Intelligent System to Cancel Multiple Interferences

Osmar de Araújo Dourado Júnior*, Adrião D. Dória Neto** and Wilson da Mata*
Universidade Federal do Rio Grande do Norte, Campus Universitário,
Lagoa Nova, CEP 59072-970, Natal/RN – Brazil, Phone: +55 84 215 3713
Departamento de Engenharia Elétrica*; Departamento de Engenharia da Computação**
osmar@leca.ufrn.br, adriao@leca.ufrn.br, wilson@ct.ufrn.br.

Abstract *– This paper presents an intelligent system for interference signals cancelling in a linear antennas array. The method combines Blind Source Separation — BSS and a modular structure formed by radial basis functions neural networks– MRBF that estimates the AOA– Angle of Arrival of the multiple independent incident signals on the sensors array and supplies these informations to the GSC–Generalised Sidelobe Canceller, that through an adaptive way cancels the interference signals, mantaining the desired signal.*

1- Introduction

Adaptive antennas has motivate significant scientific works in last years [1-5]. These studies are motivated, in particular, by its applications in radar, sonar, geophysical explorations, and mobile communications. Independently of the scientific area, the common objective is increase the directivity on the interest directions and cancelling the interference signals in other directions through adaptive cancelling algorithms for the array gains adjustment.

Adaptive Beamformer is a signals processor that consists by a sensors array, the antenna elements, to proceed the received signal sampling, and a weights vector put on the array output. The beamformer output is the combination among the weights and the array output signal. The optimization of the beamformer output is done by adjustments on the vector weights, resulting in modifications on the radiation pattern through null forming at the interference direction, consequently, the signal/noise ratio and the directivity are maximized.

An special class of adaptive beamformers is GSC. In this paper, GSC is the adaptive beamformer, that for its operation it requires the AOA from each incident signals. However, at the majority of the cases, these informations are not disponible. So, a system to find AOA was developed.

The most traditional methods to find AOA are based on spectral estimation techniques and among these can be mentioned the eigenvectors methods, such as MUSIC, SPRIT and Minimum-Norm [4]. These methods require statistical information and the maximum values calculation of the spectral density. For the determination of multiple AOA, they can commit errors such as spurious peaks, broadening and sharpness of the desired peaks [7].

Intelligent methods based in neural networks [8], has been developed considering one incident signal on the antennas array.

Learning, generalization and adaptability capabilities [9] become this method extremely attractive.

Antennas array acts as a signals linear combiner and the output signal from the array takes a formulation that it becomes difficult the estimation of multiple AOA through neural techniques, because they will process the array resultant signal as only one incident signal.

To enjoy the neural network estimative capability, a pre processing becomes necessary, that consists of separating the output of the array in its independent components proceeding from the different sources.

Using the BSS technique purposed by Cardoso [10] is featured the signals separation, and latter they will be processed in a parallel way by MRBF, where the AOA from each independent source is obtained, and latter to GSC, where the radiation pattern of the array will be modified by the weights adjustments. Figure 1 exhibits the purposed technique.

2- Beamforming and Blind Source Separation

The antennas array shown in figure 1 is formed by m elements, the sensors that receive under plane wave form, narrow band signals emitted from n independent sources, where $s_p(t)$ is the t-th sample of the p-th source. Its contribution to array output is given by (1), where a_p is the steering vector (2) that acts as the spatial transfer function between the p-th emitting source and the array, and A is a $m{\times}n$ column matrix composed by a_p. Where k_p (3) denotes the normalized wavenumber. It must be noticed that the correspondence between k_p and θ_p is unique. Denoting $v(t)$ a possible additive noise sample, the array output $x(t)$ is given by (4).

$$y(t) = \sum_{p=1}^{n} s_p(t) a_p = As(t) \tag{1}$$

$$\begin{bmatrix} 1 & e^{jk_p} & e^{j2k_p} \cdots e^{j(m-1)k_p} \end{bmatrix} \tag{2}$$

$$k_p = \frac{2\pi d}{\lambda} sin\theta_p,\ p = 1,2,\ldots,n \tag{3}$$

$$x(t) = y(t) + v(t) \tag{4}$$

For the signal separation $x(t)$ on n independent components, it was employed BSS method, of which formalism is resumed below, to result on the Joint

Approximate Diagonalization of Eigen-Matrices — JADE algorithm [10].

BSS rely on the assumption of mutual independence of the source signals, and for independent sources, is considerated (5). From (6) covariance is equal to the statistical sample of the signal *y(t)*, since the source signals have unitary variance (5), where I_n denotes the $n\times n$ identity matrix.

$$R_s = E\{s(t)s(t)^*\} = I_n \qquad (5)$$

$$R_y = E\{y(t)y(t)^*\} = AA^H \qquad (6)$$

The second order information will be exploited by whitening the signal part *y(t)*. Where W is a $n\times$m whitening matrix such that $W\cdot y(t)$ is spatially white. The whiteness condition is given by (7). For any whitening matrix W, it exists a unitary matrix U such that $W\cdot A=U$. Consequently, matrix A can be factored as (8). The use of second-order information reduces the determination of the $m\times n$ mixing matrix A to a determination of a $n\times n$ unitary matrix U. The whitened process $z(t)=W\cdot x(t)$ obeys a linear model (9). Then, whitened process signal now is a unitary mixture of the source signals.

$$I_n = WR_yW^H = WAA^HW^H \qquad (7)$$

$$A = W^+U = W^+[u_1,\ldots,u_n] \qquad (8)$$

$$z(t) = Wx(t) = W(As(t)+n(t)) = Us(t) + Wn(t) \qquad (9)$$

There are two approaches for the determination of the unitary factor (8). In the first approach, U is computed as the diagonalizer of a $n\times n$ cumulant matrix. This technique is computationally simple, but shows poor statistical performance because is based on n^2 cumulant statistics. Another approach is obtained an estimative for U as an optimizer of some identification criteria, which is a function of the whole cumulant, set Q_z.

JADE is presented by the following steps:

Step 1. Form the sample covariance $\hat{R}_x$ of and compute a whitening matrix $\hat{W}$.

Step 2. Form the sample 4-th order cumulants Q_z of the whitened process (9); compute the n most significant eigenpairs.

Step 3. Jointly diagonalize the eigen-set of Q_z by a unitary matrix $\hat{U}$

Step 4. Estimate A by (8).

3- MRBF

The $\hat{a}_p$ independent signals resulted from BSS operation, according to fig.ure 1, are processed by n MRBF networks, of which description is done below.

The choice for RBF Neural Networks at the MRBF system purposed by Dourado [11] was motivate by its architecture of direct propagation: input layer, just one hidden layer, and linear processing output layer. This configuration allows fast training time and a high-resolution response.

The input-output mapping is featured on two stages: a non-linear processing, where the complex space input u is mapped in an intermediate real space $\boldsymbol{g}$ (10)**,** the vector-valued gaussian radial basis functions, and a linear processing, the network output calculus (11). From (10), u is the space input, obtained by a normalization of a_p (12).

The objective of (10) is minimizing the Euclidian norm between u and $\mathbf{c}_k$, where $\mathbf{v}_k$ is a variance. From (11), $\mathbf{w}_k$ represents a complex weight that connects the k-th hidden unity to the output unity, and w_0 is a bias vector.

The most important process for neural networks is the training stage, because it will be able to he generalization. The normalized steering vectors from known AOA θ are sent to the input layer, and the **G** matrix, composed by the gaussians is obtained (13). Writing (11) in a matrix form, and taking the output equal to θ, the weight matrix $\boldsymbol{W}$ will be maximized (14). Where G^+ is the pseudo-inverse of G. Hence, the network will be trained, and ready to solve any AOA, by (15).

$$\mathbf{g}(\mathrm{u};\mathbf{c}_k) = \exp\left(-\frac{1}{\mathbf{v}_k^2}\|\mathrm{u}-\mathbf{c}_k\|^2\right) \qquad (10)$$

$$\mathbf{y} = \sum_{k=1}^{K} \mathrm{w}_k\,\mathbf{g}(\mathrm{u};\mathbf{c}_k) + \mathrm{w}_0 \qquad (11)$$

$$\mathrm{u} = \frac{a_p}{\|a_p\|^2} \qquad (12)$$

$$\mathrm{G}=\begin{pmatrix} \mathbf{g}(\mathrm{u}_1;\mathbf{c}_1) & \mathbf{g}(\mathrm{u}_1;\mathbf{c}_2) & \cdots & \mathbf{g}(\mathrm{u}_1;\mathbf{c}_k) & 1 \\ \mathbf{g}(\mathrm{u}_2;\mathbf{c}_1) & \mathbf{g}(\mathrm{u}_2;\mathbf{c}_2) & \cdots & \mathbf{g}(\mathrm{u}_2;\mathbf{c}_k) & 1 \\ \mathbf{g}(\mathrm{u}_3;\mathbf{c}_1) & \mathbf{g}(\mathrm{u}_3;\mathbf{c}_2) & \cdots & \mathbf{g}(\mathrm{u}_3;\mathbf{c}_k) & 1 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \mathbf{g}(\mathrm{u}_N;\mathbf{c}_1) & \mathbf{g}(\mathrm{u}_N;\mathbf{c}_2) & \cdots & \mathbf{g}(\mathrm{u}_N;\mathbf{c}_k) & 1 \end{pmatrix} \qquad (13)$$

$$\theta=G\bullet W \Rightarrow W=G^+\bullet\theta \qquad (14)$$

$$Y=G\bullet W \qquad (15)$$

However, if x contains a great number of elements, $\boldsymbol{G}$ will become very large and the training time will be long. To solve this problem and increase the response resolution was created the MRBF system (figure 3). In this configuration, the space input is divided in sub-regions, and each module, named expert network, is dedicated to a particular sub-region, being the supervisor network the only which is dedicate to whole space input. Each module receives u (12) at the same time, and provides a response, but just the expert network that is dedicated to the sub-region that contains the AOA will be chosen by the supervisor network to give the best AOA estimative, therefore the supervisor works as a mediator unity among the experts.

4- Generalized Sidelobe Canceller

The output beamformer is the linear combination between the array output (4) and the weights vector(16) put at the array output (17).

$$w = [w_1 \quad w_2 \cdots w_m] \tag{16}$$

$$r(t) = w^H x(t) \tag{17}$$

Assuming n linear constraints, C (20) is the $m \times n$ constraint matrix, and g is the $n \times 1$ constant gains vector. Where a_D is the steering vector formed from the AOA of one desired signal and A_I is a matrix formed by steering vectors of the interference signals.

$$C^H w = g \tag{20}$$

$$C = [a_D, A_I] \tag{21}$$

The weights vector is divided by GSC, figure 3, into two basic components: the non-adaptive componente w_q, (22) which is subjected to constraints, while w_a is obtained by an adptive algorithm. The expression for GSC weights is defined by (23). Where the $m \times (m-n)$ C_a matrix is defined as a basis for the orthogonal complement of the space spanned by the collumns of C matrix, so C_a is the null space of C^T.

$$w_q = (C^H C)^{-1} g \tag{22}$$

$$w = w_q - C_a w_a \tag{23}$$

Vector w_a is unaffected by constraints and the adaptive process to estimate it by LMS algorithm:

LMS Algorithm

LMS is an important member of the stochasstic gradient family, and it does not require correlation functions measurements and matrix invertion.

The adaptive process for w_a is the following:

$$r(t) = w_q^H x(t) - w_a^H C_a^H x(t) \tag{24}$$

$$d(t) = w_q^H x(t) \tag{25}$$

$$h(t) = C_a^H x(t) \tag{26}$$

$$r(t) = d(t) - w_a^H h(t) \tag{27}$$

$$w_a(n+1) = w_a(n) + \eta h(t) r(t)^* \tag{28}$$

$$w_a(n+1) = w_a(n) + \eta C_a^H x(t) x(t)^H \left[w_q^H - C_a^H w_a(n)\right]^* \tag{29}$$

This process is calculated from $n=0,1,2,..,$ untill a stop criteria, and η is the learning rate parameter.

5- Simulations for the Joint Operation of BSS and MRBF

From figure1, n uncorrelated plane waves, represented by (16), where B is amplitude, arrive on the array at a given discrete instant t, and the mixture matrix A is formed by the steering vectors (2) that carry the *p-th* AOA information from each $s_p(t)$.

$$s_p(t) = Be^{-jt\pi} \tag{16}$$

So, the BSS algorithm receives the signal from output array (4) and returns estimatives for $s_p(t)$ and A. A columns are sent to MRBF and folowing to GSC.

As BSS is a statistical technique, the number of samples of the received signal is very important, because as larger as these samples, better is A matrix estimative.

The parameters for the simulation were number of samples, sources and sensors. For five antenna elements, two desired signals sources of AOAs 20º and 60º, two interference sources of AOAs 0º and 40º and 5000 samples, the first sample of the array output is shown in TABLE 1.

The estimate for A, without the inherent indeterminacy of dilation [12], eliminated by normalization by column, since the columns are phase ordinate, was separated by BSS (TABLE 2).

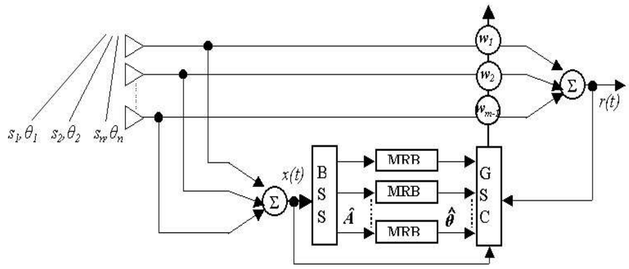

Figure 1: Joint Operation of MRBF, BSS and GSC

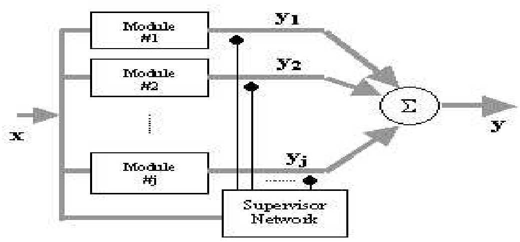

Figure 2: MRBF System

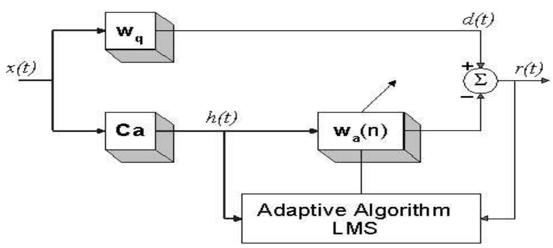

Figure 3: GSC Structure

In this paper, the desired signals are considered as having the highest power, so after take power measurements from separated signals, both the columns of desired signals and interference signals were recognized.

The vectors of desired signals are 4 and 3 columns, and 1 and 2 column are from interference signals. MRBF provided the following results: 59.1691º and 20.9455º for desiored signals AOA. The AOA of interfernces: 0.0004º and 40.0456º.

TABLE 1: First Sample of the Array Output

-6.9532 + 7.2305i
-0.2519 -10.8610i
-18.3316 - 7.8948i
-7.1801 + 4.9263i
-1.9530 -10.3158i

TABLE 2: Estimate for *A* without dilation indeterminacy

1.0000	1.0000	1.0000	1.0000
-0.4466 - 0.9082i	1.0118 + 0.0063i	0.4906 - 0.8546i	-0.7903 - 0.5257i
-0.6371 + 0.7898i	1.0135 - 0.0060i	-0.5500 - 0.9627i	0.6539 + 0.6844i
0.9764 + 0.2244i	1.0013 - 0.0030i	-1.2430 + 0.0261i	-0.1756 - 1.0437i
-0.2330 - 0.9848i	1.0100 + 0.0076i	-0.5495 + 1.1224i	-0.1595 + 0.8812i

Next, the AOA obtained by MRBF are sent to GSC. After constraint matrix (21) be formed and the optimum weights vector be obtained, the radiation pattern of the array takes a new configuration as shown in figures 4 and 5. In the optimized diagram, there are minimums at the interferences's AOA. Hence, the desired signals are preserved.

6- Conclusions

BSS, MRBF and GSC become possible this aplication where a sensors array receives more than one interest signal, it finds the source locations, and it cancels the interferences. The developed system is adequate in many applications where is not necessary only separate signals, but also know the source location, and exclude undesired signals.

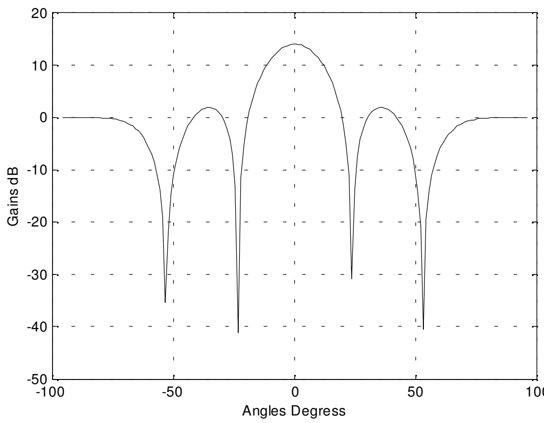

Figure 4: Radiation Pattern for five elements Linear Antennas Array

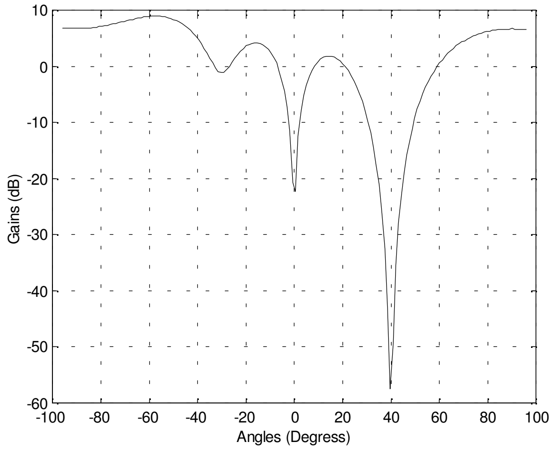

Figure 5: Radiation Pattern modified by GSC

References

[1] Yang and Ingram M. A., "*Design of partially adaptive array using singular value decomposition", IEEE Trans. Antenna Propagat.* Vol 45, pp. 843–850, May, 1997.

[2] Guimarães, A. M., .Duarte, D. N., A, and Lisboa, F. A., *"Beamforming applied to an adaptive planar antennas array", Proc. Radio and Wireless Conference,* Rawcon´98, pp.209–212, C. Spring.

[3] Anderson, S., Hagerman, B., Dam, H.,Forssén, U., Karlsson, J., Kronestedt, F. and Mazur, "*Adaptive Antennas for GSM and TDMA Systems", IEEE Personal Communications,* June 1991, pp. 74–86.

[4] Guimarães, A. M., .Duarte, D. N., A, and Lisboa, F. A*., "Joint operation of a neural network and a GSC structure applied to linear and planar arrays", Proc. International Microwave and Optoelectronics Conference,* IMOC´99, Rio de Janeiro.

[5] Arruda Jfilho, E. J. M. and Cavalcante, G. P. S., "*A neural adptive beamforming system to reduce interfering signals in móbile communications", Proc. International Microwave and Optoelectronics Conference,* IMOC´99, Rio de Janeiro.

[6] P. Stoica and A. Nehorai, *"MUSIC, Maximum Likelihood, and Cramer-Rao Boundary: Further Results and Comparsions", IEEE Trans.On Acoustics, Speech, and S. P.,* vol. 38 No. 12, Dec. 1990.

[7] Orfanidis, Sophocles J., *"Optimum Signal Processing"*, 2nd edition, McGraw Hill, New York, 1988, pp. 355-365.

[8] Southall L. H., Simmers, and O'Donnell H. T. "*Direction Finding in Phased Arrays with a Neural Network Beamforming", IEEE Trans. Antenna Propagat.*, vol. 43, pp. 1369–1374, December, 1995.

[9] S. Haykin, Neural Networks, *A Comprehensive Foundation. New York: Macmillan,* 1994. pp. 176-179.

[10] Cardoso, J. F., Souloumiac, A., *"Blind Beamforming for Non Gaussian Signals", IEE- Proceedings-F, vol. 140, n_o 6, pp. 362-370, dec. 1993.*

[11] Dourado, J., O. A., Duarte, D. N., A., *"Neural Networks of Modular Structure Applied to Linear and Planar Antennas Array"*, Proc. 2001 SBMO/IEEE MTT-S International Microwave and Optoelectronics Conference. Belém, Brazil.

[12] W. Lu and J. C. Rajapakse, " *Unique ICA Solution by Eliminating Ideterminacy".* Proc. 2001 International Joint Conference on Neural Networks, Washington , DC