Smart Adaptive Array Antennas For Wireless Communications

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ABSTRACT

Smart adaptive antenna technology is considered to be the last technology frontier that has the potential of leading to large increases in systems performance. Time domain techniques have been extensively exploited. Space domain techniques, on the other hand, have not been exploited to the same extent. When applied to wireless, the benefits of smart adaptive array a antennas are as follows: (i) increased covered, which is important in the early stages of life cycle, (ii) increased capacity, which is important in the later stages of life cycle, (iii) improved link quality, (iv) reduced costs and increased return on investment, (v) lower handset power consumption, and (vi) assistance in user location by means of direction finding.

This paper discusses an experimental neural network based smart antenna capable of performing direction finding and the necessary beamforming. The Radial Basis Function Neural Network (RBFNN) algorithm is used for both tasks and for multiple signals. The algorithm operates in two stages. The field of view of the antenna array is divided into spatial sectors, then each network is trained in the first stage to detect signals emanating from sources in that sector. According to the outputs of the first stage, one or more networks of the second stage can be activated so as to estimate the exact location of the sources. No a priori knowledge is required about the number of sources, and the networks can be designed to arbitrary angular resolution. Some experimental results are shown and compared with other algorithms, such as, the Fourier Transform and the MUSIC algorithm. The comparisons show the superior performance of the RBFNN and its ability to overcome many limitations of the conventional and other superresolution techniques, specifically by reducing the computational complexity and the ability to deal with a large number of sources.

I. INTRODUCTION

A smart antenna consists of an antenna array combined with signal processing in both space and time. The concept of using antenna arrays and innovative signal processing has been used before in the radar and aerospace technology [1]. Until, recently, however, cost effectiveness has prevented their use in commercial systems. The emergence of very fast and low-cost digital signal processors have made smart antennas a practical possibility for mobile communications systems.

Recently, the application of smart antenna arrays has been recommended for mobile communications systems to overcome the problem of limited channel bandwidth, satisfying a growing demand for a large number of mobiles on communications channels. Smart antennas, help in improving the system performance by increasing spectrum efficiency and channel capacity, extending range coverage, and steering multiple beams to track several mobiles. They are also effective in reducing delay spread, multipath fading, co-channel interferences, and bit error rate (BER). Delay spread and multipath fading can be reduced with an antenna array that is capable of forming beams in certain directions and nulls in others, thereby canceling some of the delayed arrivals. Typically, in the transmit mode, the array focuses energy in the desired direction, which yields in the reduction of multipath reflections and delay spread. On the other hand, in the receive mode, the array provides compensation in multipath fading by adding the signals emanating from other clusters after compensating for delays, as well as by canceling delayed signals emanating from directions other than that of the desired mobile. The increase in the spectrum efficiency, is a result of the capability of the antenna array to provide virtual channels in an angle domain (Spatial Division Multiple Access), which means that one can multiplex channels in the spatial dimension just as in the frequency and time dimensions [2].

Perhaps, the main merit of a smart antenna system is its capability to cancel co-channel interferences. Co-channel interference in the transmit mode is handled by focusing the main antenna beam in the direction of a desired signal and nulls in the directions of other receivers, as shown in Figure 1. The ability to smoothly track users with main lobes and interferers with null insures that the link budget is constantly maximized. This effect is similar to a person's hearing. When

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one person listens to another, the brain of the listener collects the sound in both ears, combines it to hear better and determines the direction from which the speaker is talking. If the speaker is moving, the listener, even if his eyes are closed, can continue to update the angular position based solely on what he hears. The listener also has the ability to tune out unwanted noise, interference and focus on the conversation at hand. In the receive mode, co-channel interference is reduced by knowing the location of the signal's source (mobile) and utilizing interference cancellation.

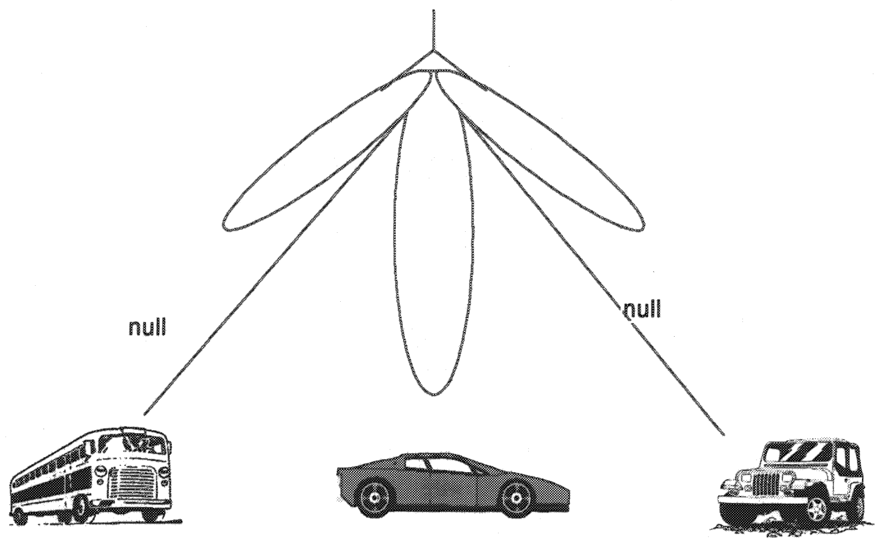

Figure 1. The principle of an adaptive array-based smart antennas. The antenna directs its main beam towards the desired mobile and nulls towards interfering mobiles.

There are many algorithms used to update the array weights, each with its speed of convergence and required processing time [3, 4]. Algorithms also exist that exploit properties of signals to eliminate the need of training signals in some circumstances. In this paper, neural networks are used along with adaptive array antennas to yield truly smart antennas that can be used for both , determining the direction of arrival of a signal (DOA) and for achieving beam-forming in real time. The new approach is based on dividing the field of view of the antenna array into angular spatial sectors, then train each network in the first stag of the architecture to detect signals emanating from sources in that sector. Once this first step is performed, one or more networks of the second stage (DOA estimation stage) can be activated so as to estimate the exact location of the sources. The main advantage of this new approach is a dramatic reduction in the size of the training set required to train each smaller neural network. Several theoretical and experimental results are shown to support the validity of this approach.

II. DIRECTION FINDING OF MOBILE SIGNAL

Consider a linear array composed of L elements. Let M (M<L) be the number of narrowband plane waves, centered at frequency ω_0 impinging on the array from directions $\{\theta_1 \quad \theta_2 \quad \cdots \quad \theta_K\}$ as shown in Figure 2. . Using complex signal representation, the received signal at the ith array element can be written as,

$$x_i(t) = \sum_{m=1}^{M} s_m(t) e^{-j(i-1)k_m} + n_i(t) \qquad ; i = 1,2,\cdots L \tag{1}$$

where $s_m(t)$ is the signal of the mth wave, $n_i(t)$ is the noise signal received at the ith sensor and

$$k_m = \frac{\omega_0 d}{c} \sin(\theta_m) \tag{2}$$

where d is the spacing between the elements of the array, and c is the speed of light in free space. Using vector notation we can write the array output in a matrix form:

$$\mathbf{X}(t) = \mathbf{A}\,\mathbf{S}(t) + \mathbf{N}(t) \tag{3}$$

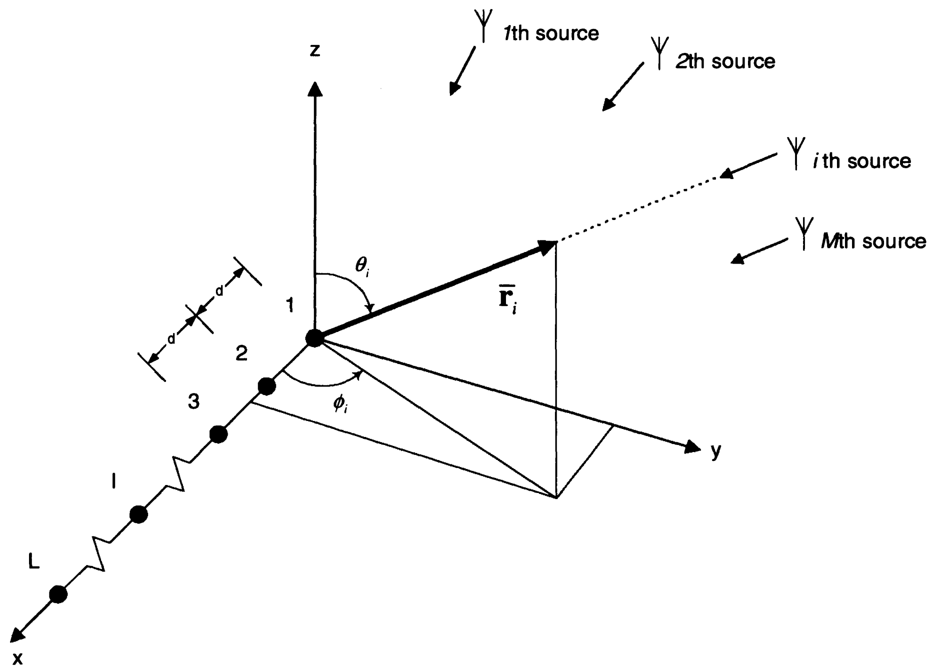

Figure 2. Geometry of Linear array with M elements

Where, **X** (t), **N**(t) and **S**(t) are given by:

$$\mathbf{X}(t) = [x_1(t) \quad x_2(t) \quad \cdots \quad x_L(t)]^T \tag{4}$$

$$\mathbf{N}(t) = [n_1(t) \quad n_2(t) \quad \cdots \quad nL(t)]^T \tag{5}$$

$$\mathbf{S}(t) = [s_1(t) \quad s_2(t) \quad \cdots \quad s_L(t)]^T \tag{6}$$

In (4) and (5) and (6) the superscript "T" indicates the transpose of the matrix. Also in (3) **A** is the LxM steering matrix of the array towards the direction of the incoming signals defined as:

$$\mathbf{A} = [a(\theta_1) \quad \cdots \quad a(\theta_m) \quad \cdots \quad a(\theta_M)] \tag{7}$$

where $\mathbf{a}(\theta_m)$ corresponds to

$$\mathbf{a}(\theta_m) = [1 \quad e^{-jk_m} \quad e^{-j2k_m} \quad \cdots \quad e^{-j(L-1)k_m}] \tag{8}$$

Assuming that the noise signals $\{n_i(t), i = 1:L)\}$, received at the different sensors, are statistically independent, white noise signals, of zero mean and variance σ^2 and also independent of **S**(t) , then the received spatial correlation matrix, **R**, of the received noisy signals can be expressed as:

$$\mathbf{R} = \mathrm{E}\{\mathbf{X}(t)\mathbf{X}(t)^H\} = \mathbf{A}\,\mathrm{E}[\mathbf{S}(t)\mathbf{S}^H(t)]\mathbf{A}^H + \mathrm{E}[\mathbf{N}(t)\mathbf{N}^H(t)] \tag{9}$$

In the above equation, "H" denotes the conjugate transpose. The antenna array can be thought of as performing a mapping G: $\mathbf{R}^M \to \mathbf{C}^L$ from the space of the DOA, $\{\Theta = [\theta_1, \theta_2, \cdots, \theta_K]^T\}$ to the space of sensor output $\{\mathbf{X}(t) = [x_1(t) \quad x_2(t) \quad \cdots \quad x_L(t)]^T\}$. A neural network is used to perform the inverse mapping F: $C^L \to R^M$. The algorithm described in this paper for the problem of direction finding is based on using radial basis function neural networks to approximate this inverse mapping F. Note that a Radial Basis Function Neural Network can approximate an arbitrary function from an input space of arbitrary dimensionality to an output space of arbitrary dimensionality [5-6]. The RBFNN consists of three layers of nodes, the input layer, the output layer and the hidden layer. The input layer is the layer where the inputs are applied, the output layer is the layer where the outputs are produced. The RBFNN is designed to perform an input-output mapping trained with examples. The purpose of the hidden layer in a RBFNN is to transform the input data from an input space of some dimensionality to a space of higher dimensionality K. The rationale behind this transformation is based on Cover's theorem [7] which states that an input/output mapping problem cast in a high-dimensionality space nonlinearly is easier to solve. The nonlinear functions that perform this transformation are usually taken to be Gaussian functions of appropriately chosen means and variances. An ad-hoc procedure is used to determine the widths (standard deviations) of these Gaussian functions. According to this procedure the standard deviation of a Gaussian function of a certain mean is the average distance to the first few nearest neighbors of the means of the other Gaussian functions. The aforementioned unsupervised learning procedure allows you to identify the weights (means and standard deviations of the Gaussian functions) from the input layer to the hidden layer. The weights from the hidden layer (see Figure 3) to the output layer are identified by following a supervised learning procedure, applied to a single layer network (the network from hidden to output layer). This supervised rule is referred to as the *delta rule*. The delta rule is essentially a gradient decent procedure applied to an appropriately defined optimization problem. Once training of the RBFNN is accomplished, the training phase is complete, and the trained neural network can operate in the performance mode (phase). In the *performance (testing) phase*, the neural network is expected to generalize, that is respond to inputs that it has never seen before, but drawn from the same distribution as the inputs used in the training set. One way of explaining the generalization exhibited by the network during the performance phase is by remembering that after the training phase is complete the RBFNN has established an approximation of the desired input/output mapping [8]. Hence, during the performance phase the RBFNN produces outputs to previously unseen inputs by interpolating between the inputs used (seen) in the training phase.

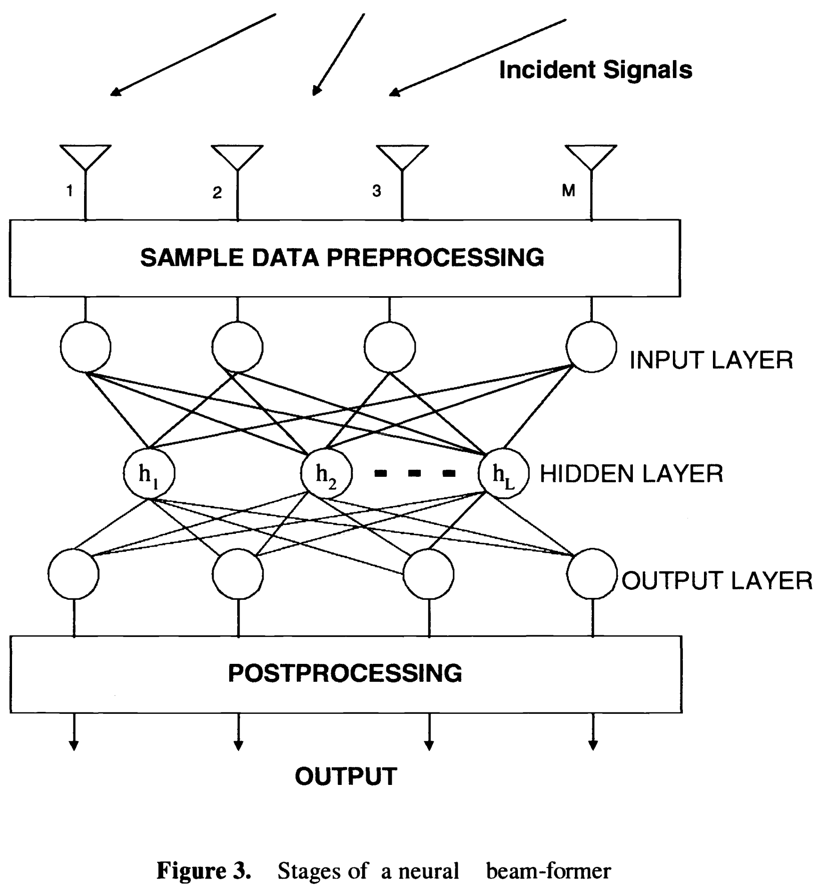

Figure 3. Stages of a neural beam-former

II.1. Sample Data Preprocessing

The input vector to the input layer of the network is the upper triangular half of the spatial correlation matrix **R** that can be organized as an L(L+1) dimensional vector of real and imaginary parts denoted **b**. This procedure is illustrated in Table 1. The dimension of the hidden layer is equal to the number of the Gaussian functions L, which can be chosen to be equal to the number of total input/output pairs in the training set if perfect recall is desired. The input vector **b** is normalized by its norm prior to being applied at the input layer of the neural network, i.e.

$$\mathbf{z} = \frac{\mathbf{b}}{\|\mathbf{b}\|} \tag{10}$$

$$\mathbf{R} = \begin{bmatrix} r_{11} & r_{12} & r_{13} \\ r_{21} & r_{22} & r_{23} \\ r_{31} & r_{32} & r_{33} \end{bmatrix} \qquad \mathbf{b} = \begin{bmatrix} r_{11} & r_{12} & r_{13} & r_{22} & r_{23} & r_{33} \end{bmatrix}$$

Table 1. Correlation matrix reduction

It should be noted here that training a single neural network to detect the angle of arrival of multiple sources is not an easy task. The exhaustive training involved becomes prohibitive for more than three or four sources, since the number of possible training data combinations is enormous. To circumvent this problem multiple, but smaller, neural networks are employed. Each network then tracks a smaller number of sources within a smaller angular sector.

III. THE NEURAL MULTIPLE SOURCE TRACKING (N-MUST) ALGORITHM

The Neural Multiple Source Tracking (N-MUST) algorithm is also based on the radial basis function neural networks (RBFNN), but it is composed of two stages, the *tracking* stage and the *estimation* stage. In the first stage, a number of RBFNNs are trained to perform the detection phase, while in the second stage another set of networks is trained for the direction of arrival estimation phase. When networks detect one or more sources in the first stage, the corresponding second stage networks are activated to perform the direction of arrival (DOA) estimation step. No prior knowledge of the number of sources present is required.

III.1 Tracking Stage

In this approach, labeled the Neural Multiple Source Tracking (N-MUST) algorithm, the antenna array can track an arbitrary number of mobile users (sources) without prior knowledge of the number of mobile users. As shown in Figure 3, there are two stages of RBFNN's. The first stage is the "detection stage" which consists of P RBFNNs, each focusing on a sector of width θ_W. The entire angular spectrum (field of view of the antenna array) is divided in P sectors. The p^{th} ($1 \le p \le P$) RBFNN is trained to determine if one or more signals exist within the $[(p-1)\,\theta_W,\ p\theta_W)]$ sector. If there are any signals present in the corresponding sector, the neural network will give the value 1 for an answer. Otherwise, the network will register a zero as its output value. This information is then passed to the second stage, the "direction of arrival" stage, which estimates the angles of these signals. Each one of the P neural networks of the detection stage, has L (L+1) input nodes representing the correlation matrix **R** and one output node. The number of hidden nodes in the second layer is also L (L+1). To illustrate how a network is trained in the detection stage, let us consider a case where the network is required to track N_s sources in the $[10^0\ 20^0]$ sector with some angular separation $\Delta\theta$. We start the training with sources at -90^0, $-90^0+\Delta\theta,\ldots$, $-90^0+(N_s-1)\Delta\theta$. We use this vector of DOA to generate the correlation matrix **R** and the normalized vector **z**. We then select the subsequent DOA vectors as -88^0, $-88^0+\Delta\theta,\ldots$, $-88^0+(N_s-1)\Delta\theta$, -86^0, $-86^0+\Delta\theta,\ldots$, $-86^0+(N_s-1)\Delta\theta$ and so on. The target output of the network is set to "1" only when one or more of the angles in the DOA vector lies in the $[10^0\ 20^0]$ range; otherwise the target output of the network is zero. In the simulations performed, a network was tested with number of sources and angular separations different than it had seen in the training. The network was able to detect the presence of the sources correctly. This suggests that considering all possible combinations of number of sources and separations need not be considered for the detection phase.

III.2. DOA Estimation Stage

The second stage of neural networks is trained to perform the actual direction of arrival estimation. The P networks of the DOA estimation stage are assigned to the same spatial sectors as in the detection stage (see Figure 1). When the output of one or more networks from the first stage is 1, the corresponding second stage network(s) are activated. The input information to each second stage network is the correlation matrix **R**, while the output is the actual DOA of the sources. The number of hidden nodes is the same as the number of input nodes given by L(L+1). Consider a system with minimum source resolution of 2^0, a single neural network trained to track sources over the antenna's field of view (e.g.180^0 wide) could be trained for angular separations $\Delta\theta$ of 2^0,4^0,6^0, ...up to some $\Delta\theta$. This results in such a huge training set that the single neural network approach becomes impractical. However, by assigning different networks for different angular spatial sectors, smaller training sets are sufficient since the network is only required to track sources in a limited spatial region. For sectors 10^0-20^0 wide, it follows that the number of distinct locations of possible sources as well as the size of the training set are significantly reduced. Whereas most direction finding algorithms require the knowledge of the number of sources, in our approach we only need to specify the minimum angular resolution that the system is required to achieve.

IV. RESULTS

Figure 4 shows a linear array of 8 elements ($d=\lambda/2$) tracking 4 sources with different angular separations in the sector [-30^0 -11^0]. The input layer consisted of 72 nodes and the sources were assumed to be of equal power, 5 dB higher than the noise power. The estimated and the theoretical angles of arrivals were very close. Figure 5, demonstrates the RBFNN-based beamforming and null steering. The adapted pattern obtained from the network is shown (dotted curve) and compared to the optimum pattern obtained from the Wiener solution (solid curve) as the array tracks the mobile signals at different spatial locations.

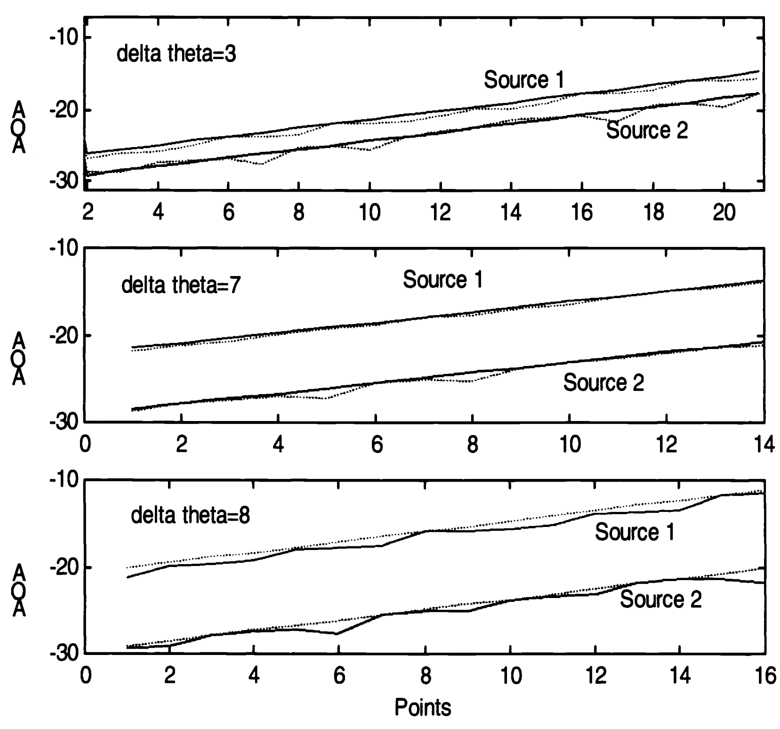

Figure 4. Response of an 8 element linear array ($d=\lambda/2$) tracking 4 sources of different angular separation in the sector [-30^0 -11^0]. The sources are of equal power, 5 dB higher than the noise power

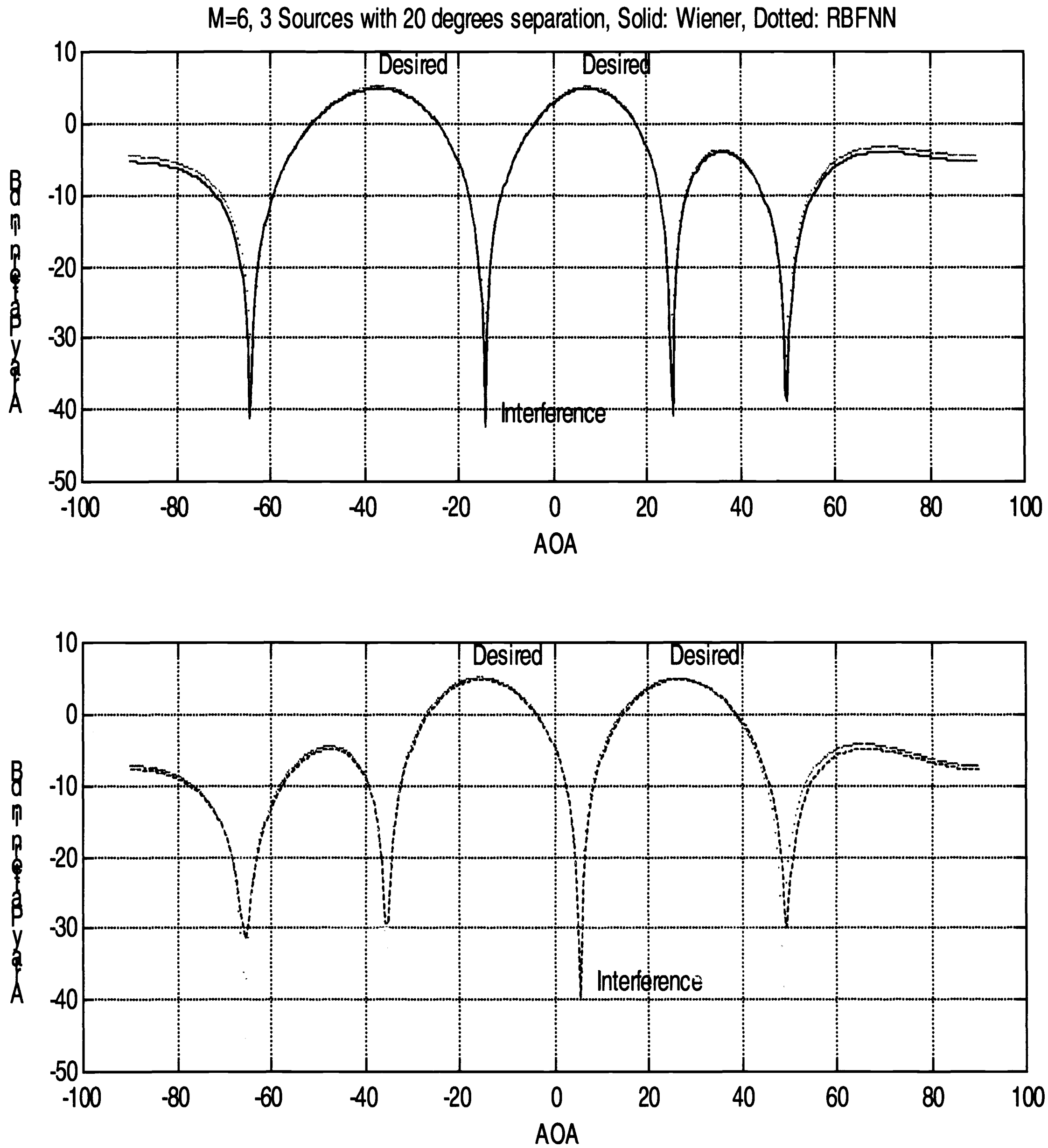

Figure 5. Antenna array beamforming energy is directed towards a desired direction and nulls towards interfering sources in two different cases

Since in practice, due to some tuning imperfections or Doppler spread, the operating frequency often changes, a 12 element array was trained with d/λ ranging from 0.4 to 0.6 and with 3 sources 4^0-7^0 of angular separation in the sector [10^0 29^0]. Figure 6 shows that the RBFNN was able to estimate the DOA of the sources accurately. The dimension of the input layer in this case was 156 nodes

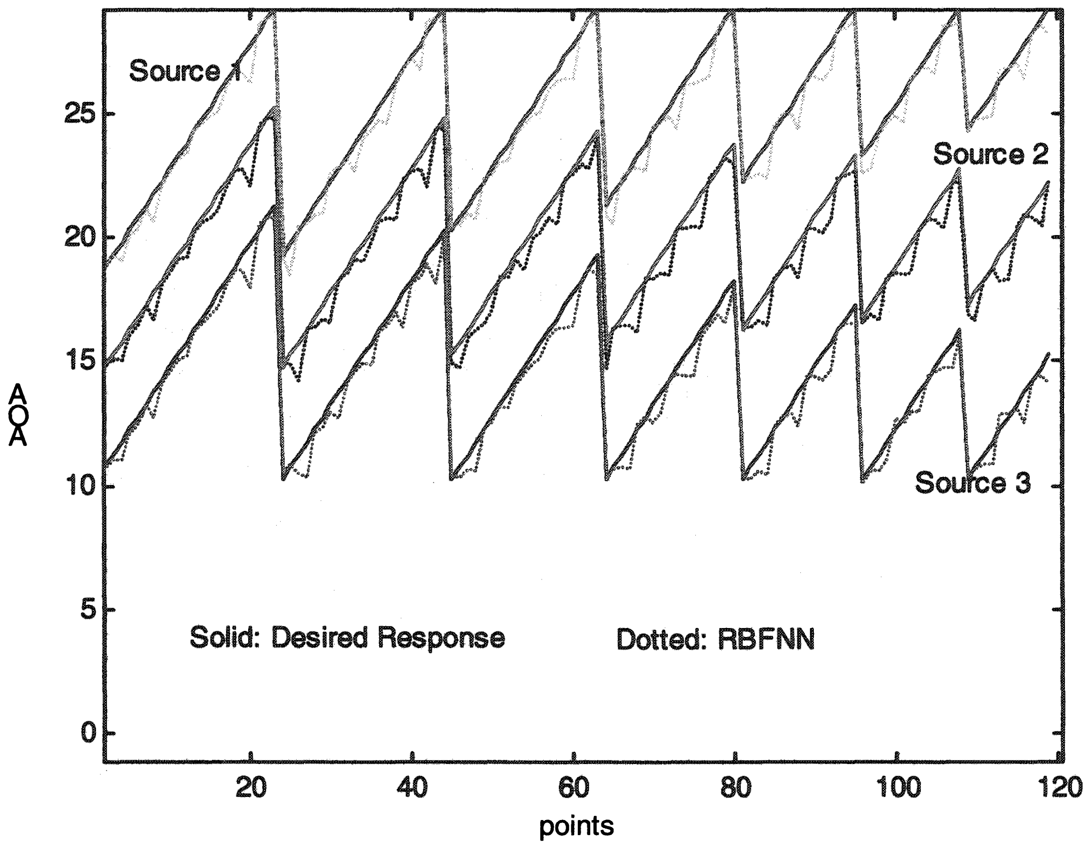

Figure 6. Response of a 12 element array which was trained with d/λ ranging from 0.4 to 0.6 and with 3 sources $4^0, 4.5^0, 5^0, \ldots, 7^0$ of angular separation in the sector $[10^0\ 29^0]$.

V. CONCLUSION

A new algorithm was presented for locating and tracking the angles of arrival of multiple sources. This algorithm is based on a family of neural networks operating in 2 distinct stages. The new approach is based on dividing the field of view of the antenna array into spatial sectors, then each network is trained in the first stage to detect signals emanating from sources in that sector. This approach can be used with adaptive array antennas to produce "smart antennas" that adjusts to an RF environment as it changes in "real – time". These neural-based smart antennas can dynamically alter the signal pattern to optimize the performance of the wireless system. The ability to smoothly track users with main lobes and interferers with null insures that the link budget is constantly maximized. The results demonstrated the high accuracy of the algorithm.. In CDMA systems, although, smart adaptive arrays, can provide additional interference suppression, by using nulls in the direction of interferers, they do not perform very well when the number of interferes is larger than the number of antennas. On the other hand, in TDMA systems, since they are fewer interferes, adaptive arrays can cancel the dominant interferers with just a few antennas.

VII. REFERENCES

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