Progress In Electromagnetics Research, Vol. 124, 137–150, 2012

IMPROVED ANTENNA ARRAY ADAPTIVE BEAMFORMING WITH LOW SIDE LOBE LEVEL USING A NOVEL ADAPTIVE INVASIVE WEED OPTIMIZATION METHOD

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Abstract—An improved adaptive beamforming technique of antenna arrays is introduced. The technique is implemented by using a novel Invasive Weed Optimization (IWO) variant called Adaptive Dispersion Invasive Weed Optimization (ADIWO) where the seeds produced by a weed are dispersed in the search space with standard deviation specified by the fitness value of the weed. The adaptive seed dispersion makes the ADIWO converge faster than the conventional IWO. This behavior is verified by applying both the ADIWO and the conventional IWO on well-known test functions. The ADIWO method is utilized here as an adaptive beamformer that makes a uniform linear antenna array steer the main lobe towards the direction of arrival (DoA) of a desired signal, form nulls towards the respective DoA of several interference signals and achieve low side lobe level (*SLL*). The proposed ADIWO based beamformer is compared to a Particle Swarm Optimization (PSO) based beamformer and a well known beamforming method called Minimum Variance Distortionless Response (MVDR). Several cases have been studied with different number of interference signals and different power level of additive zero-mean Gaussian noise. The results show that the ADIWO provides sufficient steering ability regarding the main lobe and the nulls, works faster than the PSO and achieves better *SLL* than the PSO and MVDR.

Received 2 December 2011, Accepted 9 January 2012, Scheduled 17 January 2012

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1. INTRODUCTION

Modern communications involve many new and challenging issues, especially those concerning smart antennas [1–5]. Antenna array beamforming is one of them [5–18]. It helps the array improve the reception of any desired signal and also reduce the reception of any interference or other undesired signal, improving thus the signal-to-interference ratio (SIR). To cope with that, an adaptive beamformer has to calculate the array excitation weights that steer the main lobe towards the direction of arrival (DoA) of the desired signal and create a pattern null towards the DoA of every undesired or interference signal. In practice, the above calculation is a real time procedure, since the DoA of all the incoming signals change with time. Therefore, the calculation must be completed as soon as possible.

Many adaptive beamforming (ABF) techniques have been proposed so far in order to optimize the steering ability of the array regarding the main lobe and the nulls and therefore improve the signal-to-interference-plus-noise ratio (SINR). Such a technique is the Minimum Variance Distortionless Response (MVDR) [2, 16]. Nevertheless, a radiation pattern with low side lobe level (*SLL*) is also desirable since it avoids an unreasonable spatial spread of radiated power. A conventional ABF technique like MVDR aims at improving the SINR but it cannot minimize the *SLL*. To maximize the SINR and also minimize the *SLL*, several evolutionary optimization methods have been introduced and applied as adaptive beamformers with great success [3, 12–14, 18]. The basic drawback of such methods is the increased computational time which is a prohibitive factor for real time techniques. Therefore, a fast evolutionary method would be more suitable for ABF applications.

In the present paper, the authors introduce an improved variant of the recently proposed Invasive Weed Optimization (IWO) [18–26] called Adaptive Dispersion Invasive Weed Optimization (ADIWO). The ADIWO algorithm is based on the IWO source code provided by Mehrabian and Lucas [19]. The main difference between the IWO and the ADIWO lies in the way the seeds produced by a weed are dispersed in the search space. In the conventional IWO, the standard deviation of the seed dispersion decreases as a function of the number of iterations and is the same for all the seeds at a given iteration. However, in the ADIWO, the standard deviation of the dispersion of the seeds produced by a weed is a function of the fitness value of this weed. The adaptive seed dispersion makes the ADIWO converge faster than the conventional IWO. This behavior is verified by applying both the ADIWO and IWO on well-known test functions [27].

The ADIWO algorithm is utilized here as an adaptive beamformer, which optimizes the steering ability of uniform linear arrays (ULAs) regarding the main lobe and the nulls and also achieves low *SLL*. The ADIWO based beamformer is compared to a Particle Swarm Optimization (PSO) based beamformer and the MVDR technique. The input data for all the beamformers are the signal-to-noise ratio (*SNR*) and the DoA of the incoming signals. These directions are considered to be already estimated by well-known DoA algorithms [28–34]. Due to uncertainties in the amplitudes of the interference signals that may be observed in practice, the exact element values of the interference correlation matrix are not taken into account. Therefore, the interference correlation matrix is taken as the identity matrix. Several cases have been studied with different number of interference signals and different power level of additive zero-mean Gaussian noise. The results show that the ADIWO provides sufficient steering ability regarding the main lobe and the nulls, works faster than the PSO and achieves better *SLL* than the PSO and MVDR.

2. BEAMFORMING PROBLEM FORMULATION

The beamforming problem has already been described in [12]. A ULA of M monochromatic isotropic elements receives a desired signal s from angle of arrival (AoA) θ_0 and N interference signals i_n $(n = 1, \ldots, N)$ arriving respectively from θ_n $(n = 1, \ldots, N)$, in the presence of additive zero-mean Gaussian noise with variance σ^2_{noise}. Each θ_n $(n = 0, 1, \ldots, N)$ is defined by the DoA of s or i_n and the normal to the array axis direction. The signals s, i_n $(n = 1, \ldots, N)$ and the noise signals are all uncorrelated with each other. The quiescent pattern (QP) of the array is derived when all the excitation weights are of equal amplitude and phase. This pattern has to be modified in order to steer the main lobe towards θ_0, place nulls towards θ_n $(n = 1, \ldots, N)$ and achieve low *SLL*.

According to the formulation of the beamforming problem given in [12], the steering ability of the ULA regarding the main lobe and the nulls is optimized by minimizing the fitness function given below:

$$F = \frac{\bar{w}^H \bar{A}\, \bar{A}^H \bar{w} + \sigma^2_{noise}\, \bar{w}^H\, \bar{w}}{\bar{w}^H \bar{a}_0\, \bar{a}_0^H \bar{w}} \tag{1}$$

where

$$\bar{w} = \begin{bmatrix} w_1 & w_2 & \ldots & w_M \end{bmatrix}^T \tag{2}$$

$$\bar{A} = \begin{bmatrix} \bar{a}_1 & \bar{a}_2 & \ldots & \bar{a}_N \end{bmatrix} \tag{3}$$

$$\bar{a}_n = \begin{bmatrix} 1 & e^{j\frac{2\pi}{\lambda} q \sin\theta_n} & \ldots & e^{j(M-1)\frac{2\pi}{\lambda} q \sin\theta_n} \end{bmatrix}^T, \quad n = 0, 1, \ldots, N \tag{4}$$

are, respectively, the vector of the ULA excitation weights, the $M \times N$ array steering matrix, and the array steering vector that corresponds to AoA θ_n. Also, q is the distance between adjacent elements of the ULA, while the superscripts T and H imply the transpose matrix and the Hermitian transpose matrix, respectively. The consideration about the interference correlation matrix, which is taken as the identity matrix as explained in the previous section, has already been taken into account in (1). In order to satisfy the additional requirement for low SLL, the fitness function expression must be modified as follows:

$$F = bf_1 \frac{\bar{w}^H \bar{A}\, \bar{A}^H \bar{w} + \sigma_{noise}^2\, \bar{w}^H\, \bar{w}}{\bar{w}^H \bar{a}_0\, \bar{a}_0^H \bar{w}} + bf_2\, SLL \tag{5}$$

The factors bf_1 and bf_2 are used to balance the minimization of the two terms shown in (5). The fitness function as given in (5) is used by both the ADIWO-based and PSO-based beamformers to estimate the respective array excitation weights. The calculation of the excitation weights using the MVDR technique is also described in [12].

3. ADAPTIVE DISPERSION IWO

The original IWO method was initially proposed by Mehrabian and Lucas in [19]. Since then, several studies have been published on antenna design using IWO [18, 20–22, 24, 25]. In addition, several efficient IWO variants have been proposed [23, 26]. Nevertheless, the original IWO and all the IWO variants proposed so far have a common feature concerning the way the seeds produced by a weed are dispersed in the search space: The standard deviation of the seed dispersion σ decreases as a function of the number of iterations *iter*. Obviously, the value of σ defines the exploration ability of the weeds. Therefore, as *iter* increases, the exploration ability of all the weeds is gradually reduced. At the end of the optimization process, the exploration ability has diminished so much that every weed can only fine tune its position. Then, if the optimal position has not been found yet, it will never be found.

In the ADIWO, the standard deviation σ of the dispersion of the seeds produced by a weed is a linear function of the fitness value f of this weed. Considering that the goal is the minimization of the fitness function, σ can be estimated according to the following expression:

$$\sigma = \frac{\sigma_{\max} - \sigma_{\min}}{f_{\max} - f_{\min}} f + \frac{\sigma_{\min} f_{\max} - \sigma_{\max} f_{\min}}{f_{\max} - f_{\min}} \tag{6}$$

where $\sigma_{\max}$ and $\sigma_{\min}$ are the standard deviation limits defined in the same way as in the original IWO algorithm, while $f_{\max}$ and $f_{\min}$

represent respectively the maximum and minimum fitness values at a certain iteration. The ADIWO algorithm has the same structure as the original IWO algorithm described in [19]. The only difference lies in the calculation of σ which is performed by using (6). It is easy to realize that the best weed ($f = f_{\min}$) disperses its seeds with the minimum σ ($\sigma = \sigma_{\min}$), while the worst weed ($f = f_{\max}$) disperses its seeds with the maximum σ ($\sigma = \sigma_{\max}$). Therefore, the weeds have different behavior depending on their fitness values. As the fitness value gets closer to $f_{\min}$, the exploration ability of the weed is reduced and thus the weed can only fine tune its near-optimal position. On the contrary, as f gets closer to $f_{\max}$, the exploration ability of the weed increases and thus the weed is capable of exploring the search space to find better positions. In this way, the exploration ability of the weed colony is maintained until the end of the optimization process. Moreover, the adaptive seed dispersion makes the ADIWO converge faster than the original IWO. This behavior is verified in the next section.

4. CONVERGENCE RESULTS

The ADIWO was compared to the original IWO in terms of convergence. Both algorithms were applied to minimize two well-known test functions, i.e., the generalized Rastrigin function and the generalized Rosenbrock function [27]. Both functions were applied in 30 dimensions. For each function, the ADIWO and IWO algorithms were executed 100 times in order to extract comparative graphs that display the average convergence. For both algorithms, the population size is limited to 30 weeds, the number of seeds produced by a weed ranges from 5 to zero depending on the fitness value of the weed, and finally the standard deviation limits are $\sigma_{\max} = 10$ and $\sigma_{\min} = 0.5$. The comparative graphs given in Figures 1 and 2 show that both algorithms result in the same solutions. However, the ADIWO

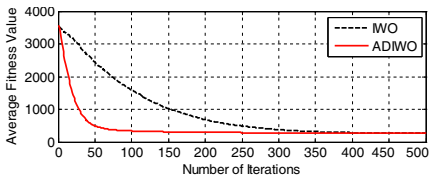

Figure 1. Comparative convergence graphs for 30-D Rastrigin function.

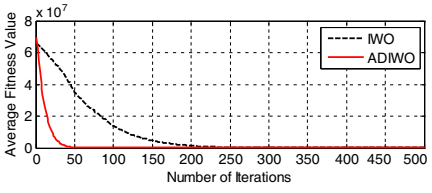

Figure 2. Comparative convergence graphs for 30-D Rosenbrock function.

algorithm outperforms the IWO algorithm regarding the convergence speed. Due to its fast convergence, the ADIWO algorithm is suitable for real time applications like ABF.

5. ADAPTIVE BEAMFORMING EXAMPLES

The ADIWO algorithm was applied as an ABF technique on a 9-element ULA ($M = 9$), with $q = 0.5\lambda$, in comparison to a PSO-based beamformer and the MVDR technique. The parameter values concerning the ADIWO algorithm are the same as in the previous section. The PSO algorithm used here is a PSO variant known as Constriction Factor PSO (CFPSO) [35]. In this algorithm, the parameters c_1 and c_2 are set equal to 2.05 and thus the constriction factor K calculated by (6) in [35] is found equal to 0.7298. In addition, both the CFPSO and the ADIWO use the same population size (i.e., 30 particles) and take 500 iterations to complete each execution.

In all the ABF cases studied here, the algorithms were executed on an Intel Core i5 computer running Microsoft Windows 7. The mean CPU time per execution required by the ADIWO algorithm was found 250 times less than the corresponding time required by the PSO algorithm. Due to the short execution time and the fast convergence, the ADIWO algorithm is more suitable for real time applications than other evolutionary optimization methods, such as the PSO.

The three ABF algorithms were applied to four sets of 100 random cases per set. Each case is a group of $N + 1$ random values different

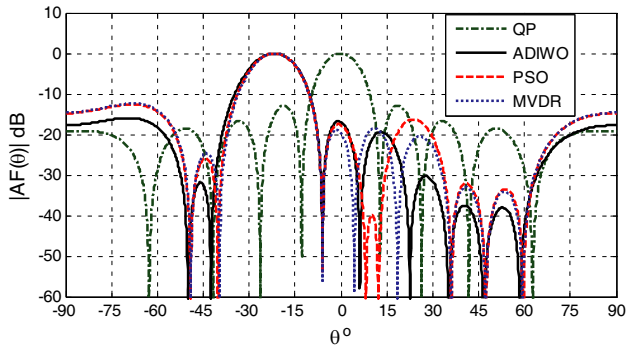

Figure 3. Optimal radiation patterns for $SNR = 10\,\text{dB}$, a desired signal arriving from $\theta_0 = -22°$, and five interference signals arriving from $\theta_1 = -49°$, $\theta_2 = -6°$, $\theta_3 = 36°$, $\theta_4 = 47°$ and $\theta_5 = 59°$ (derived SLL values: $SLL_{qp} = -12.90\,\text{dB}$, $SLL_{adiwo} = -15.96\,\text{dB}$, $SLL_{pso} = -12.59\,\text{dB}$, $SLL_{mvdr} = -12.40\,\text{dB}$).

from each other given to θ_n $(n = 0, 1, \ldots, N)$. The first two sets use five interference signals ($N = 5$) and refer respectively to $SNR = 10\,\text{dB}$ and $SNR = 30\,\text{dB}$. Also, the last two sets use seven interference signals ($N = 7$) and refer respectively to $SNR = 10\,\text{dB}$ and $SNR = 30\,\text{dB}$. For each random case, the algorithms are applied to find the near-optimal excitation vectors, respectively $\bar{w}_{adiwo}$, $\bar{w}_{pso}$ and $\bar{w}_{mvdr}$, that produce a main lobe towards the AoA θ_0 of the desired signal, N nulls towards

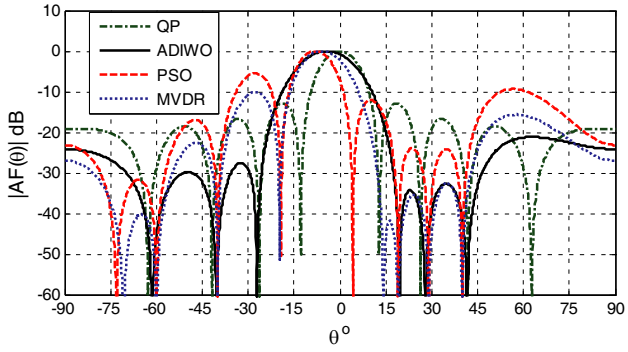

Figure 4. Optimal radiation patterns for $SNR = 30\,\text{dB}$, a desired signal arriving from $\theta_0 = -5°$, and five interference signals arriving from $\theta_1 = -60°$, $\theta_2 = -40°$, $\theta_3 = 19°$, $\theta_4 = 28°$ and $\theta_5 = 40°$ (derived SLL values: $SLL_{qp} = -12.90\,\text{dB}$, $SLL_{adiwo} = -21.18\,\text{dB}$, $SLL_{pso} = -5.52\,\text{dB}$, $SLL_{mvdr} = -10.06\,\text{dB}$).

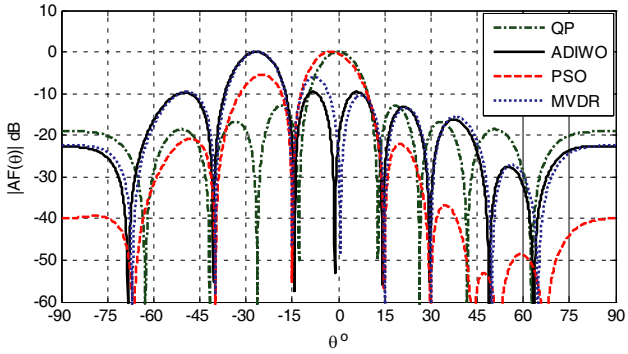

Figure 5. Optimal radiation patterns for $SNR = 10\,\text{dB}$, a desired signal arriving from $\theta_0 = -25°$, and seven interference signals arriving from $\theta_1 = -67°$, $\theta_2 = -40°$, $\theta_3 = -15°$, $\theta_4 = 15°$, $\theta_5 = 30°$, $\theta_6 = 50°$ and $\theta_7 = 65°$ (derived SLL values: $SLL_{qp} = -12.90\,\text{dB}$, $SLL_{adiwo} = -9.57\,\text{dB}$, $SLL_{pso} = -5.49\,\text{dB}$, $SLL_{mvdr} = -6.01\,\text{dB}$).

the AoA θ_n $(n = 1, \ldots, N)$ of the interference signals and, if possible, minimize the *SLL*. Then, the vectors $\bar{w}_{adiwo}$, $\bar{w}_{pso}$ and $\bar{w}_{mvdr}$ are used to produce the respective radiation patterns and thus calculate the corresponding angular deviations $\Delta\theta^{main}_{adiwo}$, $\Delta\theta^{main}_{pso}$ and $\Delta\theta^{main}_{mvdr}$ of the main lobe direction from its desired value θ_0, the angular deviations $\Delta\theta^{null}_{adiwo}$, $\Delta\theta^{null}_{pso}$ and $\Delta\theta^{null}_{mvdr}$ of the null directions from their respective desired values θ_n $(n = 1, \ldots, N)$, and the corresponding side lobe levels

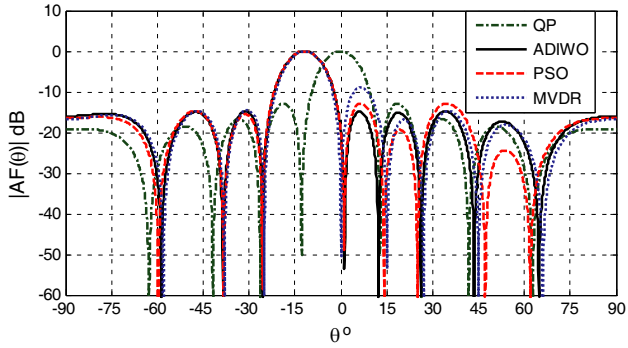

Figure 6. Optimal radiation patterns for $SNR = 30\,\text{dB}$, a desired signal arriving from $\theta_0 = -11°$, and seven interference signals arriving from $\theta_1 = -58°$, $\theta_2 = -38°$, $\theta_3 = -25°$, $\theta_4 = 0°$, $\theta_5 = 27°$, $\theta_6 = 44°$ and $\theta_7 = 65°$ (derived *SLL* values: $SLL_{qp} = -12.90\,\text{dB}$, $SLL_{adiwo} = -14.82\,\text{dB}$, $SLL_{pso} = -12.87\,\text{dB}$, $SLL_{mvdr} = -9.02\,\text{dB}$).

Table 1. Statistical analysis performed on the ABF results.

Set	1st	2nd	3rd	4th
SNR	10 dB	30 dB	10 dB	30 dB
N	5	5	7	7
$\overline{\Delta\theta}^{main}_{adiwo}$	0.64°	1.50°	1.41°	1.42°
$\overline{\Delta\theta}^{main}_{pso}$	0.62°	1.47°	1.44°	1.39°
$\overline{\Delta\theta}^{main}_{mvdr}$	0.62°	0.96°	1.39°	1.10°
$\overline{\Delta\theta}^{null}_{adiwo}$	0.20°	0.18°	0.29°	0.28°
$\overline{\Delta\theta}^{null}_{pso}$	0.17°	0.14°	0.26°	0.24°
$\overline{\Delta\theta}^{null}_{mvdr}$	0.16°	0.10°	0.17°	0.15°
$\overline{SLL}_{adiwo}$	−12.87 dB	−14.78 dB	−10.75 dB	−13.99 dB
$\overline{SLL}_{pso}$	−11.53 dB	−11.34 dB	−9.72 dB	−11.76 dB
$\overline{SLL}_{mvdr}$	−11.49 dB	−11.25 dB	−9.62 dB	−11.57 dB

SLL_{adiwo}, SLL_{pso} and SLL_{mvdr}. Finally, the average absolute angular deviation values $\overline{\Delta\theta}_{adiwo}^{main}$, $\overline{\Delta\theta}_{pso}^{main}$ and $\overline{\Delta\theta}_{mvdr}^{main}$ concerning the main lobe direction, the average absolute angular deviation values $\overline{\Delta\theta}_{adiwo}^{null}$, $\overline{\Delta\theta}_{pso}^{null}$ and $\overline{\Delta\theta}_{mvdr}^{null}$ concerning the null directions, and the average SLL values $\overline{SLL}_{adiwo}$, $\overline{SLL}_{pso}$ and $\overline{SLL}_{mvdr}$ are calculated for each set of 100 random cases. The statistical analysis performed on the ABF results is given in Table 1. It is obvious that the ADIWO provides

Table 2. Optimal excitation weight values for $SNR = 10\,\text{dB}$, a desired signal arriving from $\theta_0 = -22°$, and five interference signals arriving from $\theta_1 = -49°$, $\theta_2 = -6°$, $\theta_3 = 36°$, $\theta_4 = 47°$ and $\theta_5 = 59°$.

m	w_{adiwo}	w_{pso}	w_{mvdr}
1	−0.059−j0.356	−0.028−j0.516	−0.057−j0.467
2	−0.614−j0.195	−0.657−j0.167	−0.627−j0.176
3	−0.459+j0.426	−0.385+j0.595	−0.324+j0.443
4	0.215+j0.783	0.128+j1.000	0.195+j0.796
5	1.000+j0	1.000+j0	1.000+j0
6	0.215−j0.783	0.128−j1.000	0.195−j0.796
7	−0.459−j0.426	−0.385−j0.595	−0.324−j0.443
8	−0.614+j0.195	−0.657+j0.167	−0.627+j0.176
9	−0.059+j0.356	−0.028+j0.516	−0.057+j0.467

Table 3. Optimal excitation weight values for $SNR = 30\,\text{dB}$, a desired signal arriving from $\theta_0 = -5°$, and five interference signals arriving from $\theta_1 = -60°$, $\theta_2 = -40°$, $\theta_3 = 19°$, $\theta_4 = 28°$ and $\theta_5 = 40°$.

m	w_{adiwo}	w_{pso}	w_{mvdr}
1	0.046+j0.049	−0.513+j1.141	−0.063+j0.442
2	0.309+j0.280	0.401+j1.168	0.421+j0.509
3	0.577+j0.254	1.263+j1.062	0.929+j0.447
4	0.976+j0.220	0.500−j0.024	0.795+j0.036
5	1.000+j0	1.000+j0	1.000+j0
6	0.976−j0.220	0.500+j0.024	0.795-j0.036
7	0.577−j0.254	1.263−j1.062	0.929−j0.447
8	0.309−j0.280	0.401−j1.168	0.421−j0.509
9	0.046−j0.049	−0.513−j1.141	−0.063−j0.442

sufficient steering ability regarding the main lobe and the nulls, and achieves better *SLL* than the PSO and MVDR. This is also shown in Figures 3–6, which display the optimal radiation patterns of four typical cases chosen respectively from the four sets mentioned above. The optimal excitation weights are given respectively in Tables 2–5.

Table 4. Optimal excitation weight values for $SNR = 10$ dB, a desired signal arriving from $\theta_0 = -25°$, and seven interference signals arriving from $\theta_1 = -67°$, $\theta_2 = -40°$, $\theta_3 = -15°$, $\theta_4 = 15°$, $\theta_5 = 30°$, $\theta_6 = 50°$ and $\theta_7 = 65°$.

m	w_{adiwo}	w_{pso}	w_{mvdr}
1	0.894−j1.022	0.274+j0.477	1.119−j1.634
2	−0.284−j1.428	1.372+j0.690	−0.593−j2.135
3	−0.974+j0.456	1.886−j0.072	−1.542+j0.477
4	0.322+j0.876	1.344−j0.428	0.129+j1.020
5	1.000+j0	1.000+j0	1.000+j0
6	0.322−j0.876	1.344+j0.428	0.129−j1.020
7	−0.974−j0.456	1.886+j0.072	−1.542−j0.477
8	−0.284+j1.428	1.372−j0.690	−0.593+j2.135
9	0.894+j1.022	0.274−j0.477	1.119+j1.634

Table 5. Optimal excitation weight values for $SNR = 30$ dB, a desired signal arriving from $\theta_0 = -11°$, and seven interference signals arriving from $\theta_1 = -58°$, $\theta_2 = -38°$, $\theta_3 = -25°$, $\theta_4 = 0°$, $\theta_5 = 27°$, $\theta_6 = 44°$ and $\theta_7 = 65°$.

m	w_{adiwo}	w_{pso}	w_{mvdr}
1	−0.881+j0.566	−1.000+j0.694	−1.101+j0.943
2	−0.282+j0.739	−0.367+j1.000	−0.425+j1.169
3	0.256+j0.823	0.344+j1.000	0.202+j1.207
4	0.826+j0.633	1.000+j1.000	0.841+j0.921
5	1.000+j0	1.000+j0	1.000+j0
6	0.826−j0.633	1.000−j1.000	0.841−j0.921
7	0.256−j0.823	0.344−j1.000	0.202−j1.207
8	−0.282−j0.739	−0.367−j1.000	−0.425−j1.169
9	−0.881−j0.566	−1.000−j0.694	−1.101−j0.943

6. CONCLUSION

A robust ABF technique based on the ADIWO method has been presented. The ADIWO is a novel optimization method based on the recently proposed IWO and improved by incorporating an adaptive seed dispersion mechanism. A comparative study applied on well-known test functions reveals the superiority of this mechanism regarding the convergence speed. By recording the CPU time in four sets of 100 ABF cases per set, the ADIWO algorithm seems to be much faster than the PSO algorithm. Both the increased convergence speed and the short execution time make the ADIWO algorithm more suitable for real time applications, like ABF, than other evolutionary optimization algorithms. The ABF cases studied in the present paper take into account the knowledge of the DoA of all the signals received by the antenna array. However, the interference correlation matrix is not used here, considering uncertainties in the amplitudes of the interference signals that may be observed in practice. The statistical analysis performed on the ABF results shows that the ADIWO-based beamformer provides sufficient steering ability regarding the main lobe and the nulls, and also achieves better *SLL* than the PSO-based beamformer and the MVDR. Therefore, the ADIWO method seems to be very useful in ABF applications.

ACKNOWLEDGMENT

The authors would like to thank Dr. A. R. Mehrabian for providing the source code of the IWO algorithm.

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