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Development of blind algorithm with automatic gain control

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Abstract

In this paper, the concept of blind algorithm with automatic gain control (AGC) is introduced in adaptive antenna system for signal optimization with an aim to estimate the desired response in adaptive fashion. Blind algorithm with AGC is a hybrid two-stage adaptive filtering algorithm; sequentially combining constant modulus algorithm (CMA) and Bessel least mean square (BLMS) algorithm. Blind Bessel beamformer with AGC does not require external reference signal to update its weight vectors and step size for convergence but updates itself from own reference signal obtained from the output of CMA. Similarly, step size is obtained from the correlation matrix which is the product of the signals induced in array elements of antenna. BLMS is the modified version of LMS algorithm; based on the non-uniform step size exploiting the asymptotic decay property of Bessel function of the first kind. The output of CMA provides input and reference signals for BLMS that makes it blind. The contributions of this paper include the development of novel blind theory concept and presentation of an AGC method in order to make the Bessel beamformer blind which can update itself electronically through the correlation matrix depending on the signal array vector with the aim to make the signal power constant.

Keywords Blind Bessel beamformer · Constant modulus algorithm · Smart antenna · Beamforming

1 Introduction

Beamforming algorithms have two main categories. One category needs a training signal to update its weight vector, known as non-blind beamforming algorithms like LMS and BLMS. Another one does not require a training signal but uses some of the known properties of the desired signal such as if the arriving signal have a constant magnitude or modulus, then we have to use an algorithm to restore or equalize the amplitude of the original signal by blind beamforming algorithm like CMA. In this regard, Dominique Godard [1] was the first to introduce a family of blind equalization algorithms like CMA. However, CMA has some problems about its convergence [2]. In this context, the author in [3] proposed an algorithm which does not always require an external reference signal for its operation but adapts itself entirely through self-referencing (i.e. output of algorithm is used as feedback to train the beamformer for its optimum convergence) to the desired signal where the correct reference signal is required initially a few iterations only for least mean square (LMS) algorithm. The configuration shown in [3], uses a non blind LMS trained equalizer which first to open the inter-symbol interference (ISI) communication eye and when the eye is open, then training finished, LMS switched out and the system reverted to blind decision feedback. However, this structure still requires training, but just to open the eye at start or whenever the blind algorithm fails. Similarly, least mean square least mean square (LLMS) algorithm is presented for smart antenna using LMS–LMS algorithms [4], for getting optimum results. In [5, 6], recursive least mean square (RLMS) algorithm is developed using a combined RLS–LMS algorithm to provide a robust performance. An adaptive beamforming algorithm is proposed in [7]; a combination of the direct matrix inversion (DMI) and the recursive least square (RLS), known as DMI–RLS and is used for optimum weight estimation in order to ensure a possible faster convergence. Whereas in [8], a matrix inversion normalized least mean square (MI-NLMS) adaptive beamforming algorithm is developed for smart

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antenna application that combines the good aspects of sample matrix inversion and the normalized least mean square (NLMS) algorithms individually. Low-complexity robust adaptive beamforming (RAB) techniques based on shrinkage methods are proposed in [9] where the analysis of the effect of shrinkage on the estimation procedure is developed along with a study of its computational complexity. In [10], the author presents a novel blind adaptive beamforming algorithm based on RLS is derived. In [11, 12], modified Bessel beamformer along with its live model for Bessel beamformer at [13], are developed with AGC to provide an optimum solution for signal quality and capacity improvement either to direct a beam towards a desired user or to minimize a mean squared error (MSE) without an operator involvement for adjusting the step size parameter that controls the convergence rate of the algorithm but this algorithm still requires a reference signal to update its complex weight vector. However, various adaptive beamforming methods that have been under development over the past 10 years for a smart antenna and still a hot area for research; therefore an idea is emerged to introduce a blind Bessel beamformer with AGC that does not require training/reference to update its complex weight vector. Whereas the configuration shown in [3] still requires training either just to open the eye at start or whenever the blind algorithm fails. Further to highlight that most of the time, the availability of reference signal is difficult to obtain for training/comparison, therefore to avoid this (i.e. reference signal) problem, blind concept is introduced here in Bessel beamformer with AGC.

Accordingly, an idea is suggested in this paper that is to have first a CMA (or any other blind algorithm), output of which is to be used as the 'reference/desired signal' for a (non-blind) BLMS algorithm that follows. So a CMA/BLMS would not require any training and can be regarded as blind Bessel beamformer. Therefore the contributions of this paper are to include the development of novel blind theory concept and presentation of an AGC method in order to make the Bessel beamformer blind which can update itself electronically through the correlation matrix depending on the signal array vector with the aim to make the signal power constant. Further, in the proposed scheme, the source and the receiver are in a constant feedback and adjustment loop w.r.t. reference signal and step size which help the proposed scheme to stabilize itself in more efficient manner.

The performance of blind Bessel beamformer is evaluated in an adaptive linear array having multiple inputs including the presence of two co-channel interfering signals in additive white Gaussian noise (AWGN) channel of zero mean. In order to validate the theoretical findings with respect to proposed model, a few simulations are presented.

The paper is planned as follows. In Sect. 2, the proposed model is explained. Theoretical analysis and numerical results are presented in Sects. 3 and 4 respectively. Results are discussed in Sect. 5. Conclusion of the paper is provided in last Section.

2 Mathematical model of proposed method

A. Model for optimal weight vector

We model an adaptive antenna array system with the proposed method based on BLMS and CMA algorithms as shown in Fig. 1. CMA (trains its adaptive weights utilizing its own output as feedback) is placed 1st followed by BLMS; both of them are alienated by an array image factor. BLMS needs a reference signal, also known as training sequence, to update its complex weight vector. During the training period, the reference signal is sent by the transmitter to the receiver and receiver uses this information to compute new weight for convergence to form a beam in the desired direction. In our case, CMA provides 'reference/desired signal' for a BLMS in the proposed method.

An arrangement for Proposed Model is shown in Fig. 1 where first part of the proposed method produces an output $y_{k(CMA)}$ that is defined by

$$y_{k(CMA)} = \mathbf{W}_{CMA}\mathbf{X}_k^H = \mathbf{W}_{CMA}^T\mathbf{X}_k \tag{1}$$

where k is the iteration number.

The received signal array vector on the elements of antenna is given by

$$\mathbf{X}_k = [x_1, x_2, \ldots, x_N]^H \tag{2}$$

where H signifies the Hermitian transpose of the vector as complex symbols will be used so that proposed algorithm be adjusted appropriately and linear array with N-element are isotropic radiating elements.

Received signal array vector on the elements of antenna is composed of desired and other interfering signals [14, 15], therefore, it can also be written in the form as given by

$$\mathbf{X}_k = s_d(k)A(\theta_d) + \sum_{i=1}^{L} s_i(k)A(\theta_i) + n(k) \tag{3}$$

where s_d and s_i are the desired and interfering signals arriving at the antenna array at angles θ_d and θ_i respectively. $A(\theta_d)$ and $A(\theta_i)$ are the steering vectors for the desired and interfering signals respectively which are also characterized as an image of the desired and interfering signals array factor. L represents the number of interfering signals and n is a complex additive white Gaussian noise of zero mean at the array elements. However, when BLMS algorithm converges, its output tends to approach desired

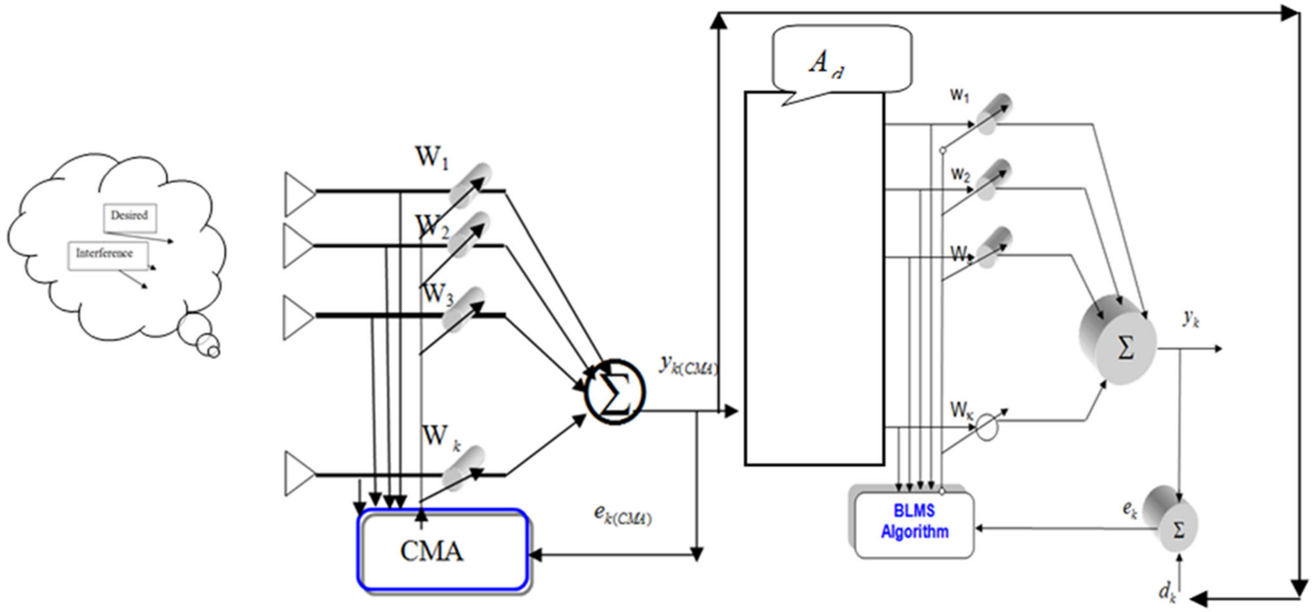


Fig. 1 Proposed model

signal (s_d) with both interfering signal (s_i) and additive white Gaussian noise (n) being suppressed. Therefore, image of the desired signal array factor (A_d) is described as

$$A_d(\theta) = \left[1, e^{-j\phi}, \ldots, e^{-j(N-1)\phi}\right] \tag{4}$$

where $\phi = \frac{2\pi d}{\lambda} \sin\theta$ is the phase shift of the wavefront observed at each sensor and d is the uniform distance between array elements. $\lambda = \frac{c}{f}$ where f is the design frequency in Hertz which is one of the carrier frequencies for 3G/4G systems.

Therefore, (4) can be written as

$$A_d(\theta) = \left[1, e^{-j\frac{2\pi}{\lambda} d\sin(\theta)}, \ldots, e^{-j\frac{2\pi}{\lambda} d(N-1)\sin(\theta)}\right] \tag{5}$$

Accordingly its weights are updated as such the input stage of the blind Bessel beamformer (BBB) scheme is based on the CMA algorithm with its weight vector at the $(k+1)$th iteration updated adaptively and is given by

$$\mathbf{W}_{k+\mathbf{1}(CMA)} = \mathbf{W}_{k(CMA)} + 2\mu e_{k(CMA)} \mathbf{X}_k \tag{6}$$

where μ and $e_{k(CMA)}$ denote step-size and error signal respectively. This error signal is used for adjustment of adaptive system by optimizing the weight vector and is given by

$$e_{k(CMA)} = \left(y_{k(CMA)} - \frac{y_{k(CMA)}}{\left|y_{k(CMA)}\right|} \right) \tag{7}$$

where $y_{k(CMA)}$ is the output of the CMA section at kth iteration as defined in (1). This output of the CMA section is also forming the input to the following BLMS section. With this filtered signal, the input signal vector of the BLMS section becomes

$$\mathbf{X}_{k(BLMS)} = A_d y_{k(CMA)} \tag{8}$$

where A_d is the image array factor of the desired signal.

It means that output $y_{k(CMA)}$ is estimated by CMA which is then fed into 2nd part (i.e. BLMS) after it has been multiplied by the image of the desired signal array factor (A_d). It is to mention that error signal used for adjustment of adaptive system by optimizing the weight vector of BLMS algorithm is sourced from output $\{y_{k(CMA)}\}$ of CMA. Whereas for updating the CMA weights, reference signal is obtained from itself referenced version (i.e. output of CMA is used as feedback to train the CMA for optimum convergence) that is estimated by using (7). Thus, in the proposed method, the immediate output $y_{k(CMA)}$ yielded from first part is multiplied by image of the desired signal array factor (A_d) that results a filtered signal $(A_d y_{k(CMA)})$. This filtered signal is further processed by BLMS section using (8).

Putting value of (1) into (8) and ignoring subscript k for simplicity in weight vector, then input signal vector of the BLMS is given by

$$\mathbf{X}_{k(BLMS)} = A_d \mathbf{W}_{CMA} \mathbf{X}_k \tag{9}$$

The weight vector of the BLMS stage, is updated according to

$$\mathbf{W}_{k+\mathbf{1}(BLMS)} = \mathbf{W}_{k(BLMS)} + 2\mu e_{k(BLMS)} J_v(N) \mathbf{X}_{k(BLMS)} \tag{10}$$

where error signal of BLMS stage is given by

$$e_{k(BLMS)} = d_k - y_{k(BLMS)} \tag{11}$$

here d_k is the reference signal, also known as pilot signal. This reference signal is used as desired response from the adaptive processor connected with the antenna array elements which guide the beamformer to map the main beam towards a specified direction only. In our case, reference signal is obtained from CMA. $y_{k(BLMS)}$ is the output of the BLMS section and is given by

$$y_{k(BLMS)} = \hat{\mathbf{W}}^T_{k(BLMS)}\mathbf{X}_{k(BLMS)} \tag{12}$$

where $\hat{\mathbf{W}}_k = J_v(N)\mathbf{W}_k$ is the initial estimate weight vector. $\mathbf{W}_k$ represents initial weight vector and $J_v(N)$ is the Bessel function (BF) of the first kind having the monotonically decreasing property. Due to this asymptotic property, BF gives a number of co-efficient in discrete form. Exploiting this asymptotic decay property, which helps the algorithm to converge in a more efficient manner to reduce MSE for a certain number of iterations and optimize gain. N represents the number of elements. In Bessel function, v denotes the order of Bessel function of the first kind and must be a real number. In this case, v is taken as one. To initialize the adaptive beamforming algorithm, we set the initial weight vector to zero.

Putting value of (9) into (12) then output of BLMS section becomes,

$$y_{k(BLMS)} = \hat{\mathbf{W}}^T_{k(BLMS)}A_d\mathbf{W}_{CMA}\mathbf{X}_k \tag{13}$$

where (13) finally becomes the output of the blind Bessel beamformer (i.e. combination of CMA/BLMS beamformer) and is given by

$$y_{k(BBB)} = \mathbf{W}_{BBB}\mathbf{X}_k \tag{14}$$

here $\mathbf{W}_{BBB}$ is the required optimum solution or optimal weight vector for proposed beamformer with input signal array vector $\mathbf{X}_k$ and is given by

$$\mathbf{W}_{k+1(BBB)} = \mathbf{W}_{k(BBB)} + 2\mu e_{k(BBB)}J_v(N)\mathbf{X}_k \tag{15}$$

Eventually, we get an optimum output using (14) through adaptation process using (15) by proposed blind beamformer with input signal array vector $\mathbf{X}_k$.

In (15), the overall error signal $\{e_{k(BBB)}\}$ is given by

$$e_{k(BBB)} = \left(y_{k(BBB)} - \frac{y_{k(BBB)}}{|y_{k(BBB)}|}\right) \tag{16}$$

and μ is defined by

$$\mu = \frac{1}{(2 * real(trace(\mathbf{R})))} \tag{17}$$

where $\mathbf{R}$ is the autocorrelation matrix relating correlation between various elements of signal array vector and is given by

$$\mathbf{R} = \left[\mathbf{X}_k * (\mathbf{X}_k)^T\right] \tag{18}$$

From (17), we can update the coefficients of the smart antenna system automatically by getting a new real value for each iteration with the aim to make the signal power constant. Therefore the autocorrelation matrix plays a significant role in the mechanism of AGC. By introducing a mechanism of AGC in the proposed algorithm, although there is complexity but it is acceptable due to another promising property of robustness towards noise and interference.

Equation (15) of the proposed algorithm implies that as the adaptation progresses, the adaptive process will finally converge to mean square error. It means that the weight matrix update of proposed algorithm approaches its true value, when the number of samples grows i.e. $k \to \infty$ and thus the estimated weights approaches the optimal solution $\mathbf{W}_{k+1(BBB)} \to \mathbf{W}$ or $\mathbf{W}_{MSE}$.

The proposed beamformer can be outlined as follows:

Step 1 Obtain signal array vector $(\mathbf{X}_k)$ in (2)
Step 2 Get output $\{y_{k(BBB)}\}$ of the blind Bessel beamformer in (14) concluding both the parts of CMA and BLMS algorithms
Step 3 Calculate overall error signal $\{e_{k(BBB)}\}$ in (16) for optimizing the weight vector
Step 4 Calculate the adaptive weights $\{\mathbf{W}_{k+1(BBB)}\}$ in (15) for proposed beamformer
Step 5 Repeat the above steps for getting optimum results in closed loop

B. Alternate Model for optimal weight vector

The proposed model as shown in Fig. 1 may be reduced to general adaptive filter structure as shown in Fig. 2 that may be proven useful for adaptive filtering tasks.

The optimal weight vector for proposed beamformer as shown in Fig. 2 alongwith an overall error signal $\{e_{k(BBB)}\}$ can be further explained as given by

$$e_{k(BBB)} = d_k - y_{k(BLMS)} \tag{19}$$

In our case, reference signal is obtained from the output of CMA, therefore

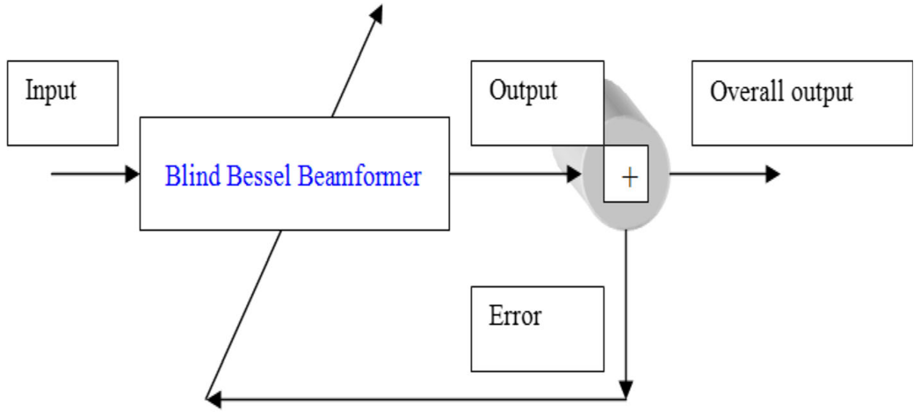
$$e_{k(BBB)} = y_{k(CMA)} - y_{k(BLMS)} \tag{20}$$

Putting value of (1) and (12) into (20) where T for transposition is dropped for simplicity, then (21) with input signal is given by

$$e_{k(BBB)} = \mathbf{X}_k(\mathbf{W}_{CMA} - \mathbf{W}_{BLMS}) \tag{21}$$

where (21) implies that as the adaptation progresses, the adaptive process will finally converge to mean square error.

Fig. 2 Generalized structure of blind Bessel beamformer



Thus the overall error signal of the blind Bessel beamformer (BBB) becomes as given by

$$e_{k(BBB)} = \mathbf{X}_k \hat{\mathbf{W}}^T_{k(BBB)} \tag{22}$$

where $\hat{\mathbf{W}}^T_{k(BBB)} = J_v(N)\mathbf{W}_{k(BBB)}$.

Differentiate (22) w.r.t. weight vector $\mathbf{W}$, where subscript k is dropped for simplicity and then we have

$$\frac{\partial e_{k(BBB)}}{\partial \mathbf{W}_{BBB}} = J_v(N)\mathbf{X}_k(1) + 0 = J_v(N)\mathbf{X}_k \tag{23}$$

Therefore, simply putting value of (23) in the gradient estimate of the form [16] given by

$$\hat{\nabla}_k = 2e_k \begin{bmatrix} \frac{\partial e_k}{\partial \mathbf{W}_0} \\ \cdot \\ \cdot \\ \frac{\partial e_k}{\partial \mathbf{W}_L} \end{bmatrix} = 2e_k\{J_v(N)\mathbf{X}_k\} \tag{24}$$

where $\frac{\partial e_{k(BBB)}}{\partial \mathbf{W}_{BBB}} = J_v(N)\mathbf{X}_k = \begin{bmatrix} \frac{\partial e_k}{\partial \mathbf{W}_0} \\ \cdot \\ \cdot \\ \frac{\partial e_k}{\partial \mathbf{W}_L} \end{bmatrix}$

For developing and analyzing a variety of adaptive algorithms, we have steepest decent method [Widrow et al., chap 2 (2.35) at Ref. [16] [Haykin, (4.36) at Refs. [17, 18]. Using this method as described by

$$\mathbf{W}_{k+1} = \mathbf{W}_k - \mu\hat{\nabla}_k \tag{25}$$

Putting (24) into (25), then we have the required weight vector

$$\mathbf{W}_{k+1(BBB)} = \mathbf{W}_{k(BBB)} + 2\mu e_{k(BBB)} J_v(N)\mathbf{X}_k \tag{26}$$

where μ is a variable step-size as defined in (17) and (26) is the required weight vector to update the beamformer in accordance with the adaptive environment.

3 Simulation results

In this section, let us assume an N = 8 element array with one fixed known desired source and two fixed interferers. All signals are assumed to operate at the same carrier frequency. Let us assume an eight—element array with the desired signal at 20° angle of arrivals (AOAs) and two interferers at − 50° and 50° AOA are shown in Fig. 3. Optimum array gain towards desired user is achieved at 20° whereas null is also placed towards interferers at − 50° and 50°. Subsequent MSE is obtained as shown in Fig. 4. Sidelobe level (SLL) w.r.t. array gain is found small which indicates that proposed method gets less interference and provides quality signal to desired users, thus it enhances capacity and security by suppressing interference. Due to optimum array gain (in terms of focusing energy), range is also be increases.

The performance curve as shown in Fig. 4 indicates that MSE behaviour of proposed algorithm follows steady path. It means that convergence is satisfactory which is observed from frequent optimum array gain also. In this case, variable step size is obtained by (17). It is to be noted that step size has significant effect on convergence and stability of the proposed beamformer. The step size at which convergence is achieved is considered final value. Results obtained are summarized in Table 1.

4 Performance comparison

A. Performance w.r.t. Array Gain

Comparison of the proposed method is also made with BLMS, CMA and LMS algorithms for further evaluation as shown in Fig. 5. In Fig. 5, a strategy with 04 desired users is adopted that are coming at same AOAs as 0° alongwith two interferers placed at − 50° and 50° which are picked up by smart antenna equipped with proposed method, BLMS, CMA and LMS beamformers respectively in order

Fig. 3 Radiation pattern of blind Bessel beamformer

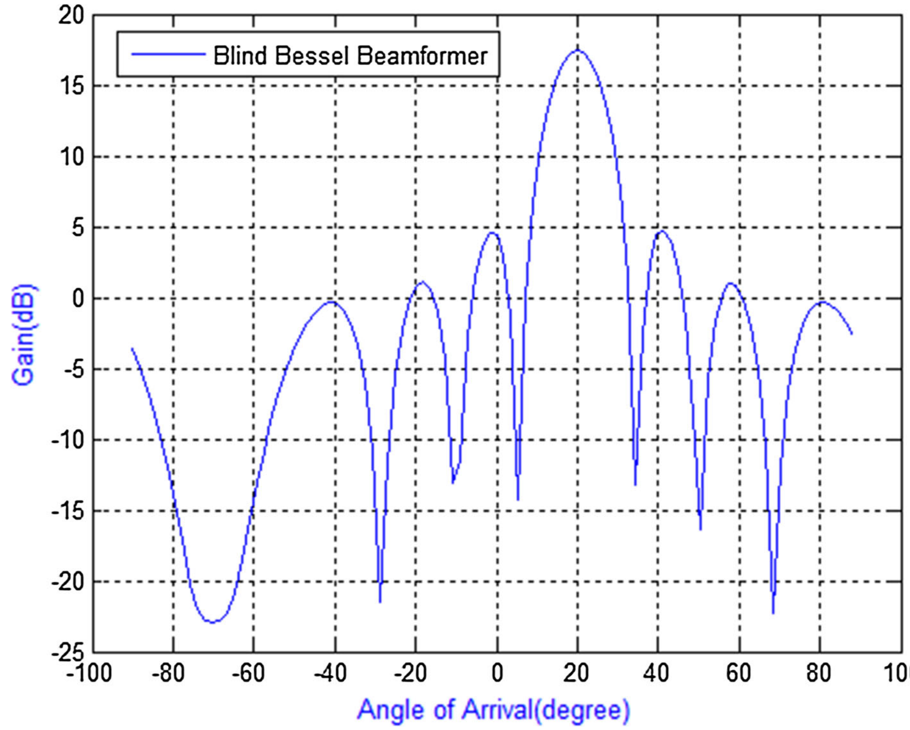


Fig. 4 System performance w.r.t. MSE

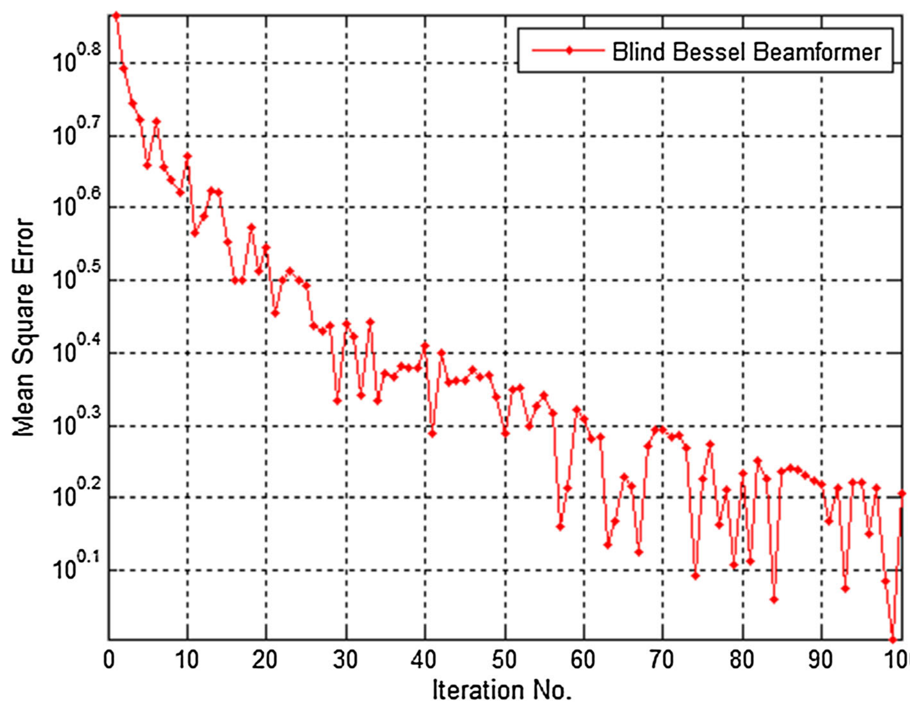


Table 1 Input and output estimates

Input parameter			Output parameter	
AOA (°)	No. of samples	Element spacing	SLL (dB)	Gain (dB)
20	100	0.5 λ	4.0	18.0

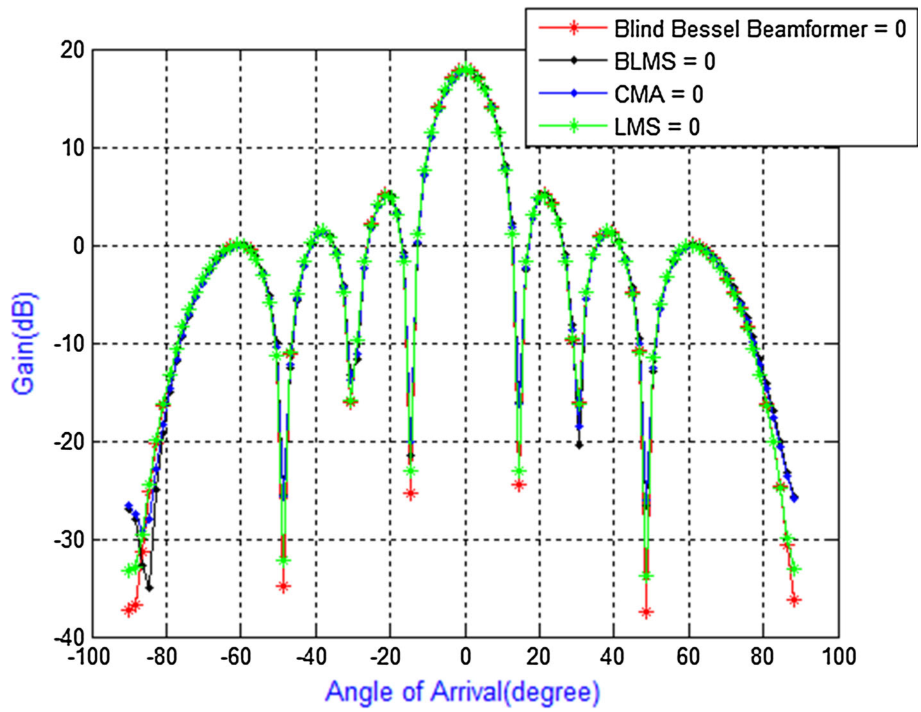


Fig. 5 Radiation patterns achieved by blind Bessel beamformer, BLMS, CMA and LMS algorithms

to assess its performance in terms of array gain. You can see that proposed method have same optimum array gain with greater null depth performance towards interferers as compared to BLMS, CMA and LMS beamformers. This improvement comes in proposed method due to self adjustment w.r.t step size which is necessary for good convergence and to avoid instability. In addition to this, proposed method is blind whereas BLMS beamformer is non blind requires reference signal to update its complex weight vector. Thus proposed method updates itself automatically and changes the directionality of its radiation patterns in response to its signal environment more effectively. However, the step sizes for BLMS, CMA and LMS beamformers are adjusted (set at 0.001) by trial and error method, requiring operator' involvement which is missing in case of proposed method where all other parameters remain constant for better comparison.

Thus the performance characteristics (such as capacity) of cellular system using smart antenna equipped with proposed method may be enhanced drastically. Therefore, proposed method is superior to BLMS, CMA and LMS algorithms.

B. Performance w.r.t. Convergence

If we compare and observe the performance curve for steady state MSE as shown in Fig. 6, then proposed algorithm has minimum MSE as compared to BLMS, CMA and LMS techniques however, all of them are not following steady path and exhibiting fluctuation. The proposed technique has a clear performance advantages (i.e. array gain with greater null depth performance towards interferers and lower MSE) over other BLMS, CMA and LMS algorithms. It in turn may reduce interference, enhance range, provide quality signal to desired users and increase capacity of the system. Therefore, its application in wireless cellular communication is important for enhancing quality and increasing capacity of the system by suppressing interference. The performance parameters as shown in Table 2 are extracted from Fig. 5.

5 Discussion on results

A Salient aspects of the results are concluded as follows:

- The proposed method does not require an external reference signal for its operation but adapts itself entirely through self-referencing (i.e. output of CMA is utilized as the input and reference signal for BLMS to train the beamformer for its optimum convergence) whereas algorithm proposed in [3] requires initially a few iterations only for LMS and uses a (non blind) LMS trained equalizer first to open the ISI communication eye and when the eye was open, the training finished/ LMS switched out and the system reverted to blind decision feedback. However, the configuration shown in [3] still requires training, but just to open the eye at start or whenever the blind algorithm fails.
- The proposed method has achieved similar beam pattern and array gain with same SLL but with greater

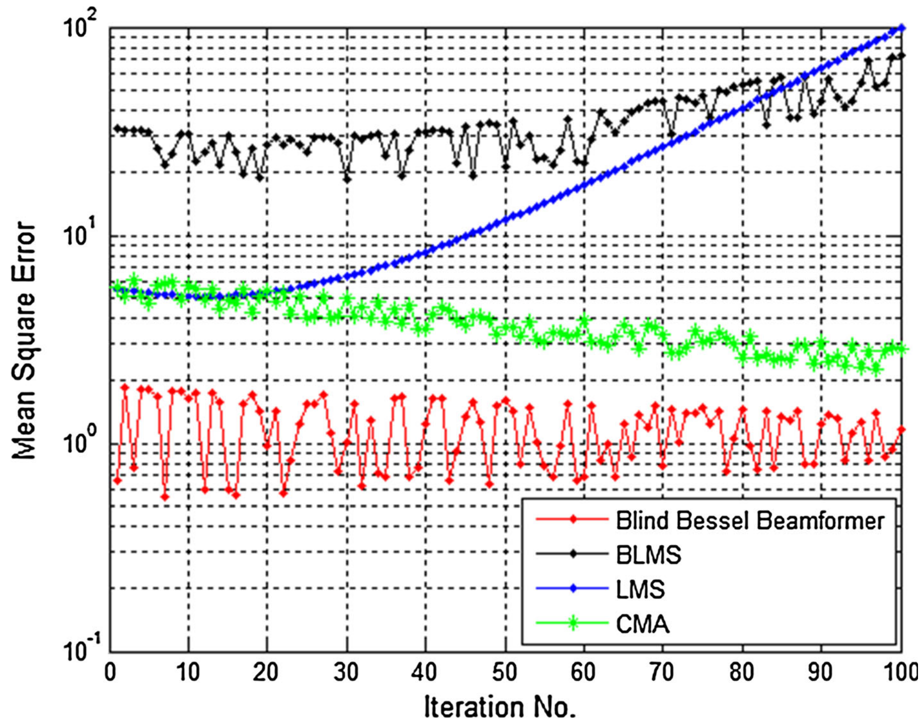


Fig. 6 System performance w.r.t. MSE of blind Bessel beamformer, BLMS, CMA and LMS algorithms

Table 2 Perpormance analysis

Algorithms	Input parameter	Output parameter	
	AOA (°)	Null depth (dB)	Gain (dB)
Blind Bessel beamformer	0	− 38	19.0
BLMS	0	− 34	19.0
CMA	0	− 28	19.0
LMS	0	− 28	19.0

null depth performance towards interferers as compared to BLMS, CMA and LMS beamformers.

- The proposed scheme has an advantage over BLMS and LMS that it does not need an external reference signal for its adaptation whereas the latter require training/external reference signal to update its complex weight vector.
- The proposed method is based on the idea to reduce system overhead and maintain gain on the signal while minimizing the total output energy. As a result, a number of bits for transmitting information are increased that leads to enhance capacity because it does not require an external reference signal to train the adaptive weights.
- The proposed method is having self adjustment property where no operator involvement exists. Whereas BLMS, CMA and LMS do not have self adjustment property but requires a step size by trial-and-error method.
- Under the given conditions, the MSE of proposed method is found most favorable and is following steady state as compared to BLMS, CMA and LMS. It means that proposed system with small MSE indicates that this system has accurately modeled, predicted, adapted and/or converged to a solution for the given system. Therefore, its application in wireless cellular communication is effective for enhancing quality and capacity of the system.
- The proposed method is slightly more complex as compared to BLMS, CMA and LMS when treated as single entity. However, at the same time, it has more array gain and small MSE in comparison with BLMS, CMA and LMS. Further, the complexity of the proposed method increases with AGC because the processor will also take time to calculate autocorrelation matrix first in order to measure the step size. This complexity of the proposed algorithm can be compromised due to its self adjustment property of AGC which results stability in the system. However, it is be noted that nowadays powerful low cost digital signal processors (DSPs) are commercially available, therefore algorithm complexity or computational cost w.r.t.

execution time would not make much difference if all other requirements such as large array gain, lower MSE and self gain control, are met by the proposed method. So, it is better to use proposed method for wireless cellular communication companies to get aforesaid advantages for cost effective solution in smart antenna.

B. From the above discussion, following generalized results may be derived that can provide cost effective solution for the current state of the art technologies.

- The proposed method enhances range and security due to optimum array gain.
- The proposed method directs its energy towards desired user only and there is no leakage of energy towards interferers, therefore it conserves energy, due to which battery life installed at Base Transceiver Station (BTS) increases. Thus, it obeys the law of conservation of energy and in turn power optimization is achieved. Power optimization means that the transmit power can be reduced in both directions (i.e. at uplink and downlink) for a given signal quality.
- With increase range, minimum BTS is required to cover the service area and thus infrastructures cost may be reduced. Burdon on subscribers may be cut down subsequently.
- As such, there is no leakage of energy towards interferers therefore security of the subscriber increases and tapping of the classified information may be reduced/restricted.
- The proposed method reduces conventional wear and tear of smart antenna as such it eliminates the need for physical movement of the antenna in order to carry out scanning for transmission and reception beams electronically through the constructive and destructive interference.

6 Conclusion

In this paper, we have introduced a hybrid adaptive beamforming algorithm with new blind concept and AGC in order to claim high performance in terms of large gain, lower MSE and self gain control property. It is recommended to wireless cellular communication companies if this breakthrough design may apply at BTS, they will find a cost effective solution for their systems to enhance range, provide quality & secure signal and increase capacity.

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