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ORIGINAL ARTICLES

Effect of signal to interference ratio on adaptive beamforming techniques

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Abstract The capability of adaptive antenna array lies in forming higher gain in the user directions and lower gain in the interferer directions. The technique used to produce such radiation pattern by calculating the excitation weights are called the adaptive beamforming (ABF) techniques. It tries to minimize the error between the desired and actual signal and maximize the signal to interference ratio (SIR). But in severe interference environment when the actual signal is weak, the effect of SIR on the radiation pattern needs to be considered. This paper describes the effect of signal to interference ratio on different adaptive beamforming techniques such as non-blind least mean square (LMS), blind constant modulus algorithm (CMA) and evolutionary Particle Swarm Optimization (PSO). The performance and validation of beamforming algorithms are studied through MATLAB simulation by varying SIR parameters for different desired and interference direction. Different weights are obtained using this beamforming algorithm to optimize the radiation pattern. The parameters for comparison are the main beam and null placement keeping signal to noise (SNR) constant for different angles of user and interferer. The mean SLL and directivity are also studied.

1. Introduction

In satellite communication systems, the receiver receives extremely weak signals from the satellite (Lian, 1997). To enhance reception and radiation patterns dynamically in response to the signal environment, such technologies depend on adaptive array signal processing (Applebaum, 1975; Kamboj and Dahiya, 2008). An adaptive antenna is an array of antenna elements followed by a sophisticated signal processor that can adjust or adapt its own radiation pattern in order to focus the reception of the antenna array in a certain direction and rejects the signal from other directions (Ballanis, 2005; Widrow et al., 1967). The necessity to remove the effect of the undesired signal to the desired one motivates advances in communication receiver antenna and hence synthesizing methods (Canabal et al., 2005; Banerjee and Dwivedi, 2013a, b; Goswami and Mandal, 2013).

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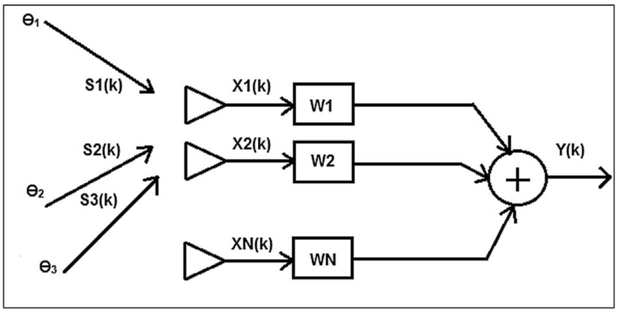

Figure 1 Uniform linear array.

An adaptive antenna array combines the outputs of antenna elements. The directional gain of the antenna is controlled by adjusting phase or amplitude or both at each individual element. The weighted signals are summed and the output is fed to a controller. These weights are computed adaptively to adapt to the changes in the signal environment. Different adaptive beamforming algorithms are employed to minimize the error between the desired signal and the array output that adjusts the weights to satisfy an optimization criterion (Das, 2008; Gu et al., 2008; Hongwei et al., 2011; Hossain et al., 2008).

The capability of adaptive antenna array lies in forming higher gain in the user directions and lower gain in the interferer directions. There are different adaptive beamforming algorithms studied in the literature which are used in the adaptive antenna array (Banerjee and Dwivedi, 2013a,b; Banerjee and Dwivedi, 2015a,b; Jiancheng et al., 2011). Beamformers based upon statistically optimum blind and non-blind adaptive beamforming are analyzed and compared on the basis of beamforming capability and rate of convergence. It is observed that the convergence rate of Least Mean Square (LMS) is slowest where as Constant CGM is the fastest among all. SMI is found to have more computational complexity. Recursive Least Square (RLS) is found to have higher side lobe level (SLL) and null depths as compared to CGM (Saxena and Kothari, 2014). It was observed that the conventional Adaptive Beamforming (ABF) technique like Minimum Variance Distortionless Response (MVDR) improves the signal-to-interference-plus-noise ratio (SINR) but is unable to reduce the SLL (Liu et al., 2011). Hence to improve the SINR with reduced SLL, many optimization techniques have been used in ABF application. Adaptive Mutated Boolean Particle Swarm Optimization (AMBPSO) technique takes the uncorrelated desired and interferer signal directions and succeeds in providing good SINR value with lower SLL as compared to conventional MVDR (Zaharis and Yioultsis, 2011). Adaptive Dispersion Invasive Weed Optimization (ADIWO) shows improvement in steering ability regarding the main lobe and the nulls, faster as compared to PSO and achieves better SLL than the PSO and MVDR (Zaharis et al., 2012). Hybrid Particle Swarm Optimization with Gravitational Search Algorithm (Hybrid PSOGSA) shows its ability for optimization in beam-forming for a larger number of user signals and speedy computation using parallel GSA as compared to sequential stand alone algorithms but cannot maximize the gain along the user direction (Magdy et al., 2015a,b). Mementic algorithm shows optimal radiation pattern design to maximize the signal to interference ratio (SIR) by perturbing the phase-position (Hsu and Shyr, 2005). But, for the case of adaptive antennas, the position of the antenna elements cannot be changed so it should be kept fixed, as the required phase controls are available at no extra cost. Hence only phase weights are considered for optimal radiation pattern which shows good null depth along the undesired direction but the array factor (AF) gain along the main lobe is not satisfactory (Rao and Sarma, 2012; Zuniga et al., 2010).

In all of the above adaptive beamforming techniques proposed so far we try to minimize the error between the desired and actual signal and maximize the signal to interference ratio (SIR). But in severe interference environment when the actual signal is weak, the effect of SIR on the radiation pattern needs to be considered.

The present study analyses different adaptive techniques such as non-blind LMS, blind CMA and evolutionary PSO. The performance of beamforming algorithms are studied through MATLAB simulation by varying SIR parameters for different desired and interference direction. Different

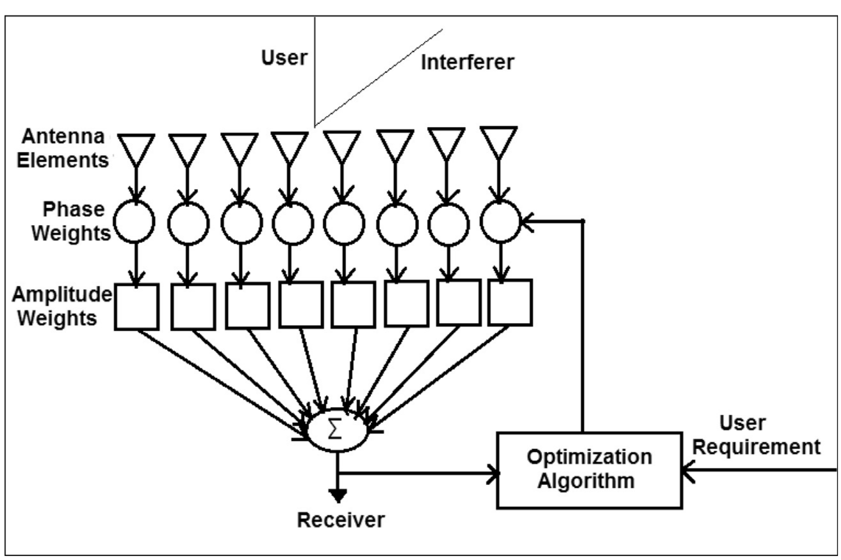

Figure 2 Block diagram of adaptive antenna array.

weights are obtained using this beamforming algorithm to optimize the radiation pattern. The parameters for comparison are the main beam and null placement keeping signal to noise (SNR) constant for different angles of user and interferer. The mean SLL and directivity are also studied.

The rest of the paper is arranged as follows: Section II describes the mathematical model of signal, Section III formulates the adaptive beamforming problem, Section IV, V and VI describes adaptive beamforming using PSO, LMS and CMA, Section VII compares the results and Section V concludes the whole study.

2. Signal model

Consider a Uniform Linear Array (ULA) with N elements as shown in Fig. 1.

Let S be narrowband signals that are received at ULA with different directions of arrivals (DOAs) $\theta_1, \theta_2, \ldots \theta_S$. Let s(t) be the $S\ X\ 1$ signal vector from the Sth source with DOA equal to θ_S.

$$S(k) = [S_1(k) \quad S_2(k) \quad \ldots \quad S_s(k)] \tag{1}$$

We define the input signals as $x_0(t), x_1(t), \ldots, x_{N\text{-}1}(t)$. As they reach the antenna elements, the $N\ X\ 1$ signal vector $x(t)$ can be written as

$$X(k) = \sum_{s=1}^{s} S_s(k) * SV(\theta_s) \tag{2}$$

where $SV(\theta)$ is the steering vector or array response vector of $N\ X\ 1$ which controls the direction of the antenna beam.

$$SV(\theta) = [1 \quad \exp(-j\pi \sin(\theta)) \quad \exp(-2j\pi \sin(\theta)) \quad \ldots \quad \exp(-j(N-1)\sin(\theta))]^T \tag{3}$$

Now if the signals 1,2 … S consist of U number of desired users arriving from $\theta_1, \theta_2, \theta_3, \ldots \theta_U$, I the number of interferences arriving from $\theta_1, \theta_2, \theta_3, \ldots \theta_I$ with variance σ_i^2 and noise with variance σ_n^2, then the input signal consists of the user signal, interferer signal and noise. The received signal can be written as

$$X(k) = \sum_{s=1}^{U} S_u(k) * SV(\theta_u) + \sum_{i=1}^{I} S_i(k) * SV(\theta_i) + N(k) \tag{4}$$

where $SV(\theta_u) = [1 \quad \exp(-j\pi \sin(\theta_u)) \quad \ldots \quad \exp\ (-j\pi(N-1) \sin(\theta_u))]$ is the steering vector of the desired signal along the user and $SV(\theta_i) = [1 \quad \exp(-j\pi \sin(\theta_i)) \quad \ldots \quad \exp(-j\pi (N-1)\sin(\theta_i))]$ is the steering vector along the interferer direction.

3. Adaptive beamforming problem formulations

An ULA will receive the incoming signals which will be multiplied by the weights of antenna elements which are then summed to get the output in the form of received signal. The received signal will be graphically represented in the form of the radiation properties as a function of space coordinates known as radiation pattern. The radiation pattern of the linear array for far field is represented in terms of array factor (AF) by (Banerjee and Dwivedi, 2015a,b),

$$AF = \sum_{n=1}^{N} X(k) * w_n \tag{5}$$

Where N = number of elements, $w_n = a_n * \exp(jb_n)$ = complex array weights at element n, a_n = amplitude weight at element n, b_n = phase shift weight at element n.

In adaptive antenna beamforming, the radiation pattern of ULA is controlled through various adaptive algorithms. Adaptive algorithm dynamically optimizes the radiation pattern according to the changing electromagnetic environment. The output or received signal is given to the adaptive algorithm where it checks the output radiation pattern with the desired radiation pattern. If the received actual radiation pattern does not meet the user demands, then adaptive algorithm will try to adjust the weights of the antenna array such that the actual and desired radiation pattern remains same. The antenna array pattern is optimized to have maximum possible gain in the direction of the desired signal and nulls in the direction of the interferers. Fig. 2 shows the block diagram of an adaptive antenna array.

4. Adaptive beamforming using particle swarm optimization

Particle Swarm Optimization (PSO) was developed by Eberhart and Shi (Eberhart and Lu, 2001). It is used as an adaptive algorithm to search the optimized adaptive antenna radiation pattern. This is done using the algorithm summarized in the Table 1 (Arora, 2015). In every iteration, PSO algorithm will try to increase the AF gain of the desired user and decrease the AF gain of the interfering user as compared of the previous iteration (Mandal et al., 2012). The converged value of weights produces an optimized adaptive antenna radiation pattern.

The amplitudes excitations are kept constant whereas the phase excitations are selected as the optimization parameters. Hence the AF can be written as

$$AF = \sum_{n=1}^{N} X(k) * \exp^{jb_n} \tag{6}$$

The objective function is formulated to find the values of phase of the element of antenna array in order to focus the main lobe toward the desired user while low gain toward interfering user. It is formulated using the AF equation for $\beta = 0$.For 1 user and 2 interferer, there are three cost functions: $AF(\theta_{s1})$: the first cost function is the magnitude of the radiation pattern in the user direction θ_{s1} and $AF(\theta_{i1})$, $AF(\theta_{i2})$: the other two cost functions are the magnitude of the radiation pattern in the interferer directions θ_{i1} and θ_{i2}. The aims are to maximize the AF gain of the desired user and minimize the AF gain of the interfering user. This is multi-objective optimization.

Fitness function for Beamforming

$$= AF(\theta_{s1}) - [AF(\theta_{i1}) + AF(\theta_{i2})] \tag{7}$$

where

$$AF(\theta_{s1}) = \sum_{n=1}^{N} \exp^{-j\pi(n-1)(\sin\theta_{s1})} * \exp^{jb_n} \tag{8}$$

$$AF(\theta_{i1}) = \sum_{n=1}^{N} \exp^{-j\pi(n-1)(\sin\theta_{i1})} * \exp^{jb_n} \tag{9}$$

$$AF(\theta_{i2}) = \sum_{n=1}^{N} \exp^{-j\pi(n-1)(\sin\theta_{i2})} * \exp^{jb_n} \tag{10}$$

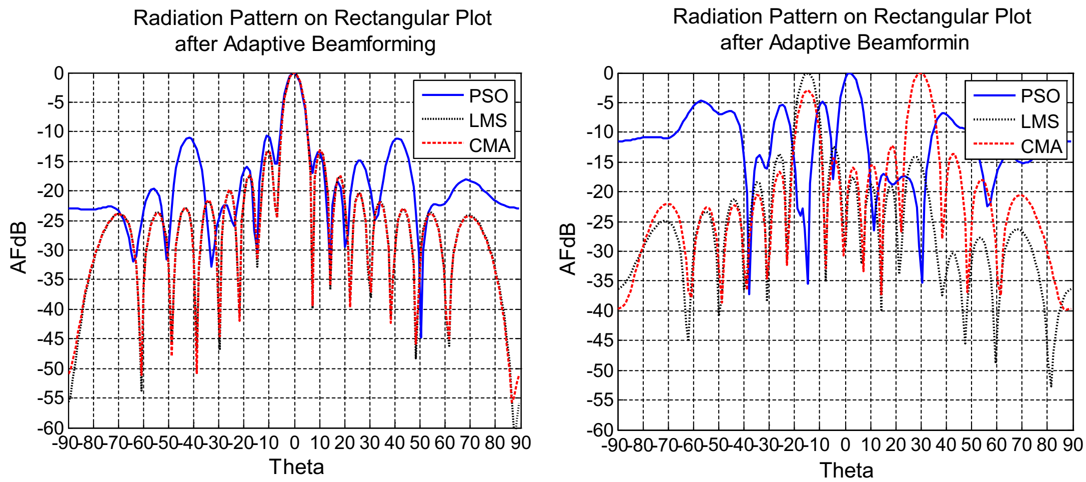

Figure 3 Best radiation pattern found by PSO, LMS and CMA for 16 element antenna array with user at 0° and interferers at −15° & 30° with SNR = 30 dB (a) Rectangular Plot for SIR = 30 dB (SLL_{PSO} = −15.41 dB, SLL_{LMS} = −19.12 dB, SLL_{CMA} = −19.14 dB) (b) Rectangular Plot for SIR = −30 dB (SLL_{PSO} = −10.35 dB).

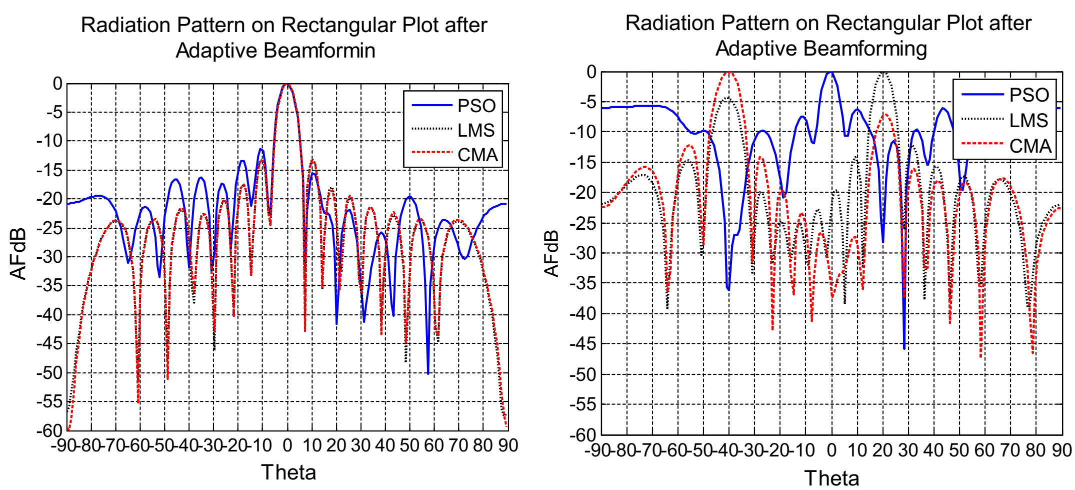

Figure 4 Best radiation pattern found by PSO, LMS and CMA for 16 element antenna array with user at 0° and interferers at −40° & 20° with SNR = 30 dB (a) Rectangular Plot for SIR = 30 dB (SLL_{PSO} = −17.46 dB, SLL_{LMS} = −19.15 dB, SLL_{CMA} = −19.32 dB) (b) Rectangular Plot for SIR = −30 dB (SLL_{PSO} = −7.63 dB).

The following steps show how PSO is used to find the optimal radiation pattern of an adaptive antenna.

Step 1: Initialize population, number of iterations, tuning parameters (φ_1 and φ_2) and weights (w). The particle corresponds to phase bn in the interval [−2π, 2π].

Step 2: Initialize starting position $bn(i,k)$ for the kth variable in the population by $b_n(i,k) = b_n(i,\min) + (b_n(i,\max) - b_n(i,\min))u(i)$ where $k = 1, 2, - - - npop$ and $u(i)$ is the random number generated between 0 and 1. Initialize the velocities of the kth variable as $v(i,k) = 0$.

Step 3: Evaluate the normalized received current for each particle $b_n(i)$. Compute FF (i, k) as per (7).

Step 4: Compute pbest(i, k) = FF (i, k) and gbest(i) = max (pbest (i, k)) with its location pbest (k) and gbest.

Step 5: Update velocity v (i + 1, k) and position b_n (i + 1, k) using $v(i+1,k) = w * v(i,k) + \varphi 1(p(b_n ik) - b_n(i,k))u(i) + \varphi 2(g(ib_n) - b_n(i,k))u(i) b_n(i+1,k) = b_n(i,k) + v(i+1,k)$.

Step 6: Update Fitness function for BF (i + 1, k).

Step 7: If Fitness function for BF (i + 1, k) > Fitness function for BF (i, k), then pbest(i + 1, k) = Fitness function for BF (i + 1, k).

Step 8: Update gbest (i + 1, k) = max (pbest(i + 1, k)).

Step 9: If $i < i_{max}$ then increment i and go to step-5, else stop.

5. Adaptive beamforming using least mean square algorithm

Least mean square (LMS) algorithm was first developed by Widrow and Hoff in 1960. The optimum weights can be estimated with the LMS algorithm. The algorithm recursively computes and updates the weight vector. Successive corrections to the weight vector in the direction of the negative of the gradient vector eventually lead to the MMSE between the beamformer output and the reference signal. At this

Table 1 AF gain along main lobe and null for PSO, LMS and CMA for different values of SIR for scenario#1 and scenario#2 (*MB-Main Beam, *NP-Null Position).

SIR (dB)	Scenario	PSO			LMS			CMA		
		G_S1	G_I1	G_I2	G_S1	G_I1	G_I2	G_S1	G_I1	G_I2
30	#1	0	−30	−23	0	−33	−38	0	−32	−37
	#2	0	−32	−42	0	−48	−40	0	−40	−47
20	#1	0	−25	−53	0	−32	−50	0	−37	−43
	#2	0	−22	−21	0	−43	−36	0	−37	−34
10	#1	0	−34	−45	0	−48	−36	0	−30	−28
	#2	0	−44	−30	0	−35	−36	0	−39	−26
0	#1	0	−32	−37	0	−34	−40	*MB and *NP are not exact		
	#2	0	−38	−45	0	−39	−44	*NP are not exact		
−10	#1	0	−34	−35	0	−37	−39	*MB and *NP are not exact		
	#2	0	−51	−48	0	−66	−38	*MB and *NP are not exact		
−20	#1	0	−41	−42	*MB and *NP are not exact			*MB and *NP are not exact		
	#2	0	−50	−34	*MB and *NP are not exact			*MB and *NP are not exact		
−30	#1	0	−35	−35	*MB and *NP are not exact			*MB and *NP are not exact		
	#2	0	−36	−28	*MB and *NP are not exact			*MB and *NP are not exact		

Table 2 Comparison of PSO, LMS and CMA for different values of SIR for scenario#1 and scenario#2 (*C-Main beam and null are converging at the exact position, *NC-Main beam and null are not converging at the exact position).

SIR	Scenario#1			Scenario#2		
	PSO	LMS	CMA	PSO	LMS	CMA
30	*C	*C	*C	*C	*C	*C
20	*C	*C	*C	*C	*C	*C
10	*C	*C	*C	*C	*C	*C
0	*C	*C	*NC	*C	*C	*NC
−10	*C	*C	*NC	*C	*C	*NC
−20	*C	NC	*NC	*C	*NC	*NC
−30	*C	NC	*NC	*C	*NC	*NC

point the weight vector assumes to be its optimum value. The algorithm contains three steps in each recursion: the computation of the processed signal with the current set of weights, the generation of the error between the processed signal and the desired signal, and the adjustment of the weights with the new error information. The following steps summarize the above three steps (Banerjee and Dwivedi, 2013a,b).

Step 1: Initialize number of iteration i_{max} and the value of μ.
Step 2: Initialize weight W_{LMS}, error E_{LMS} and output y_{LMS} as 0.
Step 3: Compute output, $y_{LMS}(i, k) = W_{LMS}(i, k)^H x(k)$.
Step 4: Compute error, $E_{LMS}(i, k) = S_u(k) - y_{LMS}(i, k)$.
Step 5: Compute weight, $W_{LMS}(i + 1, k) = W_{LMS}(i, k) + \mu x(k) E_{LMS}{}^*(i, k)$.
Step 6: If $i > i_{max}$, then stop, otherwise go to step (3) to update output, error and weight.

6. Adaptive beamforming using constant modulus algorithm

The constant modulus algorithm (CMA) was first proposed by Godward. It is used for blind equalization of signals that have

Table 3 Optimized excitation weights for SIR = 30 dB for scenario #1 and scenario#2.

N	(W_{PSO})#1	(W_{PSO})#2	(W_{LMS})#1	(W_{LMS})#2	(W_{CMA})#1	(W_{CMA})#2
1	1.00 + 0.00i	1.00 + 0.00i	1.00 + 0.00i	1.00 + 0.00i	1.00 + 0.00i	1.00 + 0.00i
2	0.84 − 0.54i	−0.28 + 0.95i	0.99 + 0.00i	0.99 + 0.00i	1.00 − 0.02i	0.99 + 0.00i
3	0.59 + 0.80i	0.88 − 0.46i	0.99 + 0.00i	0.98 + 0.00i	0.98 − 0.00i	0.98 + 0.01i
4	0.99 + 0.02i	−0.09 + 0.995i	0.99 + 0.00i	0.99 + 0.00i	0.97 + 0.00i	0.99 + 0.01i
5	0.53 − 0.84	0.66 + 0.750i	0.99 + 0.00i	0.99 + 0.01i	0.99 + 0.02i	0.99 + 0.01i
6	−0.04 − 0.99i	−0.72 + 0.688i	0.99 + 0.00i	0.98 + 0.00i	0.99 − 0.00i	0.99 + 0.01i
7	0.66 − 0.74i	0.63 + 0.770i	1.00 + 0.00i	0.99 + 0.00i	0.97 − 0.00i	0.99 − 0.00i
8	0.54 + 0.83i	−0.99 + 0.032i	1.00 + 0.00i	0.99 + 0.00i	0.98 − 0.00i	0.98 + 0.01i
9	−0.29 − 0.95i	0.29 − 0.954i	0.99 + 0.00i	0.98 + 0.00i	0.98 + 0.00i	0.98 + 0.01i
10	−0.92 − 0.37i	−0.40 + 0.912i	0.99 + 0.00i	0.99 + 0.00i	0.98 − 0.01i	1.00 + 0.00i
11	−0.14 + 0.98i	0.82 − 0.571i	0.99 + 0.00i	0.99 + 0.00i	0.99 − 0.01i	1.00 + 0.00i
12	−0.79 + 0.60i	0.03 − 0.999i	0.99 + 0.00i	0.99 + 0.00i	0.98 + 0.00i	0.99 + 0.00i
13	0.17 + 0.98i	−0.34 + 0.939i	0.99 − 0.00i	0.99 − 0.00i	0.99 + 0.01i	0.99 − 0.00i
14	−0.62 − 0.78i	0.44 − 0.896i	0.99 + 0.00i	0.99 + 0.00i	0.99 − 0.00i	0.98 + 0.00i
15	0.82 − 0.56i	−0.44 + 0.896i	0.99 + 0.00i	0.99 + 0.00i	0.97 − 0.01i	0.99 + 0.00i
16	0.21 − 0.97i	−0.90 − 0.431i	1.00 + 0.00i	0.98 + 0.00i	0.97 + 0.00i	0.99 + 0.00i

a constant modulus where reference signals are not available. The algorithm contains three major steps in each recursion: the computation of the output signal with the current set of weights, the generation of the error, and the adjustment of the weights with the new error information. The following steps summarize the above three steps (Saxena and Kothari, 2014).

Step 1: Initialize number of iteration i_{max} and the value of μ.
Step 2: Initialize weight W_{CMA}, error E_{CMA} and output y_{CMA} as 0.
Step 3: Compute output, $y_{CMA}(i, k) = W_{CMA}(i, k)^{H}x(k)$.
Step 4: Compute Error, $E_{CMA}(i, k) = y_{CMA}(i, k)/|y_{CMA}(i, k)| - y_{CMA}(i, k)$.
Step 5: Compute Weight, $W_{CMA}(i+1, k) = W_{CMA}(i, k) + \mu x(k)E_{CMA}{}^{*}(i, k)$.
Step 6: If $i > i_{max}$, then stop, otherwise go to step (3) to update output, error and weight.

7. Numerical simulation results

A 16 element ULA with $\lambda/2$ inter element spacing is taken. PSO, LMS and CMA were applied on a 16-element ULA. Three algorithms were compared on the basis of the SIR. In order to compare the performance, the simulations are done using MATLAB. All the algorithms were executed for 200 iterations and the termination criterion is set for the number of iterations. For PSO, the population size is assumed as 100 and tuning parameter φ_1 and φ_2 are set to 2.0. Phase excitation b_n is chosen as the design variable in the PSO with lower and upper limit taken in the range of $[-2\pi, 2\pi]$ with initial values of position and velocities are taken as random. For LMS and CMA, μ is taken as 0.001 and the initial weight and error are set to 0.

Based upon the aims to maximize the AF gain of the desired user and minimize the AF gain of the interfering user. PSO will try to maximize the value of the AF gain along User1 while minimize the AF gain along interferer1 and interferer2. LMS will recursively compute and update the weight vector between the output signal and the desired signal. CMA will update the information based upon the new error information.

To validate the study, two different scenarios are studied with different positions of interferer. In scenario#1, the ULA receives a desired signal arriving from angle $\theta_{s1} = 0$ and 2 interference signals arriving from angles $\theta_{i1} = -15$ and $\theta_{i2} = 30$. In scenario#2, the ULA receives a desired signal in the same direction with 2 interference signals arriving from angles $\theta_{i1} = -40$ and $\theta_{i2} = 20$. Seven cases are studied for each scenario for different SIR values keeping SNR = 30 dB.

For each case, it was observed that PSO algorithm produces main lobe along θ_{s1} and nulls toward θ_{i1} and θ_{i2}. The AF gain along the main lobe is 0 dB whereas the AF gain toward the null is -20 dB to -50 dB as shown in Table 1. The maximum SLL is -15 dB to -17 dB with directivity of 7 dB as shown in Figs. 3 and 4.

LMS algorithm also produces main lobe gain of 0 dB along the θ_{s1} direction and null gain of -33 dB to -66 dB for SIR = 30 dB to SIR = -10 dB as shown in Table 1. As SIR reduces more than -10 dB, LMS fails to point the main beam and null along the user and the interferer direction in both the scenarios.

CMA algorithm works well for SIR = 30 dB to SIR = 10 dB. As SIR starts deteriorating CMA does not produce the main beam along the user and fails to point lower gain along the interferer as shown in Table 1. In both the scenarios, LMS and CMA give reduced SLL.

The comparative Table 2 for both the scenarios shows that PSO is better as compared to LMS and CMA for every value of SIR. LMS and CMA fail to adapt for lower value of SIR. However LMS and CMA show better SLL as compared to PSO. Table 3 gives the optimized excitation weights for PSO, LMS and CMA for SIR = 30 dB.

8. Conclusions

In this paper, ABF based on PSO, LMS and CMA method have been simulated for 16 elements ULA. A performance analysis and validation are done by changing the values of SIR for two different positions of interferers. The main lobe gain and null depth are calculated to validate this approach. It is shown that the PSO-based beamformer provides accurate 0 dB main beam gain and null depth of -20 dB to -50 dB with better SLL for each case of SIR. However, CMA fail to provide main beam and null placement for SIR < 0 dB and LMS for SIR < -20 dB. Therefore, the PSO method seems to be simple and appropriate in ABF applications based on the fitness function. ABF using PSO shows mean side lobe level (SLL) of -15 dB to -17 dB with a directivity of 7 dB for each case of SIR. LMS and CMA show better SLL than PSO. It can be further studied with complex fitness functions in order to improve the value of SLL.

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