World Academy of Science, Engineering and Technology
International Journal of Physical and Mathematical Sciences
Vol:2, No:8, 2008

Application of the Neural Network to the Synthesis of Multibeam Antennas Arrays

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***Abstract*—**In this paper, we intend to study the synthesis of the multibeam arrays. The synthesis implementation's method for this type of arrays permits to approach the appropriated radiance's diagram. The used approach is based on neural network that are capable to model the multibeam arrays, consider predetermined general criteria's, and finally it permits to predict the appropriated diagram from the neural model. Our main contribution in this paper is the extension of a synthesis model of these multibeam arrays.

***Keywords*—**Multibeam, modelling, neural networks, synthesis, antennas.

I. Introduction

IN the domain of smart antenna, several methods of synthesis exist such as stochastic and determinist method [1,2, 3]. Considering the diversity of aims searched for by users, we don't find a general method of synthesis which is applicable synthesis to all cases, but rather an important number of methods to every type of problem. This diversity of solutions can be exploited to constitute a useful data base for a general approach of synthesis of a multibeam array.
In this paper, we are interest to present the neural networks method that will be applied to the synthesis of multibeam arrays. A big flexibility between features of the antennas array: amplitude of feeding, ondulation domain, and secondary lobe level… is introduced. Since, there is no restriction for the parameters' number of the system in entrance and exit.

II. Mutibeam Arrays

An array can form multiple narrow beams towards different directions. For example, suppose it is desired to form three beams towards the steering angles φ1, φ2, and φ3. The weights for such a multibeam array can be obtained by superimposing the weights of a single broadside array,[4] say w(m), steered towards the three angles. Defining the corresponding scanning phase's ψi = kd cosφi, i = 1, 2, 3, we have:

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$$a(m) = A_1 e^{-jm\psi_1} w(m) + A_2 e^{-jm\psi_2} w(m) + A_3 e^{-jm\psi_3} w(m) \qquad (1)$$

where m = 0,±1,±2, . . . ,±M and we assumed an odd number of array elements N = 2M + 1. The complex amplitudes A1, A2, A3 represent the relative importance of the three beams. The corresponding array factor becomes:

$$A(\psi) = A_1 w(\psi - \psi_1) + A_2 w(\psi - \psi_2) + A_3 w(\psi - \psi_3) \qquad (2)$$

and will exhibit narrow peaks towards the three steering angles. More generally, we can form L beams towards the angles φi, i = 1, 2. . . L by superimposing the steered beams:

$$a(m) = \sum_{i=1}^{L} A_i e^{-jm\psi_i} w(m), \quad m = 0, \pm 1, \pm 2, ..., \pm M \qquad (3)$$

where ψi = kd cosφi, i = 1, 2, . . . , L. For an even number of array elements, N = 2M, we replace Eq (3) with:

$$a(\pm m) = \sum_{i=1}^{L} A_i e^{\pm j(m-1/2)\psi_i} w(\pm m), \quad m = 1, 2, ..., M \qquad (4)$$

For either even or odd N, the corresponding array factor will be the superposition:

$$A(\psi) = \sum_{i=1}^{L} A_i w(\psi - \psi_i) \qquad (5)$$

The basic broadside array weights w(m) can be designed to achieve a desired sidelobe level or beam width. As the broadside beam w (m) is steered away from 90^o, the beamwidths will broaden. To avoid grating lobes, the element spacing d must be less the quantity d_0 (and greater than $d_0/2$):

$$d_0 = \min d_i \text{, where } d_i = \frac{\lambda}{1 + |\cos\phi_i|} \text{ ,i=1, 2... L} \qquad (6)$$

This minimum is realized at the beam angle closest to endfire. If the steering angles are closer to each other than about one -3dB beamwidth, the mainlobes will begin to merge with each other reducing the resolvability of the individual beams.

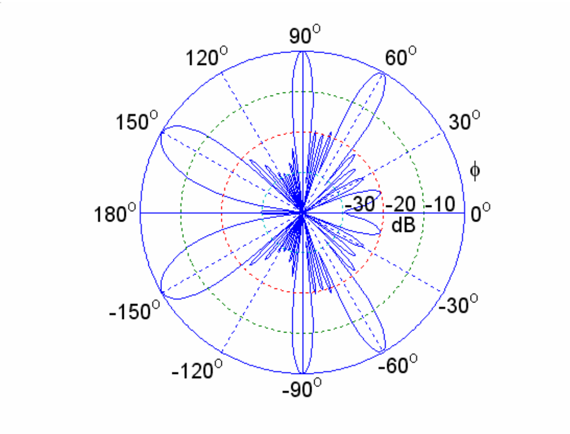

Fig. 1 Multi-beam arrays with R = 20 dB sidelobes in polar coordinates

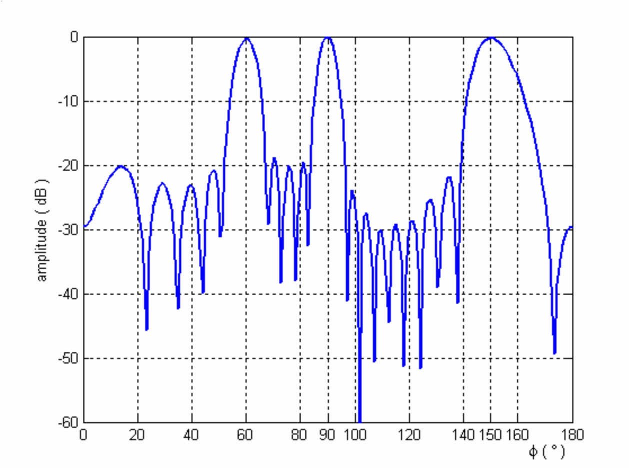

Fig. 2 Multi-beam arrays with R = 20 dB sidelobes

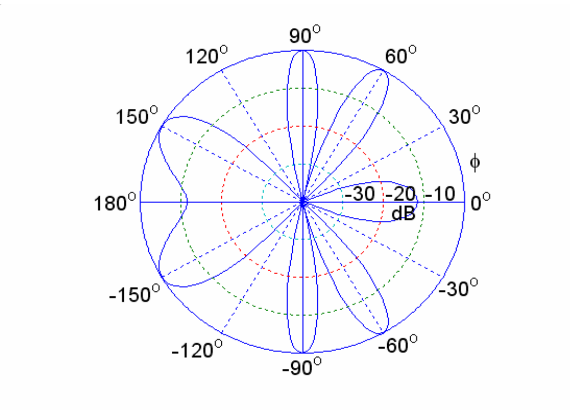

Fig. 3 Multi-beam arrays with R = 40 dB sidelobes in polar coordinates

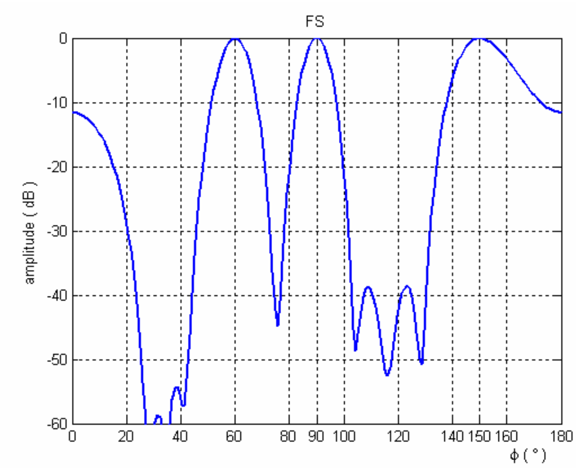

Fig. 4 Multi-beam arrays with R = 40 dB sidelobes

Figs. 1, 2, 3 and 4 shows the gains of two 20-element three-beam arrays with half wavelength spacing, and steered towards the three angles of 60°, 90°, and 150°. The broadside array was designed as a Taylor-Kaiser array with sidelobe level of R = 20 and R = 40 dB.

III. Formulation

The artificial neuron networks (RNA) are the inspired mathematical models of the structure and the behaviour of biologic neural. They are composed of interconnected units that we call formal or artificial neural capable to achieve some particular functions. The RNA permits to approach nonlinear and high complex relations of complexity degrees. Cells of entrances are destined to collect information that is transformed by the hidden cells until cells of exit. This system possesses one or several hidden layers (figure.1). Generally we use in this type of networks a sigmoid activation function.

$$g(x) = \frac{1}{1+\exp(-x)} \tag{7}$$

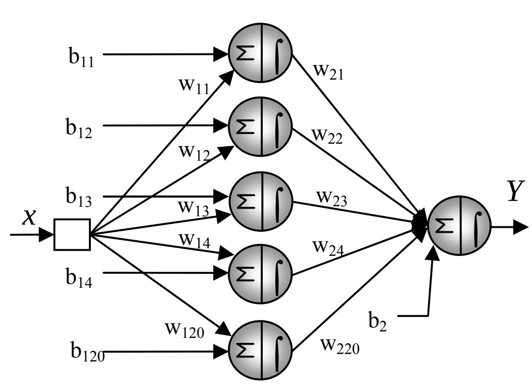

Fig. 5 Network architecture

The training in this type of network, consist in a practice. We present entrance for the network and ask him to modify their attitudes to recover the corresponding exit [5,6].

The algorithm consists at the first time to propagate entrances until we get one calculated exit by the network. The second stage compares the calculated exit to the known real exit. We modify the synaptic weights then to have in the next iteration a minimum mistake committed between the calculated exit and known exit. We retro-propagate the mistake committed until the layer of entrance then while modifying the weight.

The expression of the new values of synaptic weight joining neurons is given by the following relation [4]

$$w_{ij}(k+1) = w_{ij}(k) + \lambda D_i P_i \qquad (8)$$

With

λ : Training step

P_j: the entrance of the j neuron.

W_{ij}: Weight associated to the connection of the i neuron toward the j neuron.

D_i: Drifted of mistake of the i neuron.

IV. Results

The neural network is constructed by an iterative process on the elements of database content in the training file. Every iteration permits to minimize mean square error between exits of the RNA and given elements. We will retail here the procedure of implementation of the neural network. We take the case of survey a network presenting the radiance diagram of a straight network of N =20 beaming elements. This network is called perceptron organized of three layers: the first and the third are respectively the entrance layer and the exit layer organized by a lonely neuron, the second is the hidden layer. This procedure must be preceded by a training stage to fix the different parameters of the network. Stages of advanced conception are general and can applied on any type of perceptron network whatever is the number of entrances and the number of hidden layers.

A. Training Phase

After several tests, a multilayer network is kept with the following topology:

- A neuron in the layer of entrance representing the level of lobes wanted.
- 20 neurons in the hidden layer
- A neuron in the layer of exit representing the law of amplitude for a symmetrical network to 20 beaming elements.

Once the architecture of the network has been decided, the phase of training permits to calculate synaptic weights taking to every formal neuron. It uses the algorithm of Quasi-Newton [5, 6]. This algorithm consists in presenting to the network of training examples of training, games of activities of entrance neurons as well as those of activities of exit neurons. We examine the gap between the exit of the network and the exit wished and we modify synaptic weights of connections until the network produces a very near exit from the desired one. The training by MATLAB is supervised [6]. Linear functions and hyperbolic tangent, are affected to the hidden layer and the layer of exit respectively. The essential aim here [9], is to find the best training that permits to give a good model.

Several tests are necessary. We have to act on parameters influencing on the training. These parameters are:

- Number of neurons in the hidden layer,
- Activation function,
- Training step.

The training phase represents the evolution of the mean square error between exits of the RNA and samples given according to the number of epochs, the gotten final error is 0.00034509.

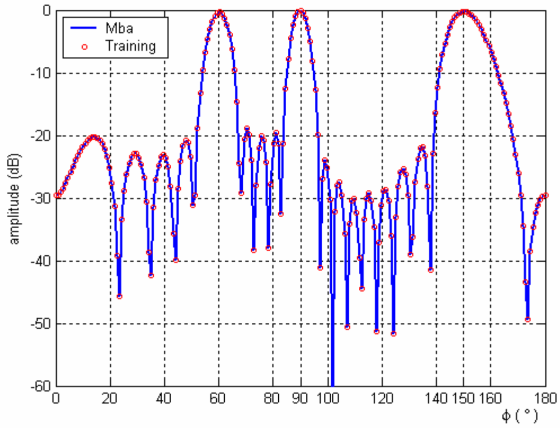

Fig. 6 Multi-beam arrays with R = 20 dB sidelobes

Figs. 4, 6, 7, 8 and 9 present synthesis results of mltibeam arrays. We present in this part the multibeam arrays and the training phase.

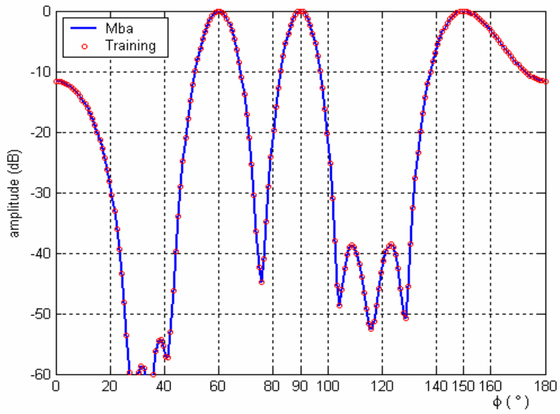

Fig. 7 Multi-beam arrays with R = 40 dB sidelobes

The relative amplitudes of the three beams were equal to unity. We note the broadening of the beam widths of the larger beam angles. The left array has narrower mainlobes than the right one because its sidelobe attenuation is less. But, it also exhibits more constructive interference between mainlobes causing somewhat smaller sidelobe attenuations than the desired one of 20 dB.

V. Conclusion

In this paper, we only developed a technique of synthesis of multibeam arrays. We used multilayer neural networks of Feed forward type, in particular, the multilayer MLP, because this type is adapted for our theory. We are interested to the multibeam arrays, particularly to their modelling and optimization by neural network. The neural approach reduced the resolution time at the application phase or generalization. The precision of the model constructed depends on the data base of the training phase. However, multilayer neural networks present the inconvenience in time resolution due to the training phase and the absence of a general law to define the architecture of the network.

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