Design of a Novel Antenna Array Beamformer Using Neural Networks Trained by Modified Adaptive Dispersion Invasive Weed Optimization Based Data

Zaharias D. Zaharis, Christos Skeberis, Thomas D. Xenos, Pavlos I. Lazaridis, and John Cosmas, *Senior Member, IEEE*

Affiliations and e-mails:

Zaharias D. Zaharis is with the Telecommunications Centre, Aristotle University of Thessaloniki, 54124 Thessaloniki, Greece (e-mail: zaharis@auth.gr).

Christos Skeberis and Thomas D. Xenos are with the Department of Electrical and Computer Engineering, Aristotle University of Thessaloniki, 54124 Thessaloniki, Greece (e-mail: cskeberis@auth.gr; tdxenos@eng.auth.gr).

Pavlos I. Lazaridis and John Cosmas are with the School of Engineering and Design, Brunel University, London UB8 3PH, U.K. (e-mail: pavloslazaridis@hotmail.com; john.cosmas@brunel.ac.uk).

Corresponding author: Zaharias D. Zaharis (zaharis@auth.gr)

Abstract—A new antenna array beamformer based on neural networks (NNs) is presented. The NN training is performed by using optimized data sets extracted by a novel Invasive Weed Optimization (IWO) variant called Modified Adaptive Dispersion IWO (MADIWO). The trained NN is utilized as an adaptive beamformer that makes a uniform linear antenna array steer the main lobe towards a desired signal, place respective nulls towards several interference signals and suppress the side lobe level (SLL). Initially, the NN structure is selected by training several NNs of various structures using MADIWO based data and by making a comparison among the NNs in terms of training performance. The selected NN structure is then used to construct an adaptive beamformer, which is compared to MADIWO based and ADIWO based beamformers, regarding the SLL as well as the ability to properly steer the main lobe and the nulls. The comparison is made considering several sets of random cases with different numbers of interference signals and different power levels of additive zero-mean Gaussian noise. The comparative results exhibit the advantages of the proposed beamformer.

Index Terms—Adaptive beamforming, antenna beamforming, invasive weed optimization, neural networks

I. Introduction

A large variety of algorithms has been proposed so far to implement innovative adaptive beamforming (ABF) techniques applied to antenna arrays [1]-[9]. Several of these techniques have been designed for broadcasting applications [10]-[15]. The main purpose of an ABF algorithm is to make an antenna array steer the main lobe of its radiation pattern towards a desired incoming signal and place pattern nulls towards respective interference incoming signals provided that the direction of arrival (DoA) of every signal is time dependent. In other words, a typical ABF technique is a real time procedure that aims at maximizing the signal-to-interference-plus-noise ratio (*SINR*). In order to avoid an unreasonable spatial spread of radiated power, a beamformer is additionally required to minimize the side lobe level (*SLL*). To meet both requirements of maximum *SINR* and minimum *SLL*, the beamformer is usually implemented by applying evolutionary optimization methods [4], [6], [7]. Such a method recently introduced is a novel variant of the Invasive Weed Optimization (IWO) [4], [16]-[19] called Adaptive Dispersion Invasive Weed Optimization (ADIWO) [9]. The adaptive seed dispersion mechanism involved in the ADIWO increases the convergence speed compared to the speed of the typical IWO and makes the ADIWO an attractive method for real time procedures like the ABF ones.

In order to make the ADIWO increase its ability to fine-tune the optimal position without losing its exploration ability, a Modified ADIWO (MADIWO) is proposed in the present paper. In the MADIWO, the adaptive seed dispersion mechanism has properly been modified in order to help more weeds fine-tune the optimal position, while the rest weeds are capable of exploring the search space to find better positions. In this way, the MADIWO algorithm converges almost as fast as the ADIWO algorithm, while it achieves better fitness values at the end of the optimization process.

However, the iterative structure of an algorithm is always a limitation to the convergence speed. A solution to this problem would be a method that has the efficiency of the MADIWO algorithm but responds instantly. Such a solution introduced in the present study is based on a neural network (NN) [2], [3], [20]-[26] trained by data, which are extracted by the MADIWO method. After proper training, the NN is capable of approximating the efficiency of the MADIWO algorithm. On the other hand, a NN does not have iterative structure and thus it responds immediately. Consequently, a properly trained NN can be used instead of the MADIWO method for real time applications.

Such a NN is proposed here to be used as an enhanced adaptive beamformer that aims at maximizing the *SINR* and minimizing the *SLL* of uniform linear arrays (ULAs). Initially, several NNs of various structures are trained using MADIWO based data. Afterwards, a comparison in terms of training performance among the NNs takes place. The best NN derived from the above comparison is used to construct the enhanced adaptive beamformer mentioned before. This NN based beamformer is then compared to MADIWO based and ADIWO based beamformers, regarding the ability to minimize the *SLL* as well as the ability to properly steer the main lobe and the nulls. The comparison is made considering several sets of random cases with different numbers of interference signals and different power levels of additive zero-mean Gaussian noise. The results show that the MADIWO based beamformer and the proposed one achieve similar *SLL* values, provide almost the same steering ability regarding the main lobe and the nulls, and finally outperform the ADIWO based beamformer. The above behavior combined with the advantage of instant response makes the proposed beamformer an attractive choice for broadcasting applications.

II. Beamforming Problem and Fitness Function Definition

The description of the beamforming model has already been given in [6]. M monochromatic isotropic sources with interelement distance equal to q compose a ULA, which receives a desired signal from angle of arrival (AoA) θ_0 and N interference signals from respective angles of arrival (AoAs) θ_n (n=1,…,N). Every AoA is defined by the direction of arrival (DoA) of the respective incoming signal and the normal to the array axis direction. DoA estimation algorithms are usually applied to calculate the values of θ_n (n=0,1,…,N) [1], [22]. The ULA also receives Gaussian noise signals of zero-mean value and variance σ_{noise}^2. The noise signals are considered uncorrelated with each other and with every incoming signal.

The values of θ_n (n=0,1,…,N) and the signal-to-noise ratio (SNR) are considered as input data by all the beamformers. Each beamformer aims at calculating the array excitation weights w_m (m=1,…,M) that satisfy simultaneously two different requirements, i.e., maximize the $SINR$ and minimize the SLL. These two requirements define a beamforming problem, which is inherently multi-objective. The problem can be converted into a single-objective one by minimizing a fitness function, which balances the above requirements as given below:

$$F = k_1\, SINR^{-1} + k_2\, SLL \tag{1}$$

where k_1 and k_2 are balance factors. The value of $SINR$ can be estimated by the following expression:

$$SINR = \frac{\overline{w}^H \overline{a}_0\, \overline{a}_0^H \overline{w}}{\overline{w}^H \overline{A}\, \overline{R}_{ii}\, \overline{A}^H \overline{w} + \sigma_{noise}^2\, \overline{w}^H\, \overline{w}} \tag{2}$$

where

$$\overline{w} = \begin{bmatrix} w_1 & w_2 & \cdots & w_M \end{bmatrix}^T \tag{3}$$

$$\overline{A} = \begin{bmatrix} \overline{a}_1 & \overline{a}_2 & \cdots & \overline{a}_N \end{bmatrix} \tag{4}$$

$$\overline{a}_n = \begin{bmatrix} 1 & e^{j\frac{2\pi}{\lambda}q\sin\theta_n} & \cdots & e^{j(M-1)\frac{2\pi}{\lambda}q\sin\theta_n} \end{bmatrix}^T, \quad n = 0,1,...,N \tag{5}$$

are, respectively, the excitation weight vector, the M×N array steering matrix, and the array steering vector that corresponds to AoA θ_n. Also, $\overline{R}_{ii}$ is the interference correlation matrix, while the superscripts T and H indicate respectively the transpose and the Hermitian transpose operation. Finally, the noise variance is calculated from the value of SNR in dB as follows:

$$\sigma_{noise}^2 = 10^{-SNR/10} \tag{6}$$

III. Adaptive Dispersion Invasive Weed Optimization

The ADIWO method has been proposed and compared to the original IWO method in [9].

Its basic difference from the original IWO and other IWO variants lies in the way the seeds produced by a weed are dispersed in the search space. According to the original IWO method and its variants, the standard deviation σ of the seed dispersion decreases as a function of the number of iterations *iter*. Moreover, σ is the same for all the weeds that disperse seeds at a certain iteration. In the ADIWO method, however, σ is different for every weed and depends on the fitness value f of the weed according to the linear formula:

$$\sigma = \frac{\sigma_{\max} - \sigma_{\min}}{f_{\max} - f_{\min}} f + \frac{\sigma_{\min} f_{\max} - \sigma_{\max} f_{\min}}{f_{\max} - f_{\min}} \tag{7}$$

where $\sigma_{\max}$ and $\sigma_{\min}$ are the standard deviation limits, while $f_{\max}$ and $f_{\min}$ are the maximum and minimum fitness values at a certain iteration. So, the weeds have different behavior depending on their fitness value. Weeds with fitness values close to $f_{\min}$ (optimal fitness value) display a reduced exploration ability and can only fine tune their position. Weeds with fitness values close to $f_{\max}$ exhibit an increased exploration ability and are capable of exploring the search space to find better positions. In this way, the adaptive seed dispersion helps the weed colony maintain its exploration ability until the end of the optimization process and thus makes the ADIWO algorithm converge faster than the original IWO [9].

IV. Modified Adaptive Dispersion Invasive Weed Optimization

In the MADIWO algorithm, the adaptive seed dispersion mechanism described above has been modified. The modification concerns the σ-f dependence, which is expressed by the following formula:

$$\sigma = r_1 f^2 + r_2 f + r_3 \tag{8}$$

where

$$r_1 = \frac{\sigma_{\max} - \sigma_{\min}}{\left(f_{\max} - f_{\min}\right)^2} \tag{9}$$

$$r_2 = \frac{\sigma_{\max} - \sigma_{\min}}{f_{\max} - f_{\min}} - r_1 \left(f_{\max} + f_{\min} \right) \tag{10}$$

$$r_3 = \frac{\sigma_{\min} f_{\max} - \sigma_{\max} f_{\min}}{f_{\max} - f_{\min}} + r_1 f_{\max} f_{\min} \tag{11}$$

A graphical presentation of (8) is given in Fig. 1. For a given fitness value f, the value of σ extracted from (8) is less than the respective value extracted from (7). The difference between the two values of σ is gradually increased with increasing f until a certain fitness value equal to $\left(f_{\max} + f_{\min}\right)/2$ and then is gradually decreased until f reaches $f_{\max}$. In this way, the MADIWO algorithm retains the ability of the ADIWO method to explore the search space for better positions, while it makes more weeds fine-tune the global optimum point, and thus it achieves better fitness values than the ADIWO algorithm as shown below.

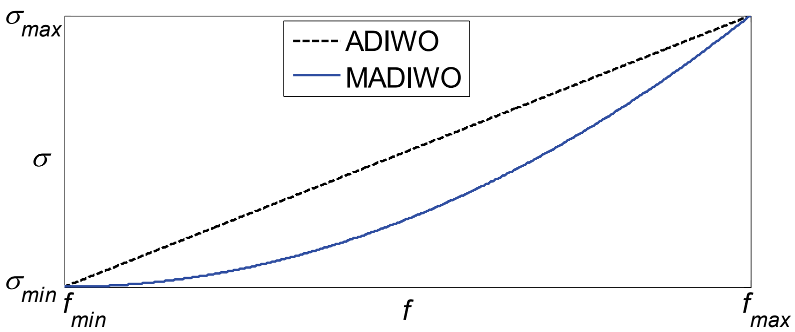

Fig. 1. Variation of standard deviation for ADIWO and MADIWO.

V. Algorithmic Settings

In the MADIWO and ADIWO algorithms used below, the population size is limited to 30 weeds, the number of seeds dispersed by a weed ranges from zero to five depending on the fitness value of the weed, the standard deviation limits are $\sigma_{\max} = 10$ and $\sigma_{\min} = 0.5$, and finally 500 iterations are used to complete each algorithm execution.

The MADIWO and ADIWO methods are applied as ABF techniques to a set of L random cases, considering an 11-element ULA (M=11) with q=0.5λ. Each l-th case (l=1,…,L) is a group of N+1 random values different from each other and given to θ_n (n=0,1,…,N). These values constitute an angle vector $\bar{\theta} = \begin{bmatrix} \theta_0 & \theta_1 & \dots & \theta_N \end{bmatrix}^T$. For each random case, the two methods are applied to find the near-optimal excitation weight vectors, respectively $\bar{w}_{madiwo}$ and $\bar{w}_{adiwo}$, which steer the main lobe towards θ_0 and place N nulls towards θ_n (n=1,…,N), maximizing thus the *SINR*, and additionally minimize the *SLL*. In this way, two respective sets of L vector pairs per set $\left(\bar{\theta}_l, \bar{w}_{madiwo,l}\right)$ and $\left(\bar{\theta}_l, \bar{w}_{adiwo,l}\right)$ (l=1,…,L) are created. Such sets can be used either for NN training or to compare the beamformers with each other.

VI. Selection of Neural Network Structure

So far, NNs have been applied to solve various problems in the areas of electromagnetics and wireless communications [20]-[26]. Due to their efficiency and instant response, NNs have been successfully applied in several ABF problems [2], [3].

The feed-forward back-propagation architecture is selected for all the NNs studied below. Each NN consists of (a) an input layer of N+1 nodes, which is fed by any angle vector $\bar{\theta}$, (b) two hidden layers that use Hyperbolic Tangent Sigmoid (HTS) transfer function and consist respectively of n_{hl1} and n_{hl2} nodes, and (c) an output layer of M nodes, which extracts the appropriate excitation weight vector $\bar{w}_{NN}$ that maximizes the *SINR* and minimizes the *SLL*.

In order to find an efficient NN structure, various configurations are selected and compared to each other. All the configurations use an input layer of 8 nodes and an output layer of 11 nodes, considering 7 interference signals and a desired one (N+1=8) received by an 11-element ULA (M=11). The number of nodes of each hidden layer (n_{hl1} or n_{hl2}) ranges from 10 to 50 at increments of 10. The training functions selected for comparison are the Gradient Descent (GD), the Gradient Descent with Momentum (GDM), the Gradient Descent with Adaptive Learning Rate (GDALR), the Scaled Conjugate Gradient (SCG) and finally the

Levenberg-Marquardt (LM). Also, the GDM is chosen as learning function for all the NN configurations.

The training process is applied to every NN by using a set of 5000 (L=5000) MADIWO-based vector pairs $\left(\bar{\theta}_l, \bar{w}_{madiwo,l}\right)$ (l=1,…,5000). The angle vectors $\bar{\theta}_l$ (l=1,…,5000) are applied to the input layer, while the excitation weight vectors $\bar{w}_{madiwo,l}$ (l=1,…,5000) are applied to the output layer. The metric used for NN evaluation is chosen to be the Mean Squared Error (MSE) produced at the end of the training process. For each NN configuration, the training process is repeated 10 times and the minimum MSE (best training performance) is recorded.

The performance results for all the above-discussed NN configurations are given in Table I. It seems that the best training performance is achieved by a NN structure trained by the LM function and composed of two hidden layers with $n_{hl1} = 20$ and $n_{hl2} = 50$. This structure is denoted as *LM-8-20-50-11*, where the numbers 8 and 11 refer to the number of nodes of the input layer and the output layer, respectively.

In the same way, we apply the training process to a similar NN structure that uses the LM training function. The only difference is that the input layer consists of 6 nodes, considering 5 interference signals and a desired one (N+1=6) received by the same 11-element ULA (M=11). The structure also contains the same two hidden layers with 20 and 50 nodes respectively, as mentioned above. This structure (*LM-6-20-50-11*) is trained by using a set of 5000 MADIWO-based vector pairs $\left(\bar{\theta}_l, \bar{w}_{madiwo,l}\right)$ (l=1,…,5000). The *LM-8-20-50-11* and *LM-6-20-50-11* are two different structures of a NN-based beamformer, and they are going to be compared to respective structures of MADIWO-based and ADIWO-based beamformers in the next section.

TABLE I. Performance results for various NN configurations.

n_{hl1}:n_{hl2}	*GD*	*GDM*	*GDALR*	*SCG*	*LM*
10:10	0.0457	0.0481	0.1099	0.0239	0.0178
20:10	0.0388	0.0380	0.1141	0.0231	0.0161
30:10	0.0323	0.0352	0.0963	0.0238	0.0147
40:10	0.0327	0.0328	0.0899	0.0237	0.0134
50:10	0.0306	0.0404	0.0742	0.0233	0.0131
10:20	0.0437	0.0398	0.0935	0.0230	0.0153
20:20	0.0372	0.0352	0.1118	0.0225	0.0139
30:20	0.0343	0.0348	0.0845	0.0227	0.0124
40:20	0.0305	0.0328	0.0994	0.0214	0.0119
50:20	0.0295	0.0308	0.0876	0.0220	0.0109
10:30	0.0387	0.0371	0.0936	0.0233	0.0136
20:30	0.0383	0.0369	0.0907	0.0210	0.0121
30:30	0.0322	0.0336	0.0996	0.0209	0.0113
40:30	0.0309	0.0315	0.0820	0.0204	0.0109
50:30	0.0296	0.0292	0.0879	0.0200	0.0111
10:40	0.0381	0.0368	0.1024	0.0224	0.0130
20:40	0.0332	0.0352	0.0937	0.0208	0.0109
30:40	0.0334	0.0337	0.0945	0.0194	0.0112
40:40	0.0304	0.0297	0.1073	0.0202	0.0106
50:40	0.0282	0.0305	0.1012	0.0190	0.0122
10:50	0.0355	0.0365	0.0920	0.0221	0.0117
20:50	0.0354	0.0347	0.1049	0.0211	**0.0101**
30:50	0.0312	0.0335	0.1091	0.0199	0.0108
40:50	0.0293	0.0307	0.0905	0.0198	0.0124
50:50	0.0291	0.0309	0.0921	0.0187	0.0126

VII. Evaluation of the NN Based Beamformer

In order to make a comparison among the beamformers, four scenarios are implemented considering an 11-element ULA (M=11) with q=0.5λ. The first two scenarios use five interference signals (N=5) and a desired one, considering *SNR* values respectively equal to 10dB and 20dB. In the last two scenarios, seven interference signals (N=7) and a desired one are used, considering *SNR* values respectively equal to 10dB and 20dB. The *LM-6-20-50-11* NN-based beamformer is employed for the first two scenarios, while the *LM-8-20-50-11* beamformer is employed for the last two scenarios.

Each scenario includes the production of 1000 (L=1000) MADIWO-based pairs $\left(\overline{\theta}_l, \overline{w}_{madiwo,l}\right)$, 1000 ADIWO-based pairs $\left(\overline{\theta}_l, \overline{w}_{adiwo,l}\right)$, and 1000 NN-based pairs $\left(\overline{\theta}_l, \overline{w}_{NN,l}\right)$

(l=1,…,1000). Then, each vector $\overline{w}_{madiwo,l}$, $\overline{w}_{adiwo,l}$ or $\overline{w}_{NN,l}$ is used to produce the respective radiation pattern and thus calculate the corresponding absolute angular deviation $\Delta\theta_{madiwo,l}^{main}$, $\Delta\theta_{adiwo,l}^{main}$ or $\Delta\theta_{NN,l}^{main}$ of the main lobe direction from its desired value $\theta_{0,l}$, the absolute angular deviations $\Delta\theta_{madiwo,l}^{null}$, $\Delta\theta_{adiwo,l}^{null}$ or $\Delta\theta_{NN,l}^{null}$ of the null directions from their respective desired values $\theta_{n,l}$ (n=1,…,N), and the corresponding side lobe level $SLL_{madiwo,l}$, $SLL_{adiwo,l}$ or $SLL_{NN,l}$. Finally, the average absolute angular deviation values $\overline{\Delta\theta}_{madiwo}^{main}$, $\overline{\Delta\theta}_{adiwo}^{main}$ and $\overline{\Delta\theta}_{NN}^{main}$ concerning the main lobe direction, the average absolute angular deviation values $\overline{\Delta\theta}_{madiwo}^{null}$, $\overline{\Delta\theta}_{adiwo}^{null}$ and $\overline{\Delta\theta}_{NN}^{null}$ concerning the null directions, and the average SLL values $\overline{SLL}_{madiwo}$, $\overline{SLL}_{adiwo}$ and $\overline{SLL}_{NN}$ are calculated for each scenario. All the above average values are given in Table II. It is obvious that both the NN-based and MADIWO-based beamformers exhibit similar behavior regarding the steering ability and the ability to provide a low SLL value, and also outperform the ADIWO-based beamformer. The same behavior is observed in Figs. 2-5, which display the optimal radiation patterns of four typical cases chosen respectively from the four scenarios.

TABLE II. Statistical analysis performed on the ABF results.

Scenario	1st	2nd	3rd	4th
N	5	5	7	7
SNR	10dB	20dB	10dB	20dB
$\overline{\Delta\theta}_{NN}^{main}$	0.62°	0.58°	0.84°	0.82°
$\overline{\Delta\theta}_{madiwo}^{main}$	0.61°	0.57°	0.83°	0.80°
$\overline{\Delta\theta}_{adiwo}^{main}$	0.64°	0.62°	1.40°	1.37°
$\overline{\Delta\theta}_{NN}^{null}$	0.25°	0.24°	0.32°	0.29°
$\overline{\Delta\theta}_{madiwo}^{null}$	0.24°	0.22°	0.30°	0.27°
$\overline{\Delta\theta}_{adiwo}^{null}$	0.30°	0.29°	0.39°	0.37°
$\overline{SLL}_{NN}$	–13.97dB	–14.55dB	–12.25dB	–12.32dB
$\overline{SLL}_{madiwo}$	–14.46dB	–14.85dB	–12.66dB	–12.78dB
$\overline{SLL}_{adiwo}$	–12.85dB	–12.97dB	–10.82dB	–10.98dB

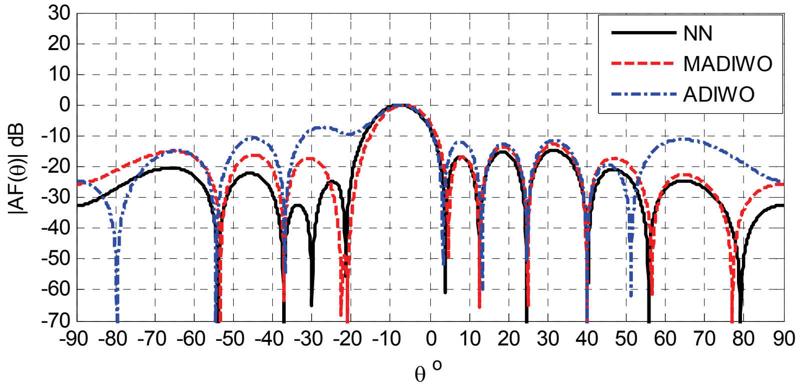

Fig. 2. Optimal patterns for SNR=10dB, a desired signal received from θ_0=–7°, and 5 interference signals received from AoAs respectively equal to –54°, –37°, 13°, 25° and 40°.

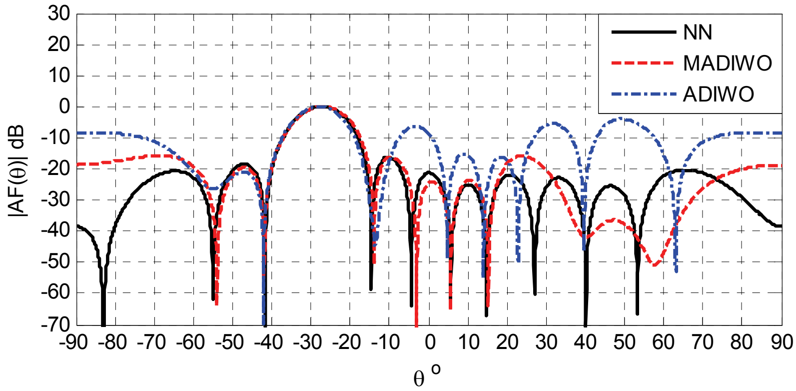

Fig. 3. Optimal patterns for SNR=20dB, a desired signal received from θ_0=–27°, and 5 interference signals received from AoAs respectively equal to –55°, –42°, –14°, 5° and 15°.

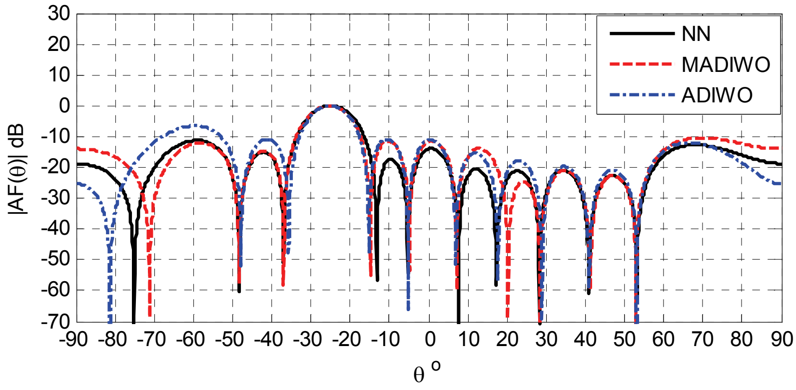

Fig. 4. Optimal patterns for SNR=10dB, a desired signal received from θ_0=–25°, and 7 interference signals received from AoAs respectively equal to –48°, –37°, –5°, 7°, 29°, 41° and 53°.

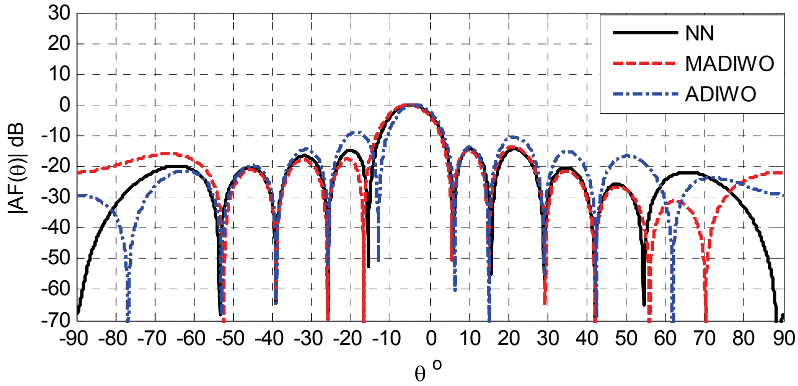

Fig. 5. Optimal patterns for *SNR*=20dB, a desired signal received from θ_0=–5°, and 7 interference signals received from AoAs respectively equal to –53°, –39°, –26°, 6°, 15°, 29° and 42°.

VIII. Conclusion

An efficient enhanced adaptive beamformer based on NNs has been presented. The beamformer makes a ULA steer the main lobe towards a desired signal, place respective nulls towards several interference signals and achieve low *SLL*. The data used to train the NNs have been extracted by a powerful ABF technique based on the MADIWO method. Therefore, the NN-based beamformer is expected to have similar efficiency as the MADIWO-based beamformer, regarding the ability to minimize the *SLL* as well as the ability to properly steer the main lobe and the nulls.

In order to study the NN-based beamformer in terms of efficiency, an optimal NN structure is selected by making a comparison in terms of training performance among several NN configurations, and then this structure is compared to MADIWO-based and ADIWO-based beamformers regarding their abilities to maximize the *SINR* and minimize the *SLL*. The statistical results as well as the radiation patterns of typical beamforming cases show that both the NN-based and MADIWO-based beamformers exhibit similar behavior regarding the steering ability and the ability to provide a low *SLL* value, and also outperform the ADIWO-based beamformer. This behavior combined with the advantage of instant response makes the NN-based beamformer very useful in practice.

References

[1] J. Li and P. Stoica, *Robust Adaptive Beamforming*. New Jersey: John Wiley & Sons, Inc., 2006.

[2] A. H. El. Zooghby, C. G. Christodoulou, and M. Georgiopoulos, "Neural network-based adaptive beamforming for one- and two-dimensional antenna arrays," *IEEE Trans. Antennas Propagat.*, vol. 46, no. 12, pp. 1891–1893, Dec. 1998.

[3] Xin Song, Jinkuan Wang, and Xuefen Niu, "Robust adaptive beamforming algorithm based on neural network," in *Proc. IEEE International Conference on Automation and Logistics*, 2008, pp. 1844–1849.

[4] M. Roshanaei, C. Lucas, and A. R. Mehrabian, "Adaptive beamforming using a novel numerical optimisation algorithm," *IET Microwaves, Antennas Propagat.*, vol. 3, no. 5, pp. 765–773, Aug. 2009.

[5] J. A. Srar, C. Kah-Seng, and A. Mansour, "Adaptive array beamforming using a combined LMS-LMS algorithm," *IEEE Trans. Antennas Propagat.*, vol. 58, no. 11, pp. 3545–3557, Nov. 2010.

[6] Z. D. Zaharis and T. V. Yioultsis, "A novel adaptive beamforming technique applied on linear antenna arrays using adaptive mutated boolean PSO," *Progress In Electromagnetics Research*, vol. 117, pp. 165–179, 2011.

[7] R. Mallipeddi, J. P. Lie, P. N. Suganthan, S. G. Razul, and C. M. S. See, "A differential evolution approach for robust adaptive beamforming based on joint estimation of look direction and array geometry," *Progress In Electromagnetics Research*, vol. 119, pp. 381–394, 2011.

[8] Z. Lei, L. Wei, and R. J. Langley, "Adaptive beamforming with real-valued coefficients based on uniform linear arrays," *IEEE Trans. Antennas Propagat.*, vol. 59, no. 3, pp. 1047–1053, Mar. 2011.

[9] Z. D. Zaharis, C. Skeberis, and T. D. Xenos, "Improved antenna array adaptive beamforming with low side lobe level using a novel adaptive invasive weed optimization method," *Progress In Electromagnetics Research*, vol. 124, pp. 137–150, 2012.

[10] Chin Choy Chai and Ying Chang Liang, "Joint MIMO beamforming and power adaptation at base station and broadcasting relay transmitters with quality-of-service (QoS) constraints," in *Proc. 67th IEEE Vehicular Technology Conference*, 11-14 May 2008, pp. 1026–1031.

[11] P. Mousavi, M Fakharzadeh, and S. Safavi-Naeini, "1K element antenna system for mobile direct broadcasting satellite reception," *IEEE Trans. Broadcast.*, vol. 56, no. 3, pp. 340–349, Sept. 2010.

[12] Jongrok Park and Sanghoon Lee, "MIMO beamforming for QoS enhancement via analog, digital and hybrid relaying," *IEEE Trans. Broadcast.*, vol. 56, no. 4, pp. 494–503, Dec. 2010.

[13] M. Lertsutthiwong, T. Nguyen, and B. Hamdaoui, "Efficient wireless broadcasting through joint network coding and beamforming," *International Journal of Digital Multimedia Broadcasting*, vol. 2012, Article ID 342512, 2012.

[14] Jongrok Park and Sanghoon Lee, "M2-m2 beamforming for virtual MIMO broadcasting in multi-hop relay networks," *IEEE J. Select. Areas Commun.*, vol. 30, no. 8, pp. 1358–1369, Sept. 2012.

[15] L. Yang, G. Ren, W. Zhai, and Z. Qiu, "Beamforming based receiver scheme for DVB-T2 system in high speed train environment," *IEEE Trans. Broadcast.*, to be published.

[16] S. Karimkashi and A. A. Kishk, “Invasive weed optimization and its features in electromagnetics,” *IEEE Trans. Antennas Propagat.*, vol. 58, no. 4, pp. 1269–1278, Apr. 2010.
[17] F. M. Monavar and N. Komjani, “Bandwidth enhancement of microstrip patch antenna using jerusalem cross-shaped frequency selective surfaces by invasive weed optimization approach,” *Progress In Electromagnetics Research*, vol. 121, pp. 103–120, 2011.
[18] G. G. Roy, S. Das, P. Chakraborty, and P. N. Suganthan, “Design of non-uniform circular antenna arrays using a modified invasive weed optimization algorithm,” *IEEE Trans. Antennas Propagat.*, vol. 59, no. 1, pp. 110–118, Jan. 2011.
[19] S. Karimkashi, A. A. Kishk, and D. Kajfez, “Antenna array optimization using dipole models for MIMO applications,” *IEEE Trans. Antennas Propagat.*, vol. 59, no. 8, pp. 3112–3116, Aug. 2011.
[20] C. Christodoulou and M. Georgiopoulos, *Applications of Neural Networks in Electromagnetics*. Boston-London: Artech House, 2001.
[21] A. Patnaik, D. E. Anagnostou, R. K. Mishra, C. G. Christodoulou, and J. C. Lyke, “Applications of neural networks in wireless communications,” *IEEE Antennas Propagat. Mag.*, vol. 46, no. 3, pp. 130–137, June 2004.
[22] N. Fonseca, M. Coudyser, J.-J. Laurin, and J.-J. Brault, “On the design of a compact neural network-based DOA estimation system,” *IEEE Trans. Antennas Propagat.*, vol. 58, no. 2, pp. 357–366, Feb. 2010.
[23] L. Gang, Y. Shiwen, and N. Zaiping, “Direction of arrival estimation in time modulated linear arrays with unidirectional phase center motion,” *IEEE Trans. Antennas Propagat.*, vol. 58, no. 4, pp. 1105–1111, April 2010.
[24] T. N. Ferreira, S. L. Netto, and P. S. R. Diniz, “Direction-of-arrival estimation using a direct-data approach,” *IEEE Trans. Aerosp. Electron. Syst.*, vol. 47, no. 1, pp. 728–733, Jan. 2011.
[25] V. P. G. Jiménez, Y. Jabrane, A. G. Armada, B. Ait Es Said, and A. Ait Ouahman, “High power amplifier pre-distorter based on neural-fuzzy systems for OFDM signals,” *IEEE Trans. Broadcast.*, vol. 57, no. 1, pp. 149–158, March 2011.
[26] M. Rawat and F. M. Ghannouchi, “A mutual distortion and impairment compensator for wideband direct-conversion transmitters using neural networks,” *IEEE Trans. Broadcast.*, vol. 58, no. 2, pp. 168–177, June 2012.