we can note that the structure of RBF-ANN at this stage (10 neurons in the hidden layer), has an ability to learn, but still incapable to generalize. The best result is obtained in case of 100 neurons in the hidden layer. In this case, all the traces used in the testing phase are well inverted (Figure 8c), if we compare with the same traces in the desired output (Figure 6b).

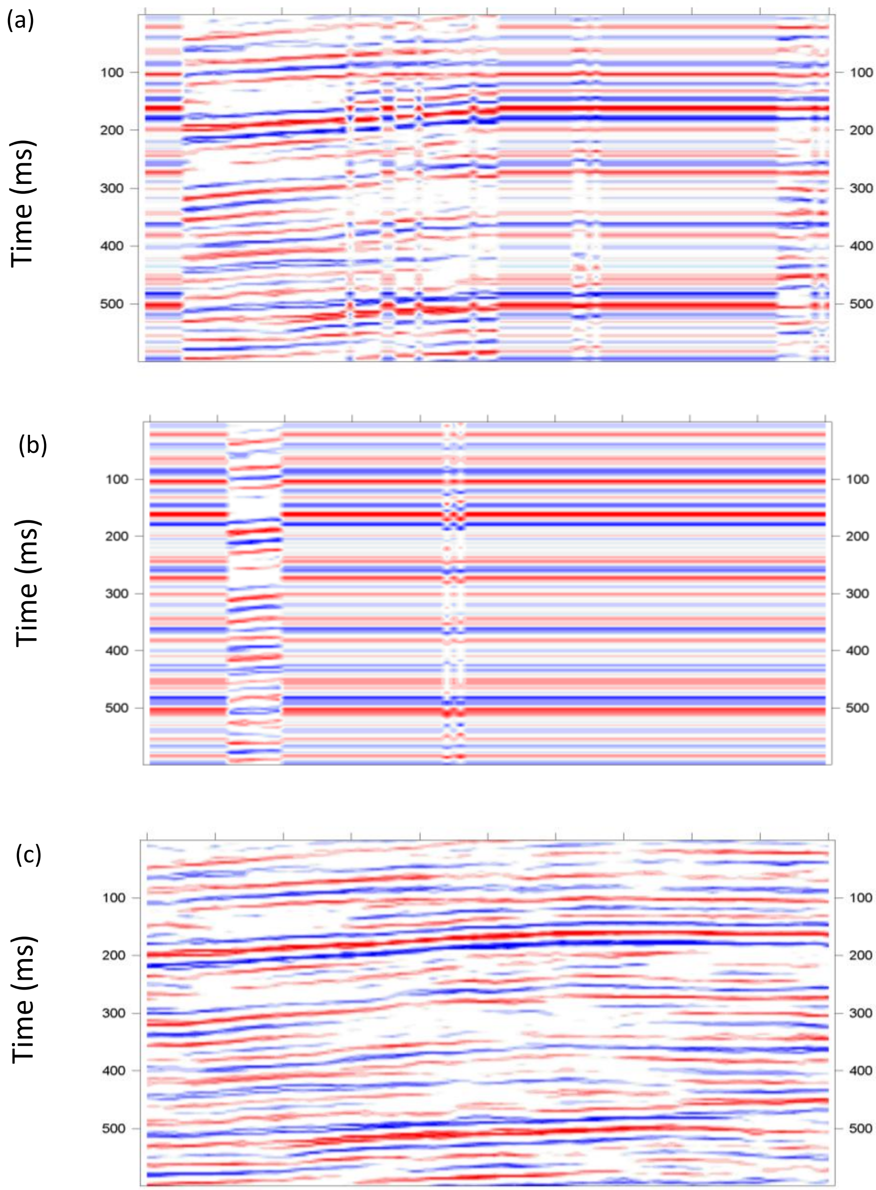


Figure 8. *a) ANN output after training, case of 10 neurons in the hidden layer, b) ANN output after training, case of 50 neurons in the hidden layer, c) ANN output after training, case of 100 neurons in the hidden layer.*

5.8 Conclusion

We described the application of the radial basis function neural network in seismic data processing, specifically in the filtering and the inversion of seismic data. This intelligent tool can deal with a complex non linear mapping function characterizing each task. The system is fully implemented, and we have demonstrated its performance earlier on a synthetic example chosen in such a way that it represents real geological structures, and in one case with inversions corresponding to real data.

The good results indicate that the training of this network was successfully performed, and the RBF network has the ability to obtain a strict convergence for synthetic and real seismic data.

A number of experiments were carried out to verify the capability of the proposed method in this chapter. The results presented in this work demonstrate that the RBF ANN can bring a significant improvement to seismic data processing (filtering and inversion).

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