A Phased Arrays Beams Synthesis Using Neural Network Model

FADLALLAH Najib[1], RAMMAL Mohamad[2], VAUDON Patrick.[1]

[1] Limoges University, IRCOM- Equipe Electromagnétisme
123, Avenue Albert Thomas – 87060 Limoges – France

[2] Lebanese University, Equipe Radiocom
Saida – Liban

Abstract: **-** This work proposes a novel approach to arbitrary phased-array with a neural adaptive synthesis beamforming system. This system combines feedforward (FF) artificial neural network (ANN) with a backpropagation (BP) learning algorithm and linear antenna arrays. The proposed neural network allows the beamforming synthesis of array antenna steered beams and the creation of null in prescripted direction of interfering signals by controlling only the phase excitation of each element. Simulation results confirm the efficacy of the proposed scheme.

***Key- Words* -** *Adaptive antenna, Beamforming, Neural Network, Diversity, Sectorisation.*

1. Introduction

Adaptive antenna arrays require extensive modelling and simulations prior to their practical implementation [1]. In a smart antenna arrays system, the beam is positioned electronically by adjusting the phase between elements of an array in a predetermined manner. This operation of synthesis [2] for antenna arrays is essential in the conception of an optimised antenna. This way requires a faster and more accurate control of the radiation of antennas [3, 4]. The required processing has the task of maximizing the gain in the direction of the user, and canceling undesired signals, like inter-user interference, multipath and jammers, which highly degrade the system performances that use the hypothesis of uncorrelated noise [5]. In technical literature, the design of digital beam-formers [6] has been accomplished considering different optimal criteria (corresponding to different design requirements), which are generally reduced to the optimization of a nonlinear function, using standard techniques of optimization. Unfortunately, these optimal criteria lead to the optimization of a nonlinear function, which can be onerous from a computational point of view. Neural Networks (NN) [7] reduce remarkably the computation time, thanks to their massive parallelism, fast convergence rates, and very large scale integration (VLSI) implementation. In fact, although NN consume time in the learning phase, they are very fast in the array synthesis processing, therefore allowing their use in real time.

The Neural Networks have been shown [8, 9] to be useful in the control of phased arrays for detection and signal location. In particular, neural networks can control arrays with various types of element and network failures and can still perform accurate signal location, despite the errors. Since a trained neural network has output nodes that correspond to input waves from specific angular directions.

In this paper we explore the neural network model feasibility of realizing beams steering and reducing interfering signals in mobile communications. We use a phase excitation control to create desired beams and we present typical examples to demonstrate the efficiency of the proposed method.

2. Synthesis Problem Formulation

Mathematically, the purpose of numerical synthesis techniques is to minimize the error between the required radiated function and the computed one. The Madsen technique [10] of optimisation is used to build the base of training of our neural network**.** This method consists of a resolution of nonlinear systems equations with the minimax criterion. The result obtained is an equiripple synthesis pattern [2].

The angular behavior of the far field E of a linear spaced array of 2N radiators can be written as

$$E(\theta_j) = \sum_{n=1}^{2N} I_n e^{jK_0 x_n \sin(\theta_j)} \quad (1)$$

With I_n, the complex weighting coefficient, x_n the position of the *n*th element.

Desired patterns are usually complex, and optimal realisable patterns can only be defined with respect to some error criterion. We will consider the minimax norm, defined as

$$Err(\theta_j) = W_j . \max_j \left\| E_c(\theta_j) - E_d(\theta_j) \right\|, \quad j=1,\ldots,M \quad (2)$$

Where *M* is the number of the sampled angular direction, *E*d is the required pattern field, and *E*c is the calculate pattern field. In pattern matching synthesis by minimax criterion, error weighting (W_j) in each direction can be adjusted to specify the desired levels of array pattern. This property may be used to steer the beam in all possible directions and to cancel interfering sources operating at the same frequency as that of the desired source, providing a spatial separation, which is large enough.

With this norm we have equal relative error (equal decibel ripple) in the pattern region and equal side lobes in the side-lobe region. For the real field synthesis case, eqn. 1 is taken and the excitation distribution is symmetrical and conjugated with the array centre. The computed formulation is:

$$Ec(\theta_j) = \sum_{n=1}^{N} I_n \cos(k_0 x_n^{'} \sin(\theta_j)) \quad (3)$$

With $x_n^{'}$, the relative position of the *n*th element with the array centre.

In the case of power synthesis, the error to minimise is equal to the difference between the modulus of the computed function and the required one. It is proved [11] that the real synthesis is preferable in case of directive beam.

3. Neural Networks For Steering Lobes And Interference Cancellation

The architecture of the beamforming neural network (BFNN) consists of an antenna measurement input pre-processing, an artificial neural network, and an output post-processing. Pre-processing and post-processing configure the network interfaces to perform particular functions [12]. The neural network approximates the function that we model by adapting its internal structure to map the problem space. This section briefly summarizes the purpose and interaction of these functional elements.

3.1 Pre-processing

Network pre-processing exploits antenna expertise to simplify and enhance neural network inputs. It removes redundant or irrelevant information, eliminates artificial discontinuities in the input function space, and reduces problem inputs to a small set of relevant information. In the pre-processing two steps should be done. The first step of pre-processing divides the space in 17 sectors, repeated every 10° in the interval from -85 degrees to +85 degrees inclusive. More accurate space division sectors can be reached by increasing the number of element arrays. The input vector to the entry of network is in the form of a 17 bit binary code (one bit for each sector); all of the bits were set to zero except two (+1 and -1) or (+1 and +1). A bin input of +1 indicates a source exactly on (main lobe) in the sector, the bin location of 0 represents no source in the sector and the bin location of -1 indicates a null interfering in the sector. This step has the advantage to decrease considerably the number of unknown variables. Convergence may then be achieved more rapidly.

The second step of pre-processing reduces the ponderation phase discontinuities between consecutive array elements. Discontinuities make it difficult for the network to learn the mapping from a small discrete set of training points. To eliminate this difficulty we use the sine and cosine of the phase ponderations as final processed inputs. We train the output nodes to emit values between -1 and +1, inclusive, which represent the cosine and sine of phase for each antenna element.

3.2 Neural Architecture and Network Training

The choice of neural network architecture is crucial for developing a successful application. In our case we chose feed-forward network (FF) for antenna's synthesis application. Because first it solves complicated non linear (NL) function models. Second it makes possible the increasing of hidden layers number and finally for its speed of convergence. For (FF) the computation will only produce correct results if the network has been adequately trained with pairs of inputs and their corresponding outputs. The training set was formed by some significant results obtained from the above method of synthesis. The Network weights are adjusted using a modified gradient descent-learning algorithm known as backpropagation (BP). The hidden and output layers use hyperbolic tangent (*tanh*) functions for being active. The resulting output gives (2xN) values.

3.3 Post-processing

For our simulation an eight elements array antenna is used. Each output vector contains eight cosines and eight sines for the phase differences between antenna elements. This technique performs well for two steering lobes and steering lobe with null interfering in any desired direction.

4. Simulation Results

In each case, the aim of the search is to find the phase of each antenna array element, for steering lobes and for power null direction.

Table 1 shows the values of neural synthesis simulation for an 8 element linear array obtained from FF with BP.

Neural Synthesized Excitations (phases)			
N	*Sector 2, Sector 5*	*Sector 2, Sector 9*	*Sector 6, sector 8*
	-49° (steering lobe) and -20° (interfering)	*-50° (steering lobe) and 20° (interfering)*	*-10° (steering lobe)and 10° (interfering)*
	ϕ	ϕ	ϕ
1	240.8921	-137.8729	-144.9535
2	50.9238	20.7271	-59.8521
3	181.2511	172.4768	-37.4712
4	-50.2685	-86.1235	-10.6771
5	50.2685	86.1235	10.6771
6	-181.2511	-172.4768	37.4712
7	-50.9238	-20.7271	59.8521
8	-240.8921	137.8729	144.9535

Table 1*: Excitations for different steering lobes and interference nulling*.

Figures (1, 2 and 3) show the simulation results for the desired signal and to place nulls in the direction of the interfering signals.

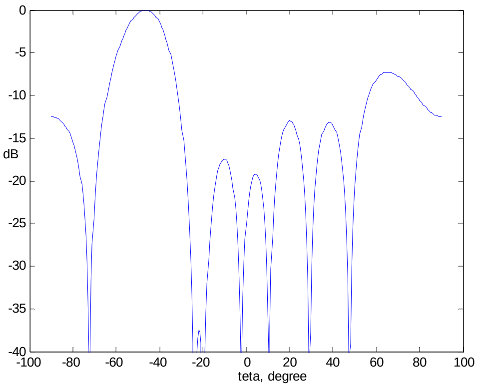

Fig. 1. *Steering lobe in sector 2 (-49°) and interference nulling in sector 5 (-20°).*

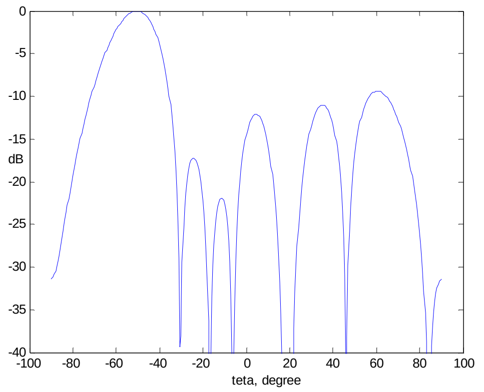

Fig. 2. *Steering lobe in sector 2 (-50°) and interference nulling in sector 9 (20°).*

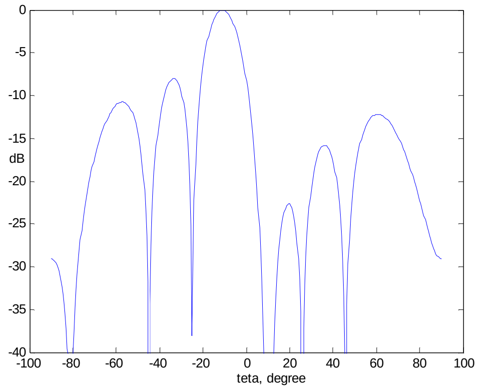

Fig. 3. *Steering lobe in sector 6 (-10°) and interference nulling in sector 8 (10°).*

Table 2 shows the simulation results for two steering lobes in some desired directions.

	Neural Synthesized Excitations (phases)		
N	*Sector 4, Sector 7*	*Sector 7, Sector 9*	*Sector 6, Sector 12*
	49° and 22° (steering lobes)	*-20° and 0° (steering lobes)*	*-30° and 31° (steering lobes)*
	ϕ	ϕ	ϕ
1	95	345	-355
2	-165	15	-175
3	-75	35	-180
4	50	85	0
5	-50	-85	0
6	75	-35	180
7	165	-15	175
8	-95	-345	355

Table 2*: Excitations for two steering lobes.*

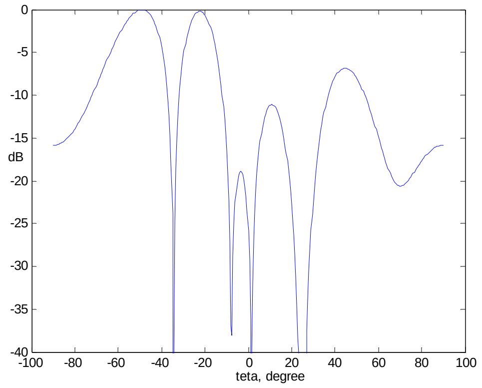

Fig. 4. *Two Steering lobes in sector 4 (-49°) and in sector 7 (-22°).*

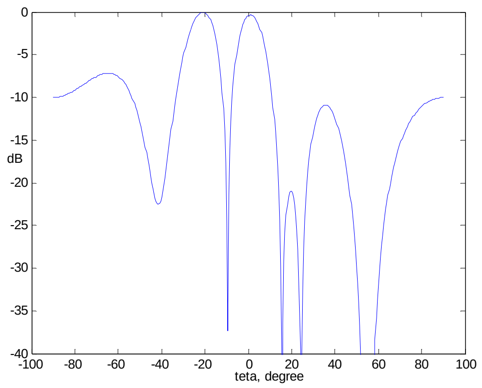

Fig. 5. *Two Steering lobes in sector 7(-20°) and in sector 9 (0°).*

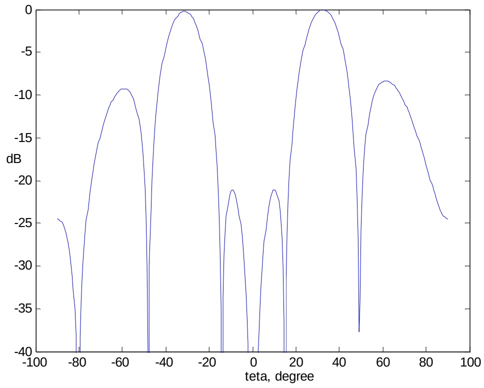

Fig. 6. *Two Steering lobes in sector 6(-30°) and in sector 12 (31°).*

We can observe from figures that this neural model is able to compute the phases for multibeam arrays of two steering lobes (Figures 4, 5 and 6).

As the figures indicate, we can observe the performance of our network. The network has shown its ability to generate reasonable results in all checked cases. This algorithm holds not only for the examples presented above, but also appears to be general for all cases of synthesized desired characteristics of steered beams, an adaptive algorithm used to adapt the weights of the array in order to track the desired signal and to place nulls in the direction of the interfering signals.

4. CONCLUSION

The presented method is very practical for neural network implementation. The convergence and the generalization of the results are efficiently reached and the obtained "not trained" solutions are very accurate. The neural approach based on the (FF) Neural Network with BP shows good simulation results and allows a real time synthesis of desired steering beam with nulling interference directions.

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