Adaptive Blind Antenna Array Beam Shaping

Candice Müller, Fernando C. C. de Castro

***Abstract*— This paper proposes a blind concurrent beamforming (BCB) algorithm that combines the Constant Modulus Algorithm (CMA) and Direct Decision (DD) in a cooperative structure. The proposed BCB is evaluated over a six-dipole uniform circular array in different interfering scenarios, and the results are compared with the classical supervised least mean squares (LMS). Notably, despite operating without a training sequence, BCB outperformed LSM in terms of symbol error rate (SER). The proposed BCB effectively place nulls in the angular direction of the interfering signals while steering the main lobe toward the desired signal (DS), except in scenarios where the interference is spatially too close to the DS. Results show that the proposed BCB approach offers a robust, blind beamforming solution with low computational complexity and high spectral efficiency.**

Keywords*— *Blind beamforming; constant modulus algorithm; direct decision.

I. INTRODUCTION

In the era of advanced information and communication technology (ICT), society is moving toward a new technological revolution, characterized by significant socioeconomic implications. New telecommunication technologies have been drived by Internet of Things (IoT), transitioning from human-centric connectivity to massive machine-type communications (mMTC). This evolution presents significant challenges, including the need for ultra-reliable low-latency communications (URLLC), enhanced mobile broadband (eMBB), and massive connectivity.

In this scenario, beamforming techniques have been widely studied and applied to enhance signal quality, suppress interference, increase energy efficiency and enable more effective utilization of spatial resources. Beamforming plays a critical role in supporting the scalability and performance requirements of next-generation networks, particularly in the context of 5G and beyond.

A well-known supervised beamforming algorithm is the least mean squares (LMS) [1]. Supervised beamforming can also be implemented with neural networks (NNs) [2-5]. Specifically, complex valued neural networks (CVNNs) have great potential for application in beamforming since the intrinsic complex structure can naturally manipulate complex-valued data, achieving superior performance and reduced training time compared with real-valued neural networks (RVNNs).

Despite achieving good performance, supervised techniques require sending a training sequence, consequently reducing spectral efficiency. The advantage of blind approaches is the bandwidth saving. A blind adaptive system usually adjusts its transfer function via steepest descent gradient (SG) algorithm, aiming to minimize a cost function J without any training sequence. A blind algorithm widely used for blind channel deconvolution is the CMA (constant modulus algorithm) [6]. CMA cost function is a non-convex function that presents multiple stationary points that often leads to a local minimum convergence, which results in a moderate mean square error (MSE) after convergence. To improve CMA performance, the direct decision (DD) approach is usually implemented with CMA. However, the switching from CMA to DD requires a minimum convergence level. Otherwise, DD algorithm may diverge. To overcome this issue, a cooperative operation of CMA and DD, controlled by a non-linear link, was proposed in [7].

In this paper, a blind concurrent beamformer (BCB), based on the concurrent CMA-DD algorithm, is presented. The concurrent operation considerably speeds up the algorithm convergence compared to the CMA switched to DD. The proposed approach is evaluated over a six dipoles uniform circular array (UCA) and its performance is compared with the classical supervised least mean squares algorithm. Several scenarios were evaluated and three of them are presented. The first scenario presents two interfering signals (ISs) located at angular positions close to the desired signal (DS). In the second scenario the two ISs are farther from the DS but signal-to-interference-plus-noise ratio is considerably reduced. Scenario 3 is more challenging, featuring five ISs. The results show that, despite not having a training sequence, BCB algorithm reaches performance even superior that the supervised LMS.

BLIND CONCURRENT BEAMFORMING

The proposed blind concurrent beamforming is presented in Fig. 1. The beamforming algorithm receives as input the voltage vector $\boldsymbol{r}(n) = [r_1\ r_2\ \dots\ r_K]$, received from the K array elements and r_k is the voltage at the k-th array element. The voltages are given by the sum of all signals that impinge on the array, i.e., the desired (DS) and interfering (IS) signals, taking into account the array coupling matrix $\underline{C}$ and the respective steering vector $\underline{\Phi}(\theta_m, \phi_m)$. The m-th steering vector expresses the magnitude and phase of the electromagnetic (EM) wave received by each k-th dipole from the direction (θ_m, ϕ_m) of the propagation path, and it is given by

$$\underline{\boldsymbol{\Phi}}(\theta_m, \phi_m) = [\Phi_1(\theta_m, \phi_m), \Phi_2(\theta_m, \phi_m), \dots, \Phi_K(\theta_m, \phi_m)]^T$$
$$\Phi_k(\theta_m, \phi_m) = \frac{\lambda}{\pi sin\left(\frac{\pi L}{\lambda}\right)}\left\{\frac{cos\left(\frac{L}{\lambda}\pi cos\theta_m\right) - cos\left(\frac{\pi L}{\lambda}\right)}{sin\theta_m}\right\}. \quad (1)$$
$$e^{-j\frac{2\pi}{\lambda}(x_k sin\theta_m cos\phi_m + y_k sin\theta sin\phi_m + z_k cos\theta_m)}$$

where L is the dipole length, λ is the wavelength and x_k, y_k and z_k are the coordinates of the dipole $k = 1,2, \dots, K$.

The signal received by each one of the dipoles are firstly sampled by the respective ADC, and then downconverted and demodulated by the receiver (RX). Thus, at discrete time n, vector $\underline{\boldsymbol{r}}$ stores K complex-valued baseband samples. Each r_k

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value of $\underline{\boldsymbol{r}}$ corresponds to the IQ (In-phase and Quadrature) symbol received at instant n by the k-th dipole of the UCA. $\underline{\boldsymbol{r}}$ is determined by

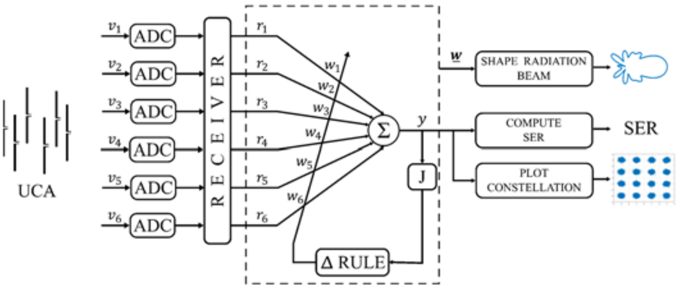


Fig. 1. Blind Concurrent Beamforming block diagram.

$$\underline{\boldsymbol{r}}(n) = \underline{\boldsymbol{C}}\,\boldsymbol{\Phi}[\,\underline{\boldsymbol{s}}(n) + \underline{\boldsymbol{a}}(n)] \tag{2}$$

where $\underline{\boldsymbol{C}} \in \mathbb{C}^{N_K \times N_K}$ is the mutual coupling matrix, N_K is the number of dipoles at the receiver, $\underline{\boldsymbol{s}}(n) \in \mathbb{C}^{N_i+1}$ is the complex-valued vector composed by the desired signal (DS) and N_i interfering signals (IS) and $\underline{\boldsymbol{a}}(n)$ is the AWGN noise, with Gaussian distribution.

The baseband IQ samples $\underline{\boldsymbol{r}}(n) = [r_1\, r_2 \ldots r_K]$, received from the K array elements, are applied to the beamforming input and the beamforming output is given by

$$y(n) = \underline{\boldsymbol{w}}(n)\underline{\boldsymbol{r}}(n)^T \tag{3}$$

in which $\underline{\boldsymbol{w}}(n)$ is the weighting vector and $[\cdot]^T$ denotes the transpose operator.

After computing the beamformer output, the weighting vector is updated according to cost function J and the delta rule which, for CMA algorithm results in

$$\underline{\boldsymbol{w}}(n+1) = \underline{\boldsymbol{w}}(n) + \eta_{CMA}(\gamma - |y(n)|^2)\underline{\boldsymbol{r}}(n)^* \tag{4}$$

where η_{CMA} is the CMA adaptive step, $[\cdot]^*$ denotes the conjugate operator and γ is the CMA dispersion constant given by

$$\gamma = \frac{\sum_{i=1}^{M}|A|^4}{\sum_{i=1}^{M}|A|^2} \tag{5}$$

where M is the constellation order and $A = \{a_0\, a_1 \ldots a_{M-1}\}$ is the constellation alphabet. The updated weighting vector is then used to compute a new beamformer output

$$\tilde{y}(n) = \underline{\boldsymbol{w}}(n+1)\underline{\boldsymbol{r}}(n)^T \tag{6}$$

The outputs $y(n)$ and $\tilde{y}(n)$ are then quantized according to the M-QAM reference constellation in order to control a non-linear link $\mathrm{NL}(y, \tilde{y})$ for the DD weighting vector update, as follows

$$\begin{aligned}\underline{\boldsymbol{w}}(n+1) &= \underline{\boldsymbol{w}}(n+1)\\ &+ \eta_{DD}\mathrm{NL}(y,\tilde{y})[Q\{y(n)\} - y(n)]\underline{\boldsymbol{r}}(n)^*\end{aligned} \tag{7}$$

where η_{DD} is the DD adaptive step and $\mathrm{NL}(y,\tilde{y})$ is given by

$$\mathrm{NL}(y,\tilde{y}) = [1 - D_Q(y,\tilde{y})] \tag{8}$$

with

$$D_Q(y,\tilde{y}) = \begin{cases}0, & Q\{y(n)\} = Q\{\tilde{y}(n)\}\\ 1 & Q\{y(n)\} \neq Q\{\tilde{y}(n)\}\end{cases} \tag{9}$$

in which $Q\{\cdot\}$ represents the quantization process operator.

II. Simulation Setup

Simulation procedure considers that the source and interference transmitters (TXs) and the receiver (RX) are on the same plane, with a zenith angle of 90°. The RX operates with a six dipoles uniform circular array (UCA) at $f = 850\,MHz$ (center of the UHF band). Dipoles are spaced by $s_d = \lambda/4$ m and have a length $\ell_d = \lambda/2$ m, radius $r_d = 5$ mm, and load impedance $Z_T = 50\Omega$, where $\lambda = c/f$ is the signal wavelength, and $c = 299{,}792{,}458$ m/s is the speed of light in vacuum. For the sake of simplicity, all sources and destinations use quadrature amplitude modulation (QAM) or white Gaussian noise (WGN) (only for interferences). The beamforming input vector $\underline{\boldsymbol{r}}(n)$ is the received signal already sampled, downconverted, and demodulated (see Eq. 2).

The signal-to-noise ratio (SNR) of the source (desired signal) and interferences are defined as SNR$_s$ and SNR$_i$, respectively. As multiple signals are taken into account in this beamforming technique, we make use of signal-to-interference-plus-noise ratio (SINR) to measure the impact of impairments in the receiver, as follows

$$SINR = \frac{P_s}{\sum_{l=1}^{N_i} P_{i_l} + \sum_{m=1}^{N_i+1} P_{a_m}} \tag{10}$$

where P_s is the power of the desired signal (DS), P_{i_l} and P_{a_m} are the l-th and m-th power of interference and resultant AWGN noise, respectively.

III. Results

This section presents the simulation results of the following scenarios:

Scenario 1: 3 transmitters (DS plus 2 IS). DS is located at 0◦ azimuth angle (16-QAM) and ISs are at azimuth angles 20◦ (4-QAM) and 240◦ (16-QAM). Source has SNR$_s$ = 25 dB and interferences have SNR$_i$ = 20 dB. Signal-to-interference-plus-noise ratio is SINR = 20 dB.

Scenario 2: 3 transmitters (DS plus 2 IS). DS is located at 120◦ azimuth angle (16-QAM) and ISs are at azimuth angles 60◦ (16-QAM) and 160◦ (64-QAM). Source has SNR$_s$ = 25 dB and interferences have SNR$_i$ = 20 dB. Signal-to-interference-plus-noise ratio is SINR = 15 dB.

Scenario 3: 6 transmitters (DS plus 5 IS). DS is located at 1◦ azimuth angle (16-QAM) and ISs are at azimuth angles 30◦ (4-QAM), 120◦ (WGN), 170◦ (16-QAM), 240◦ (WGN) and 330◦ (4-QAM). Source has SNR$_s$ = 30 dB and interferences have SNR$_i$ = 20 dB. . Signal-to-interference-plus-noise ratio is SINR = 18 dB.

The results of the proposed beamforming are compared with the classical supervised LMS (least mean squares) algorithm. The adaptive steps of BCB and LMS were empirically defined as $\eta_{CMA} = 1 \times 10^{-4}$, $\eta_{DD} = 5 \times 10^{-3}$ and $\eta_{LMS} = 1 \times 10^{-2}$. For LMS algorithm, a training sequence of 1×10^5 samples is considered.

Table I presents the symbol error rate (SER) results. In order to have a fair comparison for both algorithms BCB and LMS, the SER is computed after a number of iterations corresponding to the number of samples of the training sequence adopted to train the LMS equalizer. Note that BCB presents equal or superior performance compared to LMS, even with no training sequence.

Table I – SER comparison

Scenario	BCB	LMS
1	0	0
2	0	1.44×10^{-5}
3	5.55×10^{-6}	1.00×10^{-5}

Fig. 2 shows the MSE convergence results. As expected, LMS algorithm exhibits faster convergence especially in more challenging conditions like Scenario 3, due to its use of a training sequence. On the other hand, since BCB is a blind algorithm, it continuously updates the weighting vector. It is worth to notice that, despite its higher residual MSE, BCB achieves superior SER performance. Fig. 3, Fig. 4 and Fig. 5 present the constellations obtained using BCB and LMS (after a number of iterations corresponding to the number of samples of the training sequence adopted to train the LMS equalizer) in Scenarios 1, 2 and 3, respectively. Observe that LMS constellation displays greater dispersion among higher-energy symbols, leading to a higher SER compared to BCB.

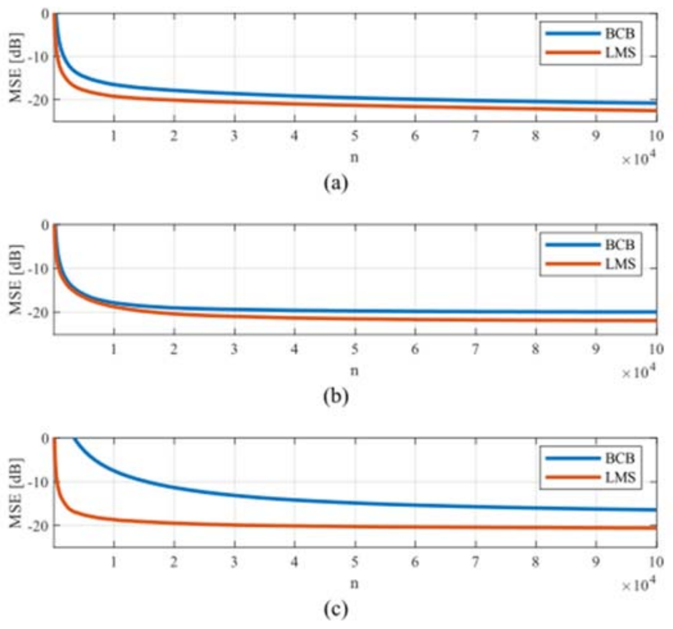


Fig. 2. Mean squared error for: (a) Scenario 1; (b) Scenario 2; (c) Scenario 3.

Fig. 6 compares the radiation pattern obtained with BCB and LMS beamformers for Scenario 1, 2 and 3. In Scenario 1, Fig. 6 (a), two interference sources (ISs) are located at angular positions close to the desired signal (DS). In this case, both beamformers successfully place nulls in the directions of the ISs. However, the main lobe is not aligned with the angular direction of DS.

In Scenario 2, Fig. 6 (b), the ISs are located at angular positions farther from the DS compared to Scenario 1, and the scenario presents lower SINR. In this case, both beamforming approaches successfully place nulls in the IS directions and align the main lobe with DS direction. Note that the resulting BCB radiation pattern exhibits greater attenuation of the ISs and reduced side lobe level compared to the LMS.

Scenario 3 represents a more challenging case, featuring five ISs. Even in this challenging scenario, the beamforming algorithms were able to successfully align the main lobe with DS direction and place nulls in the angular direction of ISs. Over again, the proposed BCB achieves greater attenuation of the ISs and reduced side lobe level than LMS algorithm.

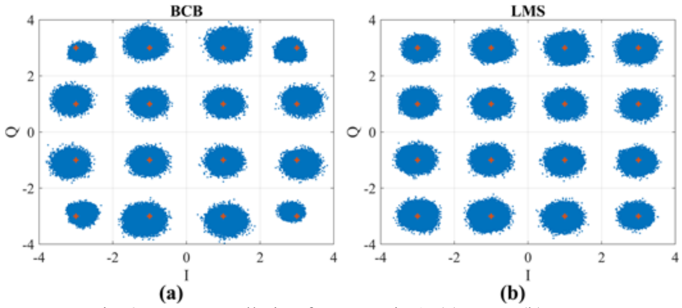


Fig. 3. Constellation for Scenario 1: (a) BCB; (b) LMS

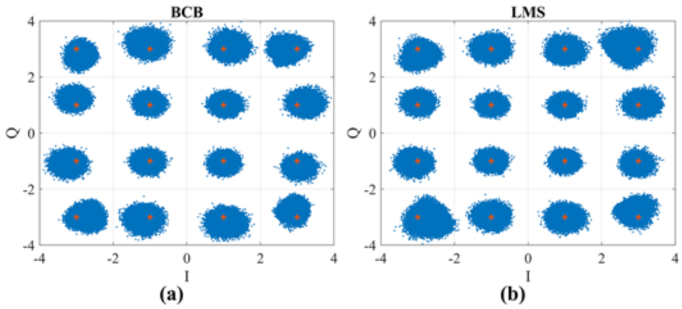


Fig. 4. Constellation for Scenario 2: (a) BCB; (b) LMS

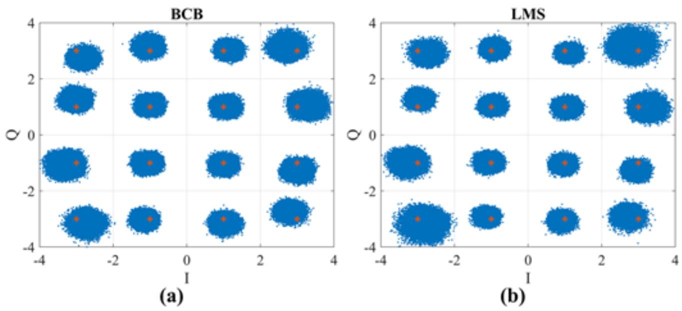
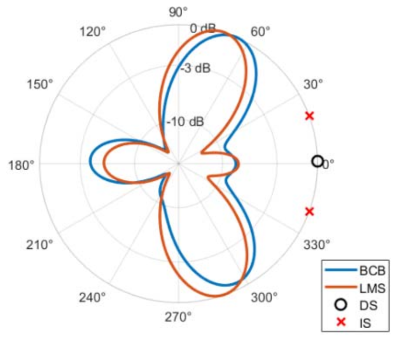


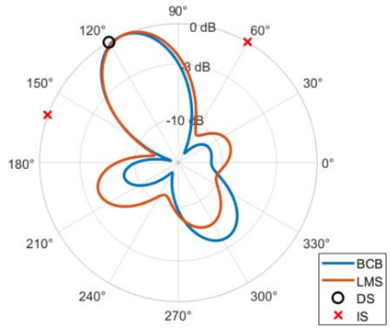
Fig. 5. Constellation for Scenario 3: (a) BCB; (b) LMS

IV. CONCLUSION

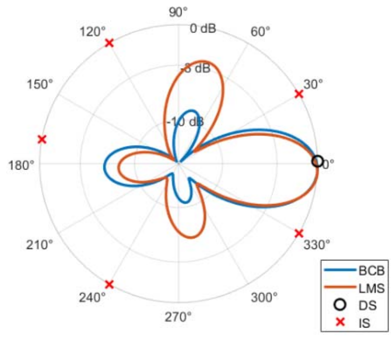
This paper proposed a blind concurrent beamforming (BCB) solution based on the constant modulus algorithm (CMA) and direct decision (DD), operating concurrently. The proposed method was evaluated across multiple scenarios, with three representative cases presented in this paper. Scenario 1 involves two interfering signals located at angular positions close to the desired signal. Scenario 2 featured two interfering signals positioned farther from the DS, but with reduced SINR compared to Scenario 1. Scenario 3 represents a more a challenging case, with five interfering signals. The performance of the proposed beamforming was evaluated in each scenario and compared against the classical supervised least mean squares algorithm.



(a)



(b)



(c)

Fig. 6. Radiation patters obtained with BCB and LMS beamformers: (a) Scenario 1; (b) Scenario 2; (c) Scenario 3.

In all scenarios, the proposed BCB successfully shaped the radiation pattern. Except from Scenario 1, in which the interfering signals are too close to the desired signal, both algorithms, BCB and LMS, successfully aligned the main lobe with the desired signal direction and place nulls in the angular directions of interference signals. In terms of symbol error rate (SER), BCB outperformed LMS, despite LMS achieved lower MSE values across all scenarios. The superior SER performance is attributed to BCB's ability to reduce the dispersion of in-phase and quadrature (IQ) symbols, particularly among the higher-energy constellation symbols, in comparison to LMS.

Overall, the results show that the BCB is a robust blind beamforming, that presents low complexity and spectral efficiency, as it does not require a training sequence like LMS does.

Acknowledgements

This work was supported by the National Council for Scientific and Technological Development – CNPq, process 408423/2022-6.

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