A JOINT BLIND-NEURAL APPROACH FOR ADAPTIVE ANTENNA ARRAY IN GPS INTERFERENCE MITIGATION

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Abstract - **This work addresses the application of blind adaptive antenna arrays for GPS in order to achieve interference cancellation, by means of the minimization of the Signal-to-Interference Ratio (SIR), which enables more accurate estimation for the user position.**
Two structures for adaptive antenna array are investigated, using the blind generalized constant modulus algorithm (GCMA). The first one is a pipeline structure and the second one is a hybrid solution, involving a multilayer perceptron neural network.
The proposed hybrid technique is presented in two different configurations and compared with the original pipeline structure. Simulations consider a critic realistic GPS situation, pointing out the effectiveness of the hybrid approach in terms of radiation patterns and dynamic convergence.

I. INTRODUCTION

The so-called Global Positioning System (GPS) has become largely used in many civil applications. Modern receivers can take advantage of spatial signal processing to improve the robustness of the GPS signal and suppress interference. In fact, GPS signals are subject to several impairments, such as multipath fading, tropospheric and ionospheric delays, power fluctuations due to scintillation, Doppler effects, clock and receiver errors and so on [1, 2].

An interesting approach is the use of adaptive antenna array to detect and locate the direction of a GPS source, in order to mitigate interfering signals. Similar techniques have been studied in other communication problems, as cellular systems for instance [3, 5].

Corresponding algorithms are derived from classic adaptive filtering approach and generalized to a space-time framework. Such algorithms can be supervised or blind, in the sense that they do not make use of a reference signal in the adaptation process.

In this work, we will deal with blind techniques that do not require either direction of arrival (DOA) estimation, or an *a priori* knowledge of the number of interference signals. First a pipeline structure for adaptive antenna array is proposed, using the generalized constant modulus algorithm (GCMA)[6, 8]. Then a new hybrid solution, based on such pipeline structure associated with a multilayer perceptron neural network (MLPNN) [7], is introduced. The use of MLPNN improves the robustness of the method in critical cases, for instance when desired and interference signals are closely spaced. Simulations have been carried out by considering different realistic GPS situations.

The article is organized as follows. Section 2 describes the blind algorithm to be used in the adaptive spatial equalizers and the corresponding GCMA-pipeline structure. In section 3, the new hybrid signal processing algorithms GCMA/MLPNN are proposed. Afterwards simulation results are presented and discussed in section 4. Finally, some conclusion remarks are posed in section 5.

II. THE GCMA-PIPELINE STRUCTURE FOR BLIND SPATIAL EQUALIZATION

Blind equalization involves no training sequence, to be used as a reference or desired signal. The main goal is to recover the input signal based on the statistical characteristics of the received one. Blind equalization is an efficient solution in terms of bandwidth. However, their cost functions may be subject to the existence of local minima.

The first class of blind algorithms largely presented in the literature is known as "Bussgang algorithms" [4], e.g. the Godard or constant modulus algorithm (CMA), which is a reference in the blind equalization field. The main principle is to optimize a cost function based on the principle of restoring the constant modulus property of the transmitted data constellation. This algorithm converges in presence of frequency shift and phase errors between transmitter and receiver, because the cost function is independent from the signal phase.

Here we will apply an alternative approach named generalized constant modulus algorithm (GCMA), where the constant value of the constellation radius is not *a priori* established. So, the utilization of an automatic control gain becomes necessary to provide power equalization too [6, 8].

The antenna weights updating is obtained by the following equations:

$$\mathbf{w}(k+1)=\mathbf{w}(k)-m\,\frac{z(k)-\bar{z}(k)}{\bar{z}^{3}(k)}\left[\bar{z}(k)y^{*}(k)\mathbf{u}(k)-z(k)\mathbf{r}(k)\right] \qquad (1)$$

$$\begin{aligned}
y(k) &= \mathbf{w}^{\mathbf{H}}(k)\mathbf{u}(k)\\
z(k) &= \left|y(k)\right|^{2}\\
\bar{z}(k) &= l\bar{z}(k-1)+(1-l)\left|y(k-1)\right|^{2}\\
\mathbf{r}(k) &= l\,\mathbf{r}(k-1)+(1-l)y^{*}(k-1)\mathbf{u}(k-1)
\end{aligned}$$

Where μ is the adaptation step, l is a smoothing factor, w is the equalizer weight vector, $\mathbf{u}$(k) is the equalizer input vector, y(n) is the equalizer output, $\bar{z}$ and r are statistical mean. The initial conditions are given by $\bar{z}(0)=1$, $\mathbf{r}(0)=[0...0]^{T}$ and $l<1$.

In the concept of adaptive spatial equalization, the equalizer processes spatial samples of an incident wave. For the antenna array system, the direction of arrival of the incoming signal plays the same role of frequency in temporal filters. The radiation pattern, which plays for spatial domain the same role as the frequency spectrum for the temporal filter, shows the array gain as a function of the direction of arrival of the captured signals.

Adaptive algorithms modify the antenna radiation pattern in according to some pre-established criterion, which optimizes the reception of the desired signals. The antenna is an active device, which controls the radiation pattern performance based on an intelligent processing. The elements of the array may be disposed in a linear, planar or circular configuration, according to the application

In the following, we will analyze the performance of adaptive linear antenna array, in order to mitigate the interfering signals by the insertion of nulls in the radiating pattern in the interference directions.

The linear antenna array is uniformly spaced, with M identical isotropic elements, as illustrated in figure 1. Each element is weighted with a complex coefficient.

The mathematical model can be described by:

$$u_n(k)=\sum_{i=0}^{D+I-1} a_n(f_i)s_i(k)e^{j(f_n(f_i))}, n=0,\dots,M-1 \quad (2)$$

Where: $a_n(f_i)$ is the complex response of the n-th array element in direction f_i and $f_n(f_i)=-2pn\frac{d}{l}\,senf_i$ is a function associated with the linear geometry.

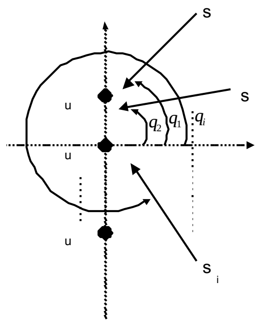

Fig. 1. Linear array.

In this way, in order to eliminate the interference using this algorithm, a pipeline structure for successive interference suppression is proposed in figure 2 [8]. In this structure each GCMAi, $i=1,\dots,4$, contains a weight set, associated with the array elements and adapted by the GCMA algorithm.

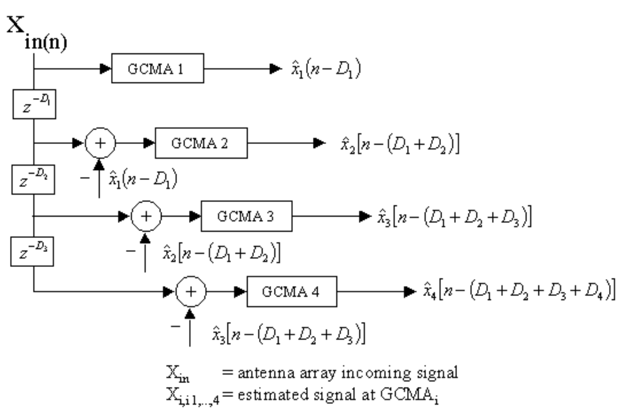

Fig. 2. Pipeline structure.

The signals arriving on the array antenna are processed by the GCMA1 stage that recovers the signal with the higher power. A preprocessing is used for the other stages, in such a way that the signal estimated from the satellites $\hat{X}_j, j=1,\dots,i-1$ and obtained in the GCMAj, $j=1,\dots,i-1$, stages are subtracted from the next GCMAi. stage. Therefore, the desired signals are recovered in a decreasing power order.

In figure 1 the GCMA 1 stage captures the signal from one of the visible satellites (D1), while the signals coming from other satellites or from interference sources are considered as interference and represented by intk, k = 1,...,5. But the i-th GCMA stages, i=2,...,4, subjected to the preprocessing, allow the capture of signals coming from other visible satellites (D2, D3, D4 , respectively).

It is important to note that the pipeline structure using a blind algorithm does not need a previous knowledge of the DOA. However, it must be supposed that the desired signal power is higher than the interference power. Under this assumption the solution has shown to be effective in many cases, even for rather severe channel conditions.

Nevertheless the performance may decrease when interference signal are close to the desired one. In fact, the capability of the scheme in separating desired and interference signals depends on the number of antennas. To avoid the use of a high number of array elements, which can present a prohibitive cost, we propose to use a more robust technique together with the pipeline structure.

III. MLP NEURAL NETWORK

Artificial neural networks are computational systems that try to mimic some capabilities from the biological nervous system, using several interconnected elements called artificial neurons.

The multilayer perceptron network (MLPNN) is composed of several hidden perceptron neurons [7]. In this work we considered MLPNN with only one intermediate layer, where the neurons of the hidden layer receive the input of the network.

Vector of *M* inputs: $\mathbf{x}=[1,x_0,x_1,\dots.x_{M-1}]^T$

Vector of *N* outputs: $\mathbf{y}=[y_0,y_1,\dots.y_{N-1}]^T$

The weight matrix between the input and the intermediate layers, for H neurons, are given by $A_{(M+1)xH}$.

The weight matrix between intermediate and the output layers, for H neurons, are given by $B_{(H+1)xN}$

By considering a hyperbolic tangent as the activation function, the network outputs are given by [7]:

$$\mathbf{y}=\left(\frac{e^{t\mathbf{x}^T\mathbf{A}}-e^{-t\mathbf{x}^T\mathbf{A}}}{e^{t\mathbf{x}^T\mathbf{A}}+e^{-t\mathbf{x}^T\mathbf{A}}}\right)^T\mathbf{B} \quad (3)$$

Where τ is a constant that control the sigmoid derivative.

The network parameters are updated by the minimization of a suitable cost function [7]. The hybrid solution to be proposed in the sequel consists of the joint employ of artificial neural networks together with the pipeline-GCMA approach presented in section II.

IV. The Hybrid Solution

The GCMA pipeline/neural was implemented in two variants, so-called “arm” or “parallel” structures, as shown in figures 3 and 4 respectively. The first one means that a MLPNN is introduced in each “arm” of the pipeline structure, to separately enhance the recovering of each desired signal. The MLPNN is active after the blind algorithms attained the convergence. After the first signal was captured, this information is sent to the next “arm” that captures the second most powerful input signal and so on, as previously stated.

The second one called “parallel”, works first as the approach of section II. After the convergence, the recovered data feeds the input of the MLPNN, which proceeds with a joint enhancement of all those outputs.

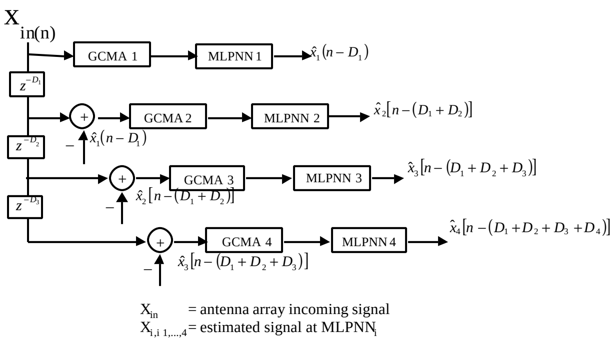

Fig. 3. GCMA-pipeline/neural: “arm”

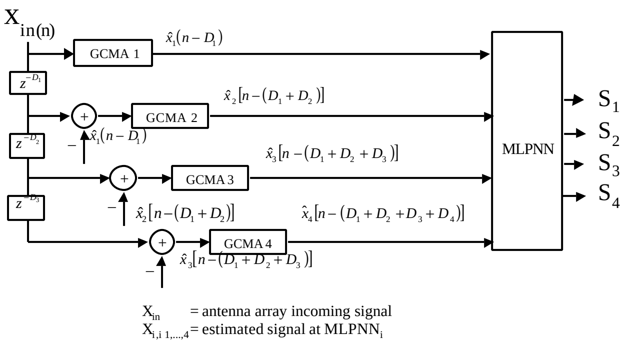

Fig. 4. GCMA-pipeline/neural: “parallel”

V. Simulations Results

In order to assess the performances of the new solution for GPS antenna array, a linear array with 10 isotropic antennas was evaluated for two scenarios. The first one involves 3 interfering signals and 4 information satellite signals. In the scenario 2 we have the same number of satellite signals but 5 interfering signals. Results of computational burden, BPSK output constellation, symbol error rate and array radiation pattern are observed for the hybrid solution and compared to the original pipeline-GCMA.

Simulations consider SIR = 3 dB, SNR = –14.8 dB, which may be considered extremely weak for any practical situation. GPS satellite signals come from the elevations angles 0°, 60°, 330°e 300°. The interference elevations angles are 315°, 85°e 275°, according with the reference of figure 1. For the hybrid structure, the array "in arm” used 5 neurons by arm, and the array "in parallel" considered 20 neurons.

Due to space limitations only some representative outputs are presented. So an output signal with a typical behavior together with the case of the worst performance are shown.

The performance of the blind GCMA in the pipeline structure, for 3 and 4 interfering signals, is illustrated by figures 5 to 8. In figures 5 and 6 the good capture of the desired signal (des3) can be observed, as well as the interference cancellation. In fact, the gap between (des3) and all other interference and desired signals, except (des2), which the corresponding gains falls below 25 dB. For (des2) the difference is about 7 dB, which is poorly satisfactory. The temporal evolution shows the good convergence properties of GCMA and confirms the attainment of the opened-eye condition, even if a phase rotation effect may be noted.

Such difficulties are pointed out by observing figures 7 and 8, corresponding to the worst case output. The small degree of freedom, which depends on the number of antennas, does not make possible the complete cancellation. The radiation pattern shows that a number of undesired signals preserves a gain level about 10 to 20 dB below the desired (des2), which does not guarantee a satisfactory recovering.

The results of the hybrid GCMA-Neural “arm” can be seen in the figures 9 to 14, when 3 and 5 interfering signals were considered. The array factor pattern shows the very good canceling of the interfering signals, for levels greater than 20dB below the captured signals. In the temporal evolution, convergence is observed in less than 300 iterations. For the most critical output, it is clear that initial convergence is slower. Anyway, after convergence the opened-eye condition is more largely attained, if compared with the previous approach (figs. 6 and 8), for both output signals.

The second approach with neural network is the so-called “parallel” and the results are presented in the figures 15 to 20. The simulations show the good performance of the structure in the situations with 3 and 5 interfering signals.

From the array factor pattern in figures 15 and 16, a good level of canceling (greater than 18 dB) is observed for the interfering signals. The temporal evolution (fig. 17) shows the easy convergence process, with less than 200 iterations. From figures 18 and 19, it is possible to observe the interference canceling in the same level that in the case of 3 interfering signals. An important issue is that applying MLPNN solves the phase rotation problem.

The number of neurons is similar for the two approaches, i.e., 5 by “arm” and 4 arms, totalizing 20 neurons and 20 neurons in the parallel structure. This leads to a similar computational complexity for both structures.

The computational burden in the hybrid solutions includes the blind algorithms processing, which is proportional to the number of antennas. In addition, the MLPNN has a complexity of 4H(M+5)+3(H+1)N sums and 2H(M+4)+2(H+1)N multiplications. In this context we believe that the use of the hybrid approach is feasible and worthwhile, due to the performance improvements.

VI. COMMENTS AND CONCLUSION

A first motivation of this work is to show how spatial processing techniques could open new and interesting perspectives in GPS applications. The mitigation of multipath and interference signals is essential for an accurate positioning. In this sense, the use of the proposed hybrid approaches in the analyzed scenarios provided rather satisfactory results.

Other more realistic scenarios, with more visible satellites, are being established for further tests. Planar array configurations are also under study in order to reduce the number of antennas, the size of the array and to solve ambiguities.

Finally, the computational burden of the hybrid algorithms was shown to be not prohibitive, if we take into account the performance in interference canceling, the algorithms convergence and overall the good results of the factor array pattern.

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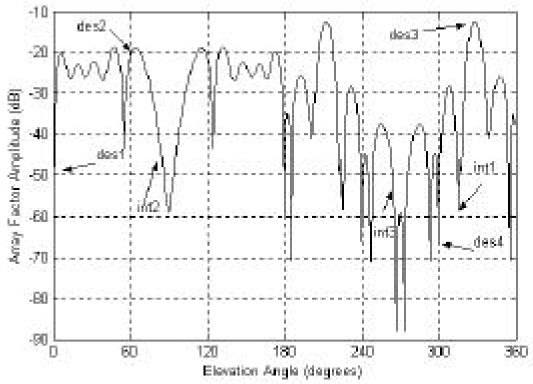

Fig. 5. Array factor pattern – output 3

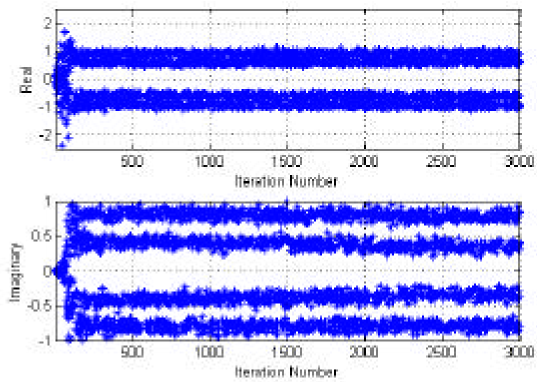

Fig. 6. Temporal evolution – output 3

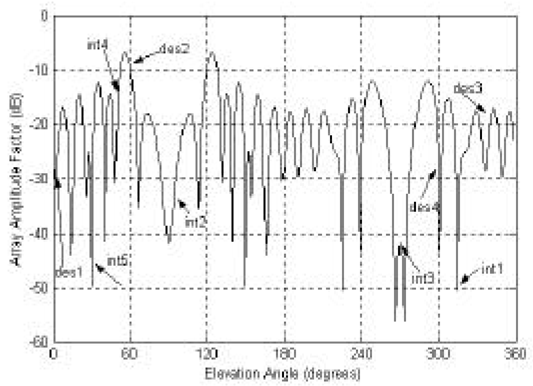

Fig. 7. Array factor pattern – output 2

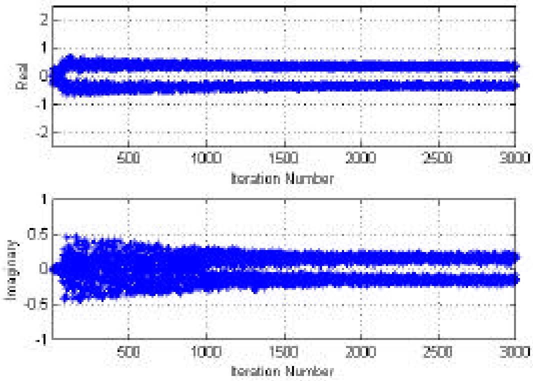

Fig. 8. Temporal evolution – output 2

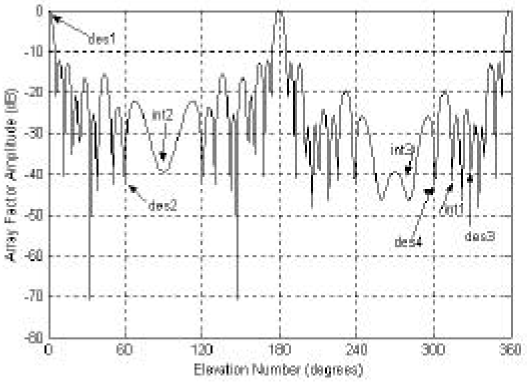

Fig. 9. Array factor pattern – output 1

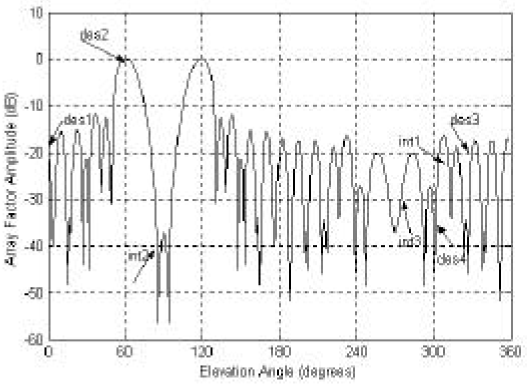

Fig. 10: Array factor pattern – output 2

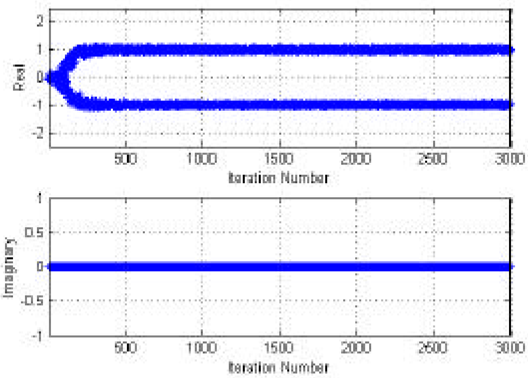

Fig. 11. Temporal evolution – output 2

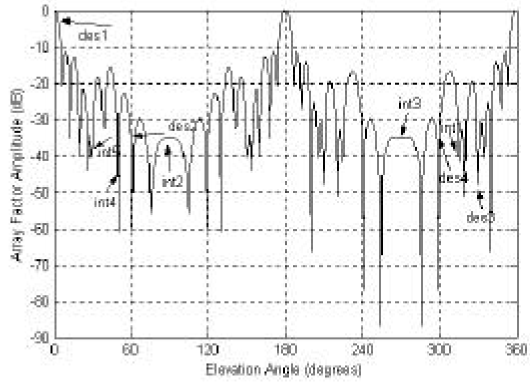

Fig. 12. Array factor pattern – output 1

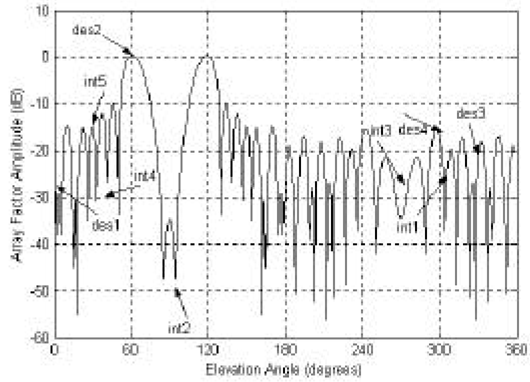

Fig. 13. Array factor pattern – output 2

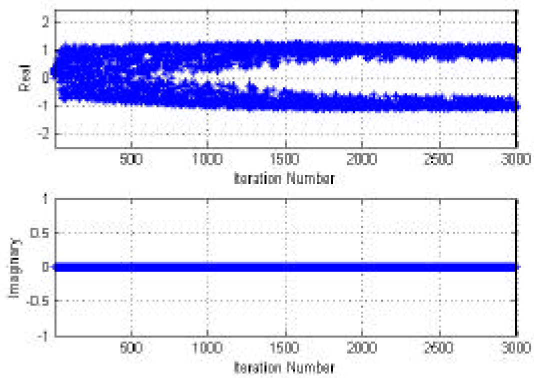

Fig. 14. Temporal evolution – output 2

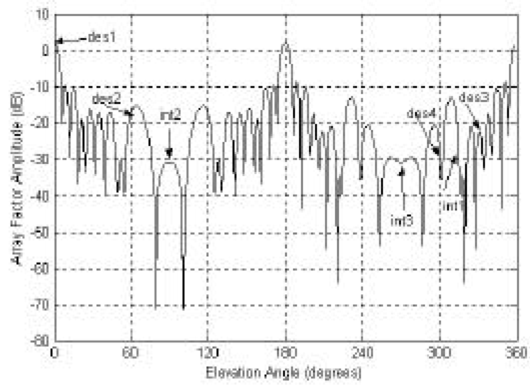

Fig. 15. Array factor pattern – output 1

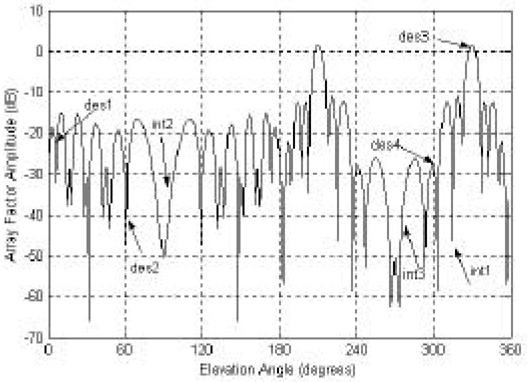

Fig.16. Array factor pattern – output 3

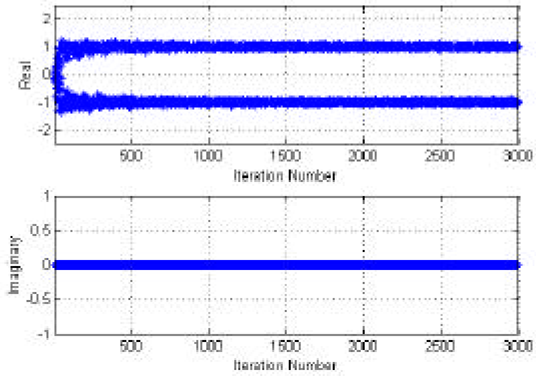

Fig. 20. Temporal evolution – output 3

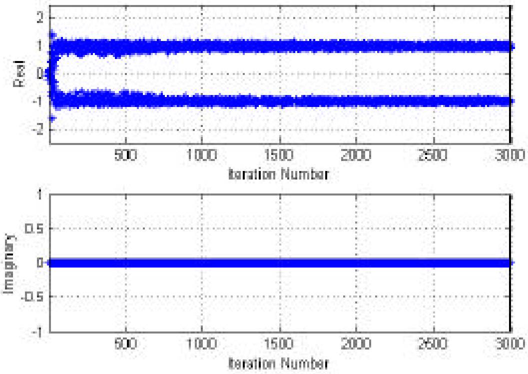

Fig. 17. Temporal evolution – output 1

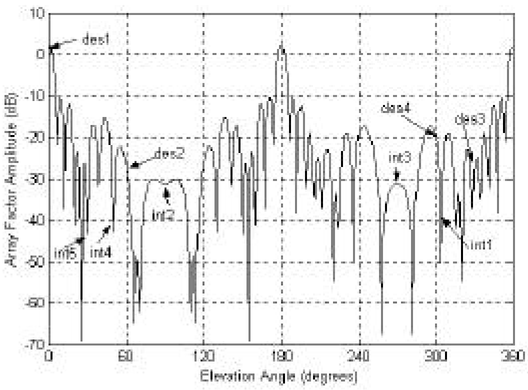

Fig. 18. Array factor pattern – output 1

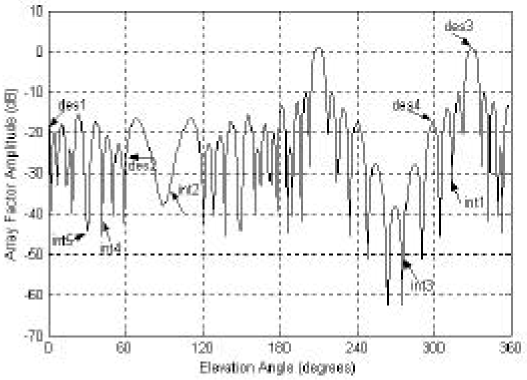

Fig.19. Array factor pattern – output 3