Neural Networks and Antenna Arrays

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Abstract: This paper considers the joint application of neural networks and antenna array systems in mobile, satellite and sensor systems. The main assumption is that there is a possibility of a large number of neurons in the network according the fact that the human brain uses a huge number of neurons. Results of detail analyze for signal detection, direction of arrival estimation, and beamforming are presented. First signal detection is performed with PNN neural network than with RBE, and systems are compared. Then DOA estimation and beamforming are presented for both neural networks. Results from computer simulations show the ability of these systems to give satisfactory performances although limitations are noted. Overall analyze gives a high contribution in finding an optimal future neuro-antenna array systems as very elegant, cost effective and efficient solution for telecommunication systems.

Key-Words: Neural Network, Antenna Arrays, Signal Detection, Beamforming

1 Introduction

The inherent nonlinearities associated with antenna radiation patterns make antennas very suitable candidates for Neural Networks (NNs). Neural networks have been used successfully in 1) estimating the Angle Of Arrival (AOA) (or Direction Of Arrival – DOA) of signals in a mobile communication environment; 2) varying the usable bandwidth of microstrip patch antennas; 3) determining the excitation coefficients in phased array antennas to change the direction of the radiation beam for target tracking; 4) compensating for surface errors in reflector antennas and in other applications.

The human brain has a vast network of processing cells called neural networks, and the science of neural networks has inspired many researchers in biological as well as nonbiological fields. This inspiration has generated keen interest among engineers, computer scientists, and mathematicians for developing some basic mathematical models of neurons, and to use the collective actions of these neural models to find solutions to many practical problems [1].

One of the main problems in wireless systems is interference rejection and often represents an inexpensive way to increase the system capacity by allowing closer proximity of cofrequency cells or beams providing additional frequency reuse. To solve this problem, first a superresolution DOA algorithm [2] is used to locate the desired as well as the cochannel mobile users. Second, an adaptive array antenna can be used to steer its radiation beam toward the mobiles of interest and nulls toward the other sources of interference in the same frequency slot [2]. One drawback of these algorithms is the difficulty of implementing them in real time because of their intensive computational complexity. NNs, on the other hand, due to their high speed computational capability, can yield results in real time. This leads to the accurate estimation of the mobile location in a few characteristic time constants of the circuit, normally, on the order of 100s of nanoseconds (provided that the NN has been trained off-line first). This will enable the system to estimate the directions of multiple users even as the mobile users move. In addition, NN can yield fast convergence rates for the adaptive beamforming mechanism (peaks and nulls in desired directions) since the weights of the adaptive array antennas can now be computed in real time [3]-[4].

Secton 2 is presenting the results gained for signal detection and Section 3 is dealing with DOA estimation. Section 4 is presenting the results for Beamforming and finally Section 5 gives the main conclusions. All the results are gained with Matlab Neural Network Toolbox simulations.

2 Neural Network for Signal Detection

A major result that has emerged in recent years, with the growth of interest in NNs, is the Multilayer Perceptron (MLP) with single hidden layer. This network is capable of approximating any smooth nonlinear input-output mapping to an arbitrary degree of accuracy, provided that sufficient number of hidden layer neurons is used. This often is referred as universal approximation theorem. Also Park and Sandberg [5]-[6] had proved the universal approximation capabilities for Radial Basis Function Networks (RBFs). This property ensures that RBFs will have at least the same theoretical capabilities as the well-known multilayer networks with sigmoidal non-linearities. The universal approximation
property is shared by a wide range of model types. This property merely indicates that a generating function can be approximated but generally says nothing about the quality of the approximation. It is clear, however, that for solving practical problems, we may be more interested which model is the best for a given task, as well as other issues such as the ease of training, robustness, memory complexity, or computational complexity. The property of best approximation has been defined as an extension of the universal approximation property. In a given set of models, the model that most closely approximates the generating function, by some defined distance measure, is defined as having the property of best approximation. Thus, the best approximation is an important attribute in choosing a model type. It has been proved that RBFs have this property [7].

Applying multilayer neural networks trained by backpropagation for signal detection showed a poor convergence of the learning algorithm, because the algorithm was stucking into local minimas. As previously explain the best approximation property of RBFs avoid that problem and can be used for signal detection. More simple solution is to apply Probabilistic Neural Network (PNN) [8]. The main disadvantage of this solution is that we should use about ten successive bits to estimate if the signal emanates from the corresponding sector. Taking into account that we are assuming a large number of neurons another possibility arises; we could use so called RBE; which is radial basis neural network with exact solution. It has linear output layer and same as PNN has neurons in hidden layer as much as there are training samples. Same as PNN we will just design the network rather than train it. It is well known that this type of network is good for function approximation problems whereas PNN is used for vector classification problems.

So we should expect some degradation of the performances but also we should expect these performances to be improved by increasing the number of antenna elements or the number of the training samples. However good performance of this network will help us to avoid the necessity of using more successive bits for signal detection [9]. The system is presented in Fig.1.

The interest in NNs stems from the capability of a human brain to organize neurons to perform certain computations (e.g., pattern recognition, perception, and motor control) many times faster than the fastest digital computer in existence today. It is worth mentioning that the brain’s efficiency is attained despite the fact that the neurons are five to six orders of magnitude slower than silicon logic gates; events in silicon chip happen in the nanosecond range, whereas natural events happen in the millisecond range. However, the brain makes up for the relatively slow rate of operation of the neuron by having a truly staggering number of neurons with massive interconnections between them. This lead us to a conclusion that one of the most important parameters in our network should be the number of neurons; we should use large number of neurons in hidden layer and also larger number of antenna elements that will define the number of neurons in the input layer. For possible large number of neurons in the hidden layer a good choice for NN in the signal detection stage is to apply PNN.

Let consider a linear array of 10 elements, where \( d=0.5 \) wavelengths, and PNN for sector with \( 20^\circ \) width \((10^\circ\div 30^\circ)\). The correlation matrix was calculated from 716 snapshots of the simulated array measurements. Fig.2 is presenting the case when the PNN was designed for 2 users separated at 2deg and with equal SNR=10dB.
Now again let consider the case of signal detection but with linear array of 15 elements, where \( d = 0.5 \) wavelengths, and RBE for sector with 20deg width (10°–30°)deg. The correlation matrix was calculated from 716 snapshots of simulated array measurements and RBE was designed for 2 users separated at 2deg and with equal SNR=10dB. Fig.3 is presenting the results, it can be concluded that RBE successfully performs the generalization but also it can be noticed that there is a need of a larger number of antenna elements for same performances.

From results it can be seen that RBE needs larger number of antenna elements for similar performances. Analyze show that similar may be achieved if the number of training samples is increased. This is a consequence of the fact the PNN is vector classification system and RBE function approximation.

Let observe the reliability of the network. In our example the number of antenna elements is \( M=20 \), SNR=20dB, 358 input samples were used for network design, and analyzed sector is (10°–30°). Two users were separated at 2deg, than the RBE was tested for two users with same separation and values for SNR but with different information bits and noise samples. Fig.4 is presenting the case when there are two failed neurons, that can be noticed for angles –21deg and 59deg, which correspond to the 112\(^{th}\) and 32\(^{nd}\) neuron in the hidden layer. Fig.4a is presenting the results after the first correction (for one neuron) and Fig.4b is presenting the output gained after the two corrections. Simulations show that this network provides us the possibility to detect failed neuron, to read the position of that neuron and also the value of the corresponding weight. If two neurons fail, there will be two mismatches of the output. Of course, this procedure of detection is possible only if couple of neurons fail.

### 3 Neural Network for DOA Estimation

Superresolution algorithms [10] have been successfully applied to the problem of DOA estimation to locate radiating sources with additive noise. One of the main disadvantages of the superresolution algorithms is that they require extensive computation and as a result they are difficult to be implemented in real time. It has been shown that NNs have the capacity to track sources...
in real time. The paper [11] where RBF NN is applied, presents a generalization of the algorithm presented in [12] in such a way that the system would be able to track an arbitrary number of sources with any angular separation without prior knowledge of the number of sources. The new approach presented in [11] provides a dramatic reduction in the size of the training set required to train each smaller network.

Let consider a sensor array with M=11 elements, and four signal sources moving at mutual distance of 2° in the sector [10°÷20°] with equal SNR=20dB. The variance of the Gaussian functions in the hidden layer was chosen to be equal of the mean distance to the seven nearest centers from the corresponding center. The number of the neurons in the input and hidden layer was equal to M and the number of the neurons in the output layer was 6 (resolution of 2°). We have used 170 training samples with angular step of 1°, and the testing was performed for angular step of 0.25°. The solid lines in Fig. 5 present the actual DOAs, and the dotted lines are the estimates. The results show the NN with hybrid learning has capability to perform the generalization successfully.

**Fig.5. AOAs (DOAs) for four users**

4 Neural Network for Beamforming

Neural networks are also successful in beamforming applications. Instead of using a RBF NN and train it, we can assume that we can use a large number of neurons in the neural network and to design a radial basis function (there is no need of training) NN with exact solution-RBE. The advantages are that we do not lose a time for training and that the mapping function is passing exactly through the points represented by the training (designing) pairs. The disadvantage is that we must use large number of neurons in the hidden layer.

Fig.6 is presenting the results of RBF NN gained for array gain (radiation pattern) for 6 sources placed at mutual distance of 20°. It can be seen that NN successfully places five nulls and successfully receives the signal of interest from the source placed at 20.4°. The suppression of interference is about 30dB. Fig.7 is presenting the case when the sources are at mutual distance of 10°. For this case the number of neurons in the hidden layer was 60 since the closer source case needs more precise training. The interference suppression is more than 60dB. This is because of the smaller mse value while training.

**Fig.6 Gain for 6 users at mutual distance of 20°**

**Fig.7 Gain for 6 users at mutual distance of 10°**

Fig.8 and Fig.9 are presenting the results gained for antenna radiation pattern for the case when M=6 elemens, K=4 users at mutual distance of 10° (Fig.8) and 20° (Fig.9) and when the RBE was designed with 151 training samples (angle step of 1°). In Fig.8 the user where unity response is required is placed at 20.54°, and three interference users are placed at 30.54°; 40.54°; 50.54°. In Fig.9 the user where unity response is required is placed at 90.54°, and the three interference users are at 50.54°; 70.54°; 110.54°. It is obvious RBE performs generalization very well and null out the interference for the two scenarios.
For larger number of users and smaller mutual distance we should use smaller angle step while generating the training samples. Fig.10 is presenting the results gained for antenna radiation pattern for the case when M=10 elements, K=10 users at mutual distance of 15° and when the NN was designed with 91 training samples (angle step of 0.5°). The user where unity response is required is placed at 30.8°, and nine interference users are placed at 45.8°; 60.8°; 75.8°; 90.8°; 105.8°; 120.8°; 135.8°; 150.8°; 165.8°. The network again gives satisfactory performances for the testing sample that the network has never seen before.

5 Conclusions

The joint application of neural networks and antenna array systems was presented. Signal detection can be performed with trained RBF NN, PNN, and RBE. If it is a possibility of large number of neurons then PNN and RBE are superior. And if the real-time performances are of importance, the best choice is RBE providing additional antenna elements or training samples.

DOA estimation may be successfully performed by trained RBF NN, but applied for limited number of radiating sources, for sensor detection or like for example ground station observation and tracking of a low orbit satellite (or couple of them). A limitations should be expected for mobile systems where the number of users is large.

Similarly for beamforming we can conclude that it can be performed with trained RBF NN and RBE, and limitations are the same. Large number of radiating sources causes a necessity of huge number of training samples that will obstacle the training algorithm from convergence.

The main conclusion would be that the joint systems of neural networks and antenna array systems are very promising in providing elegant, cost effective and efficient solutions. So far they might be applied in sensor detection systems and tracking of a low orbit satellites. For more complicated user scenarios more complex neural structures and learning algorithms must be developed.

References:


