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# A NOVEL ADAPTIVE BEAMFORMING TECHNIQUE APPLIED ON LINEAR ANTENNA ARRAYS USING ADAPTIVE MUTATED BOOLEAN PSO

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**Abstract**—The present work introduces a new optimization technique suitable for adaptive beamforming of linear antenna arrays. The proposed technique is a new PSO variant called Adaptive Mutated Boolean PSO (AMBPSO) where the update formulae are implemented exclusively in Boolean form by using an efficiently adaptive mutation process. The AMBPSO aims at estimating the excitation weights applied on the array elements considering that a desired signal and several interference signals are received by the array at respective directions of arrival. In order to exhibit the robustness of the technique, the optimization process does not take into account the interference correlation matrix. A certain power level of additive Gaussian noise is also considered by the technique. The AMBPSO has been applied in several cases of uniform linear antenna arrays with different spacing between adjacent elements and different noise power level and therefore seems to be quite promising in the smart antenna technology.

## 1. INTRODUCTION

The analysis and design of antenna arrays are very important and challenging issues in communications industry. So far, many techniques have been studied and developed in order to design arrays that satisfy specific requirements [1–9]. Due to the demanding applications in modern communications, the radiation pattern of base station arrays must be dynamically shaped according to certain requirements. Specifically, the peak of the main lobe must be steered towards a

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desired signal called signal-of-interest (SOI). On the contrary, pattern nulls must be formed in the directions of arrival (DOA) of interference or undesired signals. Antennas operating under the above requirements are called smart antennas [10–17] and the techniques used to calculate the excitation weights that produce the above-defined radiation pattern are called adaptive beamforming (ABF) techniques [18–25].

Most of the ABF techniques proposed so far try to recover the degradation in their performance caused by mismatches between the assumed and the actual conditions. A usual kind of mismatch is the steering vector uncertainly which is taken into account by a well-known ABF technique named robust Capon beamforming (RCB) [21]. However, the performance decrease caused by uncertainty in the interference correlation matrix is a major issue that needs careful consideration. Therefore, an ABF technique insensitive to that type of uncertainty would be desirable.

The present study introduces a new optimization technique suitable for adaptive beamforming of antenna arrays. This technique is a new variant of Particle Swarm Optimization (PSO) called Adaptive Mutated Boolean PSO (AMBPSO). The conventional PSO and all its variants are based on an update mechanism, where real number expressions are used. However, the update mechanism in the AMBPSO is implemented exclusively in Boolean form using an effectively adaptive mutation process. Both the Boolean update and the adaptive mutation process make the AMBPSO a robust technique.

The AMBPSO is utilized here as an ABF technique applied to uniform linear arrays (ULAs). The technique assumes a desired signal and several interference signals, all uncorrelated with each other, received by the array at respective directions of arrival. These directions are considered to be already estimated by well-known DOA algorithms [10, 11, 26–31]. A certain power level of additive Gaussian noise is also taken into account. The optimal excitation weights applied on the elements of the ULA are extracted by minimizing a suitably chosen fitness function $F$. In order to exhibit the robustness of the technique, the optimization process does not take into account the interference correlation matrix. In that manner, we try to develop a technique which does not depend on the knowledge of the interference signals but only on the knowledge of their DOA.

## 2. FORMULATION

Assume an $M$-element ULA that receives a SOI $s(k)$ arriving from angle $\theta_0$ and $N$ interference signals $i_n(k)$ arriving from different angles $\theta_n$ $(n = 1, \ldots, N)$ (see Figure 1). Each angle is called angle of arrival

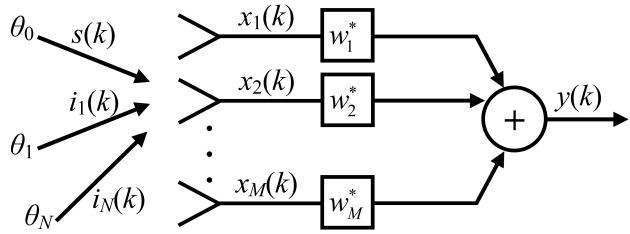


**Figure 1.** $M$-element uniform linear array.

(AOA) and defines a signal DOA with respect to a reference direction normal to the array axis. The parameter $k$ denotes the $k$-th time sample. Each element is consider to be an isotropic source, while all the arriving signals are monochromatic with $N < M$. The received signal $x_m(k)$ at the input of every $m$-th element ($m = 1, \ldots, M$) includes additive, zero mean, Gaussian noise $n_m(k)$ with variance $\sigma^2$. Thus, the input vector is:

$$\begin{aligned}\bar{x}(k) &= \bar{a}_0 s(k) + \begin{bmatrix} \bar{a}_1 & \bar{a}_2 & \ldots & \bar{a}_N \end{bmatrix} \begin{bmatrix} i_1(k) \\ i_2(k) \\ \vdots \\ i_N(k) \end{bmatrix} + \bar{n}(k) \\ &= \bar{a}_0 s(k) + \bar{A}\bar{i}(k) + \bar{n}(k) = \bar{d}(k) + \bar{u}(k) \end{aligned} \tag{1}$$

where $\bar{a}_n = \begin{bmatrix} 1 & e^{j\frac{2\pi}{\lambda} q \sin\theta_n} & \ldots & e^{j(M-1)\frac{2\pi}{\lambda} q \sin\theta_n} \end{bmatrix}^T$ $(n = 0, 1, \ldots, N)$ is the array steering vector of the $\theta_n$ AOA, $\bar{A}$ is the $M \times N$ matrix of steering vectors $\bar{a}_n$, $\bar{i}(k)$ is the vector of the $N$ uncorrelated interference signals $i_n(k)$, $\bar{n}(k)$ is the vector of the $M$ uncorrelated noise signals $n_m(k)$, and $q$ is the spacing between adjacent elements of the ULA. Also, the vector $\bar{d}(k) = \bar{a}_0 s(k)$ represents the desired input signals, while the vector $\bar{u}(k) = \bar{A}\bar{i}(k) + \bar{n}(k)$ represents the undesired (interference plus noise) input signals. Finally, the superscript $T$ denotes the transpose operation.

The array output is given by the form:

$$y(k) = \bar{w}^H \bar{x}(k) = \bar{w}^H \bar{d}(k) + \bar{w}^H \bar{u}(k) \tag{2}$$

where $\bar{w} = \begin{bmatrix} w_1 & w_2 & \ldots & w_M \end{bmatrix}^T$ is the vector of excitation weights and the superscript $H$ denotes the Hermitian transpose operation.

The array output power for the desired signal is given by:

$$\sigma_d^2 = E\left[\left|\bar{w}^H \bar{d}(k)\right|^2\right] = E\left[\left|\bar{w}^H \bar{a}_0 s(k)\right|^2\right] = S\bar{w}^H \bar{a}_0 \bar{a}_0^H \bar{w} \tag{3}$$

where $S = E[|s(k)|^2]$ is mean power of SOI. Also, the array output power for the undesired signal is given by:

$$\sigma_u^2 = E\left[\left|\bar{w}^H \bar{u}(k)\right|^2\right] = E\left[\left|\bar{w}^H \left[\bar{A}\bar{i}(k) + \bar{n}(k)\right]\right|^2\right]$$
$$= \bar{w}^H \bar{A} \bar{R}_{ii} \bar{A}^H \bar{w} + \bar{w}^H \bar{R}_{nn} \bar{w} \quad (4)$$

where $\bar{R}_{ii} = E[\bar{i}(k)\bar{i}^H(k)]$ is the interference correlation matrix and $\bar{R}_{nn} = E[\bar{n}(k)\bar{n}^H(k)]$ is the noise correlation matrix. Taking into account that $n_m(k)$ $(m = 1, \ldots, M)$ are uncorrelated, zero mean, Gaussian noise signals with variance $\sigma^2$, we get $\bar{R}_{nn} = \sigma^2 I$. Therefore, (4) can be written as:

$$\sigma_u^2 = \bar{w}^H \bar{A} \bar{R}_{ii} \bar{A}^H \bar{w} + \sigma^2 \bar{w}^H \bar{w} \quad (5)$$

Finally, the signal-to-interference-plus-noise ratio is given by:

$$SINR = \frac{\sigma_d^2}{\sigma_u^2} = \frac{S \bar{w}^H \bar{a}_0 \bar{a}_0^H \bar{w}}{\bar{w}^H \bar{A} \bar{R}_{ii} \bar{A}^H \bar{w} + \sigma^2 \bar{w}^H \bar{w}} \quad (6)$$

The fitness function $F$ can be simply defined as the inverse of $SINR$. As $F$ is minimized, $SINR$ is maximized, which means that the peak of the main lobe is steered towards the SOI and pattern nulls are formed in the directions of arrival of all the interference signals. In order to make our technique work without the knowledge of $\bar{R}_{ii}$ and $S$, we assume that $\bar{R}_{ii} = I$ and $S = 1$. Then, $F$ can be defined by the form:

$$F = \frac{\bar{w}^H \bar{A} \bar{A}^H \bar{w} + \sigma^2 \bar{w}^H \bar{w}}{\bar{w}^H \bar{a}_0 \bar{a}_0^H \bar{w}} \quad (7)$$

It is obvious from (7) that the minimization of $F$ performed by the AMBPSO does not depend on the knowledge of $\bar{R}_{ii}$ but only on the knowledge of the interference DOA. The value of $\sigma^2$ can be calculated from the signal-to-noise ratio $SNR$ in dB as follows:

$$\sigma^2 = 10^{-SNR/10} \quad (8)$$

The proposed technique is compared to an efficient well-known ABF technique called Minimum Variance Distortionless Response (MVDR) which is a variant of RCB technique [11]. The MVDR beamformer seeks for the optimum weight vector $\bar{w}$ that minimizes the power of the undesired output signal while the desired output signal is maintained. Therefore, $\bar{w}$ is calculated by minimizing the quantity $\bar{w}^H \bar{R}_{uu} \bar{w}$, while $\bar{w}^H \bar{a}_0 = 1$. The optimum $\bar{w}$ is given by:

$$\bar{w}_{mvdr} = \frac{\bar{R}_{uu}^{-1} \bar{a}_0}{\bar{a}_0^H \bar{R}_{uu}^{-1} \bar{a}_0} \quad (9)$$

where $\bar{R}_{uu} = E[\bar{u}(k)\bar{u}^H(k)]$ is the correlation matrix of $\bar{u}(k)$.

## 3. ADAPTIVE MUTATED BOOLEAN PSO

PSO can be found in many studies in the literature [14, 32–36]. A brief description of PSO is given in [32]. The Boolean PSO (BPSO) is a binary version of PSO [37] based on the swarm behavior as well. The AMBPSO is an improved version of BPSO proposed by the authors.

In the AMBPSO, the position $\bar{x}_n = [x_{n1} \ \ldots \ x_{nb} \ \ldots \ x_{nB}]$ and the velocity $\bar{v}_n = [v_{n1} \ \ldots \ v_{nb} \ \ldots \ v_{nB}]$ of every $n$-th ($n = 1, \ldots, N_P$) particle of the swarm are represented as binary strings of $B$ bits. Every position $\bar{x}_n$ must be inside the search space defined by a lower and an upper boundary, respectively $\bar{l}_n$ and $\bar{u}_n$. If a particle goes outside the search space, a large fitness value is assigned as a penalty to the particle. Since the AMBPSO aims at minimizing the fitness function, these particles are gradually moved inside the search space.

The update of $\bar{v}_n$ and $\bar{x}_n$ is made by using "*and*", "*or*" and "*xor*" operators:

$$v_{nb} = c_1 \cdot v_{nb} + c_2 \cdot (p_{nb} \oplus x_{nb}) + c_3 \cdot (g_b \oplus x_{nb}) \tag{10}$$

$$x_{nb} = x_{nb} \oplus v_{nb} \tag{11}$$

where $p_{nb}$ is the $b$-th bit of the best position $\bar{p}_n$ achieved so far by the $n$-th particle and $g_b$ is the $b$-th bit of the best position $\bar{g}$ achieved so far by the swarm. In addition, $c_1$, $c_2$, and $c_3$ are random bits with probabilities of being '1' respectively equal to $C_1$, $C_2$, and $C_3$. The exclusively Boolean update of $\bar{v}_n$ and $\bar{x}_n$ makes the AMBPSO more efficient than the popular binary PSO version of [38], where the velocity update is made by using a real number expression.

In order to control the convergence speed of the process, the AMBPSO utilizes a parameter $v_{\max}$ called maximum allowed velocity and defined as the maximum number of '1's allowed in $\bar{v}_n$. The actual number of '1's in $\bar{v}_n$ is the "velocity length" $l(\bar{v}_n)$ and is controlled by the "negative selection" (NS), which is a basic mechanism of Artificial Immune Systems (AISs) [37]. AISs are inspired by the biological immune systems. The NS is responsible for eliminating $T$-cells that recognize self antigens in the thymus. According to the NS, $\bar{v}_n$ is considered as self antigen when $l(\bar{v}_n) > v_{\max}$ and then randomly chosen '1's in $\bar{v}_n$ change into '0's until $l(\bar{v}_n) = v_{\max}$. If $l(\bar{v}_n) \leq v_{\max}$, $\bar{v}_n$ is considered as non-self antigen and is not changed.

In order to increase the exploration ability of the particles, after the completion of the NS, an adaptive mutation process is applied by changing the '0's of every $\bar{v}_n$ to '1's with "mutation probability" $m$. The mutation process starts from relatively small values of $m$ to avoid pure random search. In every iteration, $m$ undergoes a linear reduction until it reaches zero at the end of the optimization process.

The reduction in the values of $m$ provides the AMBPSO with the adaptation feature.

The AMBPSO is a technique of high computational complexity like all the other evolutionary techniques and thus needs much more CPU time than the MVDR technique to find an optimal solution. In the cases studied here, an Intel Core 2 Duo computer was used and the CPU time per execution was measured around 2 seconds. However, this problem can be overcome by using Graphics Processing Units (GPUs), which provide cheap access to high-performance parallel computing resources and make the algorithm execution 10–100 times faster [25].

A brief description of the AMBPSO algorithm is given below:

1. Choose the values of $N_P$, $B$, $C_1$, $C_2$, $C_3$, $v_{\max}$, $m$, $\bar{l}_n$ and $\bar{u}_n$ $(n = 1, \ldots, N_P)$, and the maximum number of iterations $T_{\max}$ of the optimization process.
2. Initialize random values for $\bar{v}_n$ $(n = 1, \ldots, N_P)$ and apply the NS to correct them. Also, initialize random values for $\bar{x}_n$ $(n = 1, \ldots, N_P)$ inside the search space and calculate their fitness values $F(\bar{x}_n)$.
3. Set $\bar{p}_n = \bar{x}_n$ and $F(\bar{p}_n) = F(\bar{x}_n)$ $(n = 1, \ldots, N_P)$.
4. Find $F_{\min} = F(\bar{g})$ among $F(\bar{p}_n)$ $(n = 1, \ldots, N_P)$.
5. Update $\bar{v}_n$ $(n = 1, \ldots, N_P)$ using (10) and apply NS to correct them.
6. Mutate the '0's of $\bar{v}_n$ $(n = 1, \ldots, N_P)$ according to the value of $m$.
7. Update $\bar{x}_n$ $(n = 1, \ldots, N_P)$ using (11).
8. Calculate the fitness values $F(\bar{x}_n)$ $(n = 1, \ldots, N_P)$.
9. Assign a large fitness value for $\bar{x}_n$ lying outside the search space.
10. For $n = 1, \ldots, N_P$, if $F(\bar{x}_n) < F(\bar{p}_n)$ then $\bar{p}_n = \bar{x}_n$.
11. For $n = 1, \ldots, N_P$, if $F(\bar{p}_n) < F(\bar{g})$ then $\bar{g} = \bar{p}_n$.
12. Reduce the value of $m$ according to a linear decrease expression.
13. If $T_{\max}$ is not reached, repeat the algorithm from step (5), or else report results and terminate.

## 4. NUMERICAL RESULTS

The AMBPSO algorithm was applied on a 10-element ULA. The parameters used by the algorithm were: $N_P = 20$, $C_1 = 0.1$, $C_2 = C_3 = 0.5$, $v_{\max} = 4$, $m = 0.10$, and $T_{\max} = 10000$. The ULA receives a SOI arriving from angle $\theta_0 = 30^\circ$ and 8 interference signals arriving from respective angles $\theta_n \in \{-70^\circ, -40^\circ, -30^\circ, -10^\circ, 0^\circ, 10^\circ, 50^\circ, 70^\circ\}$. All the above signals are uncorrelated with each other. Four cases

are studied with different spacing $q$ between adjacent elements and different $SNR$. In the first case, $SNR = 30\,\text{dB}$ and $q = 0.5\lambda$ which is the usual spacing for most of the ABF techniques. In the second case, our technique is tested for $q \neq 0.5\lambda$. Therefore, $q$ is set to $0.6\lambda$, while $SNR = 30\,\text{dB}$. In order to explore the efficiency of our technique for smaller and larger values of $SNR$, two more cases are studied. In the third case, $SNR = 15\,\text{dB}$ and $q = 0.5\lambda$, and in the fourth case $SNR = 50\,\text{dB}$ and $q = 0.5\lambda$.

Initially, the AMBPSO was compared to the conventional BPSO in terms of convergence. Both algorithms use the same fitness function $F$ given in (7). For each case, the AMBPSO and BPSO algorithms were executed 100 times in order to derive comparative graphs that depict

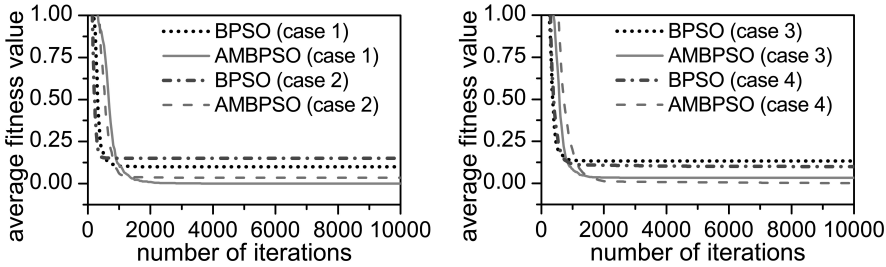


**Figure 2.** Comparative convergence graphs.

**Table 1.** Optimal weight values for $q = 0.5\lambda$ and $SNR = 30\,\text{dB}$.

| $m$ | $w_{mvdr}$ | $w_{ambpso}$ | $m$ | $w_{mvdr}$ | $w_{ambpso}$ |
|---|---|---|---|---|---|
| 1 | $0.352 - j0.227$ | $0.191 + j0.197$ | 6 | $0.342 + j0.940$ | $0.070 + j1.033$ |
| 2 | $0.017 + j0.405$ | $-0.195 + j0.490$ | 7 | $-0.921 + j0.101$ | $-0.905 + j0.228$ |
| 3 | $-0.750 + j0.152$ | $-0.692 - j0.202$ | 8 | $-0.114 - j0.757$ | $-0.214 - j0.622$ |
| 4 | $-0.220 - j0.900$ | $0.165 - j0.983$ | 9 | $0.386 - j0.122$ | $0.435 - j0.239$ |
| 5 | $1.000 + j0$ | $1.000 + j0$ | 10 | $-0.092 + j0.409$ | $0.144 + j0.096$ |

**Table 2.** Optimal weight values for $q = 0.6\lambda$ and $SNR = 30\,\text{dB}$.

| $m$ | $w_{mvdr}$ | $w_{ambpso}$ | $m$ | $w_{mvdr}$ | $w_{ambpso}$ |
|---|---|---|---|---|---|
| 1 | $0.387 - j0.377$ | $0.316 - j0.104$ | 6 | $0.392 + j0.920$ | $0.181 + j1.010$ |
| 2 | $0.483 - j0.070$ | $0.252 + j0.256$ | 7 | $-0.738 - j0.412$ | $-0.767 - j0.202$ |
| 3 | $-0.711 + j0.223$ | $-0.722 + j0.095$ | 8 | $-0.073 - j0.741$ | $-0.025 - j0.717$ |
| 4 | $-0.668 - j0.518$ | $-0.369 - j0.782$ | 9 | $0.124 + j0.472$ | $0.223 + j0.159$ |
| 5 | $1.000 + j0$ | $1.000 + j0$ | 10 | $-0.195 + j0.503$ | $-0.089 + j0.285$ |

the average convergence of $F$ (see Figure 2). Although the AMBPSO converges a little slower than the BPSO, it finally gives better solutions.

Then, the AMBPSO was compared with the MVDR technique. The optimal excitation weights of the four cases are given respectively in Tables 1–4, while the radiation patterns are shown respectively in Figures 3–6. All the cases show the superiority of the AMBPSO algorithm over a robust ABF technique such as the MVDR. Both

**Table 3.** Optimal weight values for $q = 0.5\lambda$ and $SNR = 15\,\text{dB}$.

| $m$ | $w_{mvdr}$ | $w_{ambpso}$ | $m$ | $w_{mvdr}$ | $w_{ambpso}$ |
|---|---|---|---|---|---|
| 1 | $0.354 - j0.226$ | $0.303 + j0.030$ | 6 | $0.340 + j0.940$ | $0.195 + j1.020$ |
| 2 | $0.018 + j0.407$ | $-0.093 + j0.476$ | 7 | $-0.922 + j0.100$ | $-0.901 + j0.171$ |
| 3 | $-0.751 + j0.152$ | $-0.752 - j0.053$ | 8 | $-0.113 - j0.758$ | $-0.153 - j0.671$ |
| 4 | $-0.219 - j0.901$ | $-0.011 - j0.986$ | 9 | $0.389 - j0.122$ | $0.405 - j0.192$ |
| 5 | $1.000 + j0$ | $1.000 + j0$ | 10 | $-0.092 + j0.410$ | $0.010 + j0.210$ |

**Table 4.** Optimal weight values for $q = 0.5\lambda$ and $SNR = 50\,\text{dB}$.

| $m$ | $w_{mvdr}$ | $w_{ambpso}$ | $m$ | $w_{mvdr}$ | $w_{ambpso}$ |
|---|---|---|---|---|---|
| 1 | $0.352 - j0.227$ | $0.213 + j0.034$ | 6 | $0.342 + j0.940$ | $0.159 + j0.978$ |
| 2 | $0.017 + j0.405$ | $-0.127 + j0.442$ | 7 | $-0.921 + j0.101$ | $-0.921 + j0.185$ |
| 3 | $-0.750 + j0.152$ | $-0.683 - j0.072$ | 8 | $-0.114 - j0.757$ | $-0.190 - j0.678$ |
| 4 | $-0.220 - j0.900$ | $0.036 - j0.921$ | 9 | $0.386 - j0.122$ | $0.427 - j0.194$ |
| 5 | $1.000 + j0$ | $1.000 + j0$ | 10 | $-0.092 + j0.409$ | $0.086 + j0.226$ |

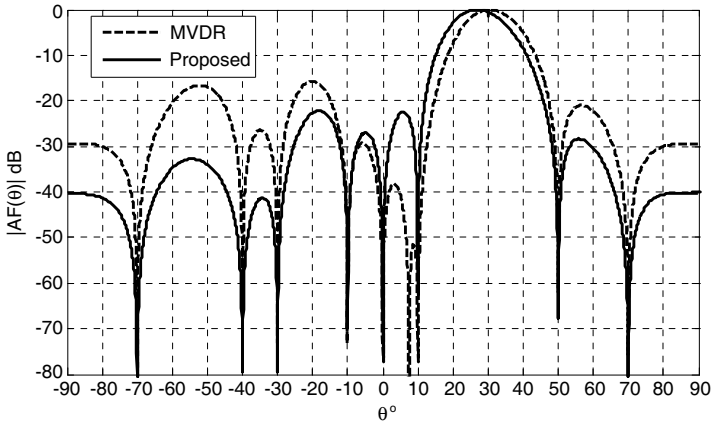


**Figure 3.** Optimal radiation patterns for $q = 0.5\lambda$ and $SNR = 30\,\text{dB}$.

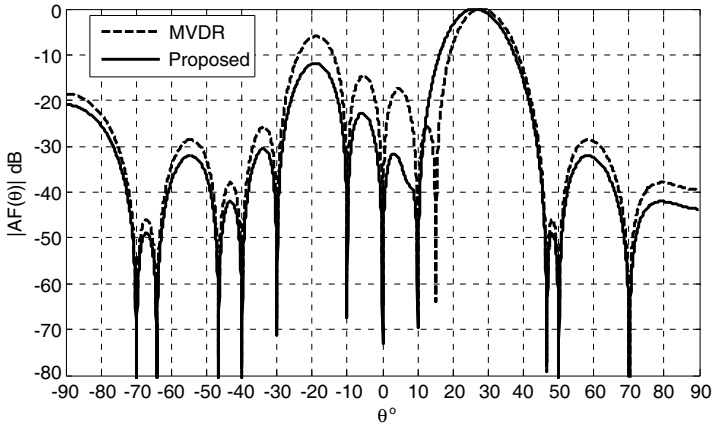


**Figure 4.** Optimal radiation patterns for $q = 0.6\lambda$ and $SNR = 30\,\text{dB}$.

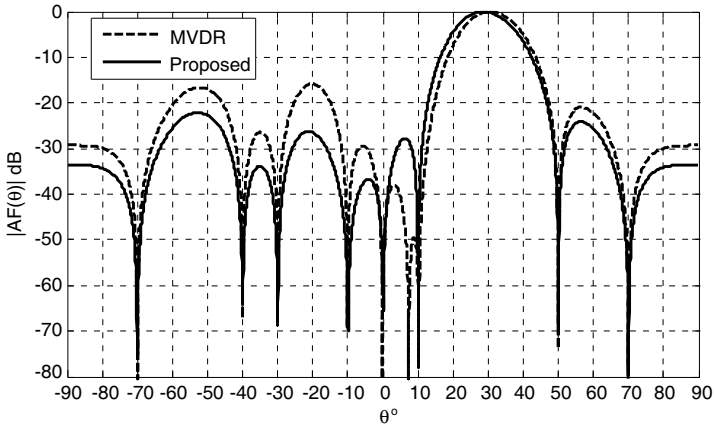


**Figure 5.** Optimal radiation patterns for $q = 0.5\lambda$ and $SNR = 15\,\text{dB}$.

techniques succeed to steer the peak of the main lobe towards the SOI and form pattern nulls in the DOA of every interference signal. However, the AMBPSO provides deeper nulls and that's why all the radiation patterns produced by the AMBPSO have lower side lobe level (SLL) than the patterns produced by the MVDR technique. In order to achieve specific values of SLL for certain angular regions, a properly defined term must be added to the fitness function $F$. Of course, the additional term increases the CPU time required by the AMBPSO to find an optimal solution.

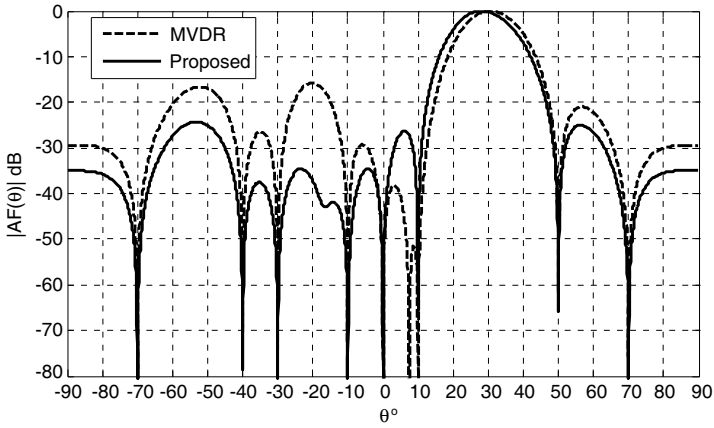


**Figure 6.** Optimal radiation patterns for $q = 0.5\lambda$ and $SNR = 50\,\text{dB}$.

**Table 5.** $SINR$ derived from MVDR and AMBPSO for various values of $SNR$, considering a 10-element ULA with $q = 0.5\lambda$.

| $SNR$ (dB) | $SINR$ (dB) derived from MVDR | $SINR$ (dB) derived from AMBPSO | | | |
|---|---|---|---|---|---|
| | | Best | Worst | Mean | STD |
| −20 | −10.0540 | −10.0522 | −10.0548 | −10.0523 | 0.0004 |
| −15 | −5.1601 | −5.1395 | −5.1512 | −5.1399 | 0.0020 |
| −10 | −0.3701 | −0.2975 | −0.3692 | −0.2998 | 0.0098 |
| −5 | 4.3345 | 4.5321 | 4.3422 | 4.5269 | 0.0218 |
| 0 | 8.8967 | 9.4241 | 8.5481 | 9.3749 | 0.1643 |
| 5 | 13.4522 | 14.3768 | 12.0647 | 14.2676 | 0.3628 |
| 10 | 18.2011 | 19.3598 | 15.1371 | 19.2810 | 0.4463 |
| 15 | 22.6889 | 24.3542 | 16.5370 | 24.1008 | 1.0643 |
| 20 | 27.3035 | 29.3509 | 17.2416 | 29.0332 | 1.2290 |
| 25 | 31.7012 | 34.3515 | 22.4314 | 33.6680 | 1.4163 |
| 30 | 36.4811 | 39.3341 | 30.2715 | 38.7648 | 0.8722 |
| 35 | 40.4633 | 44.3440 | 32.6393 | 43.1564 | 1.5287 |
| 40 | 45.2813 | 49.3461 | 36.6898 | 48.1781 | 1.2409 |
| 45 | 49.3217 | 54.3358 | 43.2386 | 52.5134 | 1.5788 |
| 50 | 54.8269 | 59.3317 | 47.6499 | 58.3221 | 1.7439 |
| 55 | 59.1356 | 64.3458 | 52.7630 | 63.0660 | 1.6119 |
| 60 | 63.4345 | 69.3468 | 56.3379 | 67.5858 | 1.8369 |

Finally, the AMBPSO is compared in terms of $SINR$ with the MVDR technique for various $SNR$ values considering a 10-element ULA with $q = 0.5\lambda$. For each value of $SNR$, the AMBPSO algorithm is executed 100 times and statistical results concerning the $SINR$ are extracted (see Table 5). The results show low standard deviation and mean values of $SINR$ close to the respective best values. Therefore, the AMBPSO algorithm seems to have stable and good performance regardless of the $SNR$ values. In addition, the mean $SINR$ achieved by the AMBPSO is always greater than the $SINR$ achieved by the MVDR technique, and their difference increases with increasing $SNR$.

## 5. CONCLUSION

The cases studied in the present work show that the AMBPSO converges a little slower than the conventional BPSO, but it finally leads to better solutions. Also, the AMBPSO can be used as an efficient ABF technique capable of producing radiation patterns better than patterns produced by a robust ABF technique such as the MVDR. The AMBPSO succeeds not only to steer the main lobe towards the SOI and form nulls in the DOA of all the interference signals but also to reduce the SLL more than the MVDR technique does. As an ABF technique, the AMBPSO does not need the knowledge of the interference correlation matrix but only the knowledge of the interference DOA. In addition, the AMBPSO algorithm exhibits stable and good behavior for every value of $SNR$, providing better $SINR$ values than those obtained by the MVDR technique. By using GPUs, the computational complexity can be overcome and then the AMBPSO algorithm can be used by adaptive beamforming networks in real-time applications. Therefore, the AMBPSO seems to be quite promising in the smart antenna technology. As a future work, the AMBPSO will be applied on more complex fitness functions in order not only to control the pattern nulls but also to achieve specific values of SLL.

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