Neural Network Synthesis Beamforming Model For Adaptive Antenna Arrays

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Abstarct: - *This work proposes a neural adaptive synthesis 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 beam with low side level and the creation of null in prescripted direction of interfering signals by controlling the amplitude and the phase excitation of each element.*

Key-Words: - 1. Phased Array, 2. Beamforming, 3. Neural Network, 4. Synthesis Antenna, 5. Backpropagation, 6. Preprocessing and PostProcessing.

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]. 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 [4].

The Neural Networks shown [5, 6] can 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 and amplitude excitation control to create desired beam and we present typical examples to demonstrate the efficiency of the proposed method.

2. SYNTHESIS PROBLEM FORMULATION

The synthesis of antenna arrays is defined as being the research of the relative parameters positions and the current of excitations (amplitudes and phases) of the sources constituting the array in order to approach the desired function of radiation as well as possible [7].

The angular behavior of the far field E of a linear uniformly 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 weighting coefficient, x_n the position of the *n*th element.

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

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

Where *M* is the number of the sampled angular direction, *E*d is the required pattern field, and *E*c is the calculated pattern field.

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. Since the above method is not practical for real time implementation, an adaptive algorithm must be 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.

3. NEURAL NETWORKS

The choice of neural network architecture is crucial for developing a successful application. The neural feed-forward network with a backpropagation learning algorithm is able to solve nonlinear function models (complicated to solve). The neural network training set was formed by some significant results obtained from the above method of synthesis. The main components of the neural beamformer include preprocessing, a neural network, and postprocessing, Fig. 1.

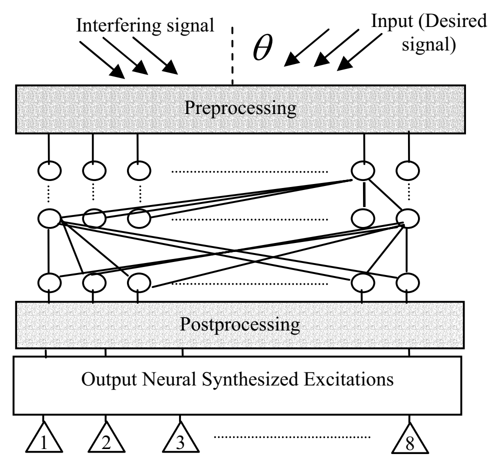

Fig. 1. A neural network Synthesis model

Preprocessing and postprocessing configure the network interfaces to perform particular functions, which are in our case synthesis and steer signal. The neural network approximates the function, that we are modelling by adapting its internal structure to map the problem space.

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 one (+1) or two (+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.

Post-processing: For our simulation an eight elements array antenna is used. Each output vector contains eight values of amplitude, eight cosines and eight sinuses for the phase differences between antenna elements. This technique performs well for steering lobe with low side level and steering lobe with null interfering in any desired direction.

4. SIMULATION RESULTS FOR NEURAL NETWORK SYNTHESIS BEAMFORMING

In adaptive antenna the flexibility of the array weighting, which should be adjusted to specify the array pattern, is an important property. This property may be exploited 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 that the spatial separation is large enough.

4.1. Neural Network Synthesis Model For Steering Lobe With Low Side Lobe Level

In this paragraph, we present (table 1) the neural synthesis simulation results (Fig. 2) for the steering lobe with a low side lobe level.

Neural Synthesized Excitations						
	-11°, sector (8)		-33°, sector (6)		-49°, sector (4)	
n	I	ϕ	I	ϕ	I	ϕ
1	0.3317	-118.76	0.3316	-342.00	0.3317	-467.758
2	0.5334	-82.422	0.5333	-245.03	0.5332	-334.1824
3	0.8181	-50.604	0.8182	-146.68	0.8184	-200.7474
4	0.9997	-18.502	1.0000	-49.21	1.0000	-66.7905
5	0.9997	18.502	1.0000	49.21	1.0000	66.7905
6	0.8181	50.605	0.8182	146.68	0.8184	200.7474
7	0.5334	82.422	0.5333	245.03	0.5332	334.1824
8	0.3317	118.758	0.3316	342.006	0.3317	467.758

Table 1: Excitations for different steering lobe with low side lobe level

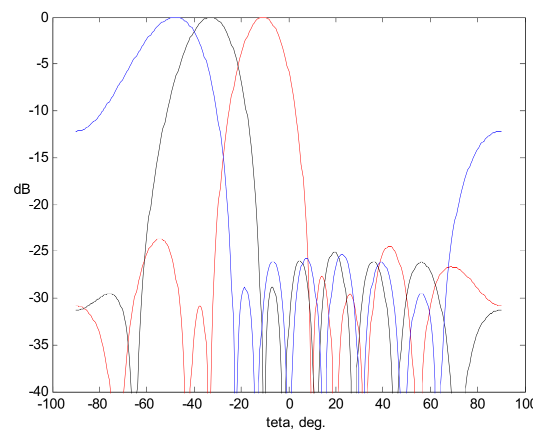

Fig. 2. Adapted pattern of eight elements linear array for desired lobe with low side lobe level at θ= -10° (sector 8), -33° (sector 6), -48° (sector 4) respectively

4.2. Neural Network Synthesis Model For Steering Lobe With Interference Nulling

The interference is one of the most important considered problems, operation and maintenance of mobile communications systems. Undesired signals can be attenuated by appropriate phase and amplitude excitation.

Table 2 presents the results of neural synthesis simulation. These simulations have been done (Fig. 3, 4 and 5) to obtain the desired signal and to place nulls in the direction of the interfering signals.

Neural Synthesized Excitations						
N	0°(interfering), 28°(steering). Sectors (9 and 12)		-40°(interfering), -8°(steering). Sectors (5 and 8)		-60° (interfering), -22°(steering). Sectors (3 and 7)	
	I	ϕ	I	ϕ	I	ϕ
1	0.260	-54.358	0.1900	-84.524	0.270	91.058
2	0.499	-148.392	0.4501	-63.064	0.499	165.202
3	0.810	126.703	0.7802	-38.505	0.800	-118.100
4	1.000	42.498	0.9971	-12.840	0.999	-39.620
5	1.000	-42.498	0.9971	12.840	0.999	39.620
6	0.810	-126.703	0.7802	38.505	0.800	118.100
7	0.499	148.392	0.4501	63.064	0.499	-165.202
8	0.260	54.358	0.1900	84.524	0.270	-91.058

Table 2: Excitations for different steering lobes and interference nulling.

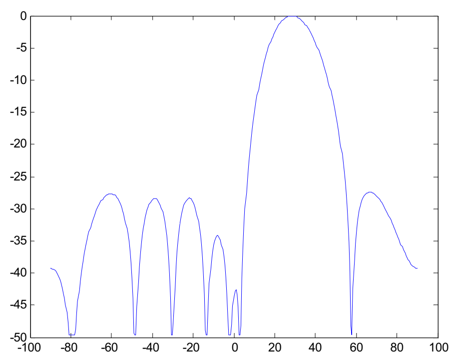

Fig. 3. Interference nulling 0° at (sector 9) and steering lobe at 28° (sector 12).

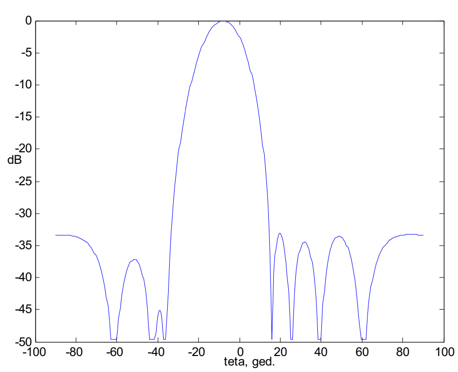

Fig. 4. Interference nulling at -40° (sector 5) and steering lobe at -8° (sector 8).

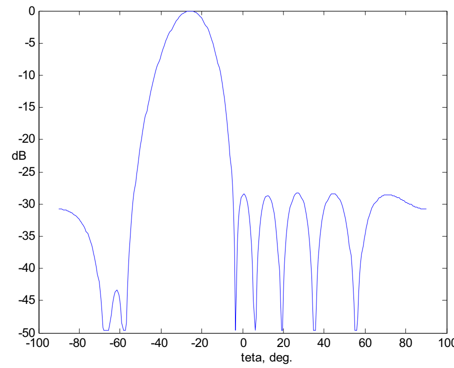

Fig. 5. Interference nulling at -60° (sector 3) and steering lobe at -22° (sector 7).

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

5. 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

8. REFERENCES

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