RESEARCH ARTICLE

Design and Performance Analysis of Blind Algorithm in Wireless Communication

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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 is to estimate the desired response in adaptive fashion. Blind algorithm with AGC is a two-stageadaptive filtering algorithm; a combination of Bessel least mean square (BLMS) and constant modulus algorithm (CMA). 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: wireless communication; signal optimization; blind bessel beamformer; constant modulus algorithm; smart antenna; beamforming

1. Introduction

Dominique Godard[1] was the first to introduce a family of blind equalization algorithms like CMA. CMA has 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 as shown in[3] uses a non blind LMS trained equalizer first to open the inter-symbol interference (ISI) communication eye and when the eye is open, the 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[7] which is 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

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normalized least mean square (MI-NLMS) adaptive beamforming algorithm is developed for smart 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 application of fractional adaptive algorithms for parameter identification of Box-Jenkins (BJ) systems. In[11,12], modified Bessel beamformer along with its live model and convergence analysis for Bessel beamformer in[13,14], 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. As such research in smart antenna is a continuous process; 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 as 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 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 a co-channel interfering signal and 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 Section 2, the proposed model is explained. Theoretical analysis and numerical results are presented in Section 3 and 4 respectively. Results are discussed in Section 5. Conclusion of the paper is provided in last Section.

2. Mathematical Model of Proposed Method

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 **Figure 1** CMA (a blind algorithm that does not require a reference signal to train the adaptive weights but beamformer output is utilized as feedback) is placed 1st followed by BLMS; both of them are alienated by an array image factor. BLMS is a non-blind algorithm which 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, reference signal is obtained from CMA i.e. CMA beamformer provides 'reference/ desired signal' for a (non-blind) BLMS beamformer in the proposed method. An arrangement for Proposed Model is shown in **Figure 1** where first part of the proposed method produces an output $y_{k(CMA)}$ that is defined by

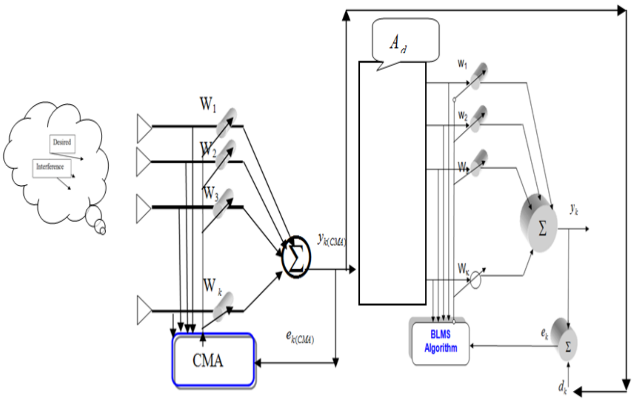

Figure 1; Proposed Model.

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

where k is the iteration number and $\mathbf{W}$ represents initial weight vector. $\mathbf{X}_k$ is the received signal array vector on the elements of antenna and given by

$$\mathbf{X}_k = [x_1, x_2, ..., x_N]^H \quad (2)$$

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 which are isotropic radiating elements and superscript T denotes transpose of a vector or a matrix.

Received signal array vector on the elements of antenna is composed of desired and other interfering signals [15-16], therefore, it can also be written in the form as given by

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

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 is also known as 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 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

$$A_d(\theta) = [1, e^{-j\phi}, ..., e^{-j(N-1)\phi}] \quad (4)$$

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 in Hertz.

Therefore, (4) can be written as

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

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

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

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

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

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

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

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

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

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

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

where error signal of BLMS stage is given by

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

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 i.e. output of CMA is to be used as the 'reference/ desired signal' for a (non-blind) BLMS algorithm. $y_{k(BLMS)}$ is the output of the BLMS section and is given by

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

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 coefficient 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,

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

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

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

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

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

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

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

and μ is defined by

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

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

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

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 $\mathbf{W}_{MSE}$.

Additionally, the algorithm summarizes the proposed beamformer 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: Updates the co-efficient of 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.

Alternate Model for Optimal Weight Vector

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

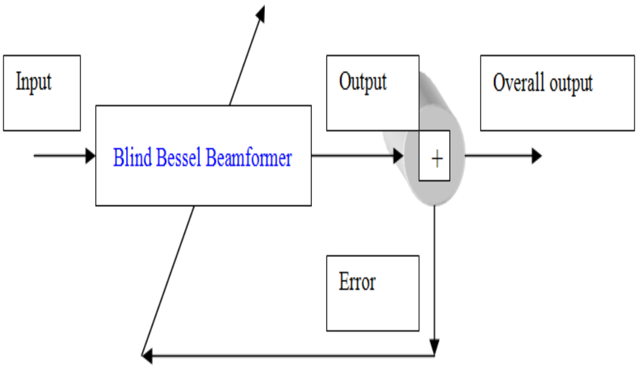

Figure 2; Generalized structure of blind bessel beamformer .

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

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

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

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

Putting value of (1) and (12) into (20) where T for transposition is dropped for simplicity, then we have

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

As such input signal $\mathbf{X}_{k(CMA)}$ and $\mathbf{X}_{k(BLMS)}$ are equal to each other when both algorithms are treated as single entity as shown in Fig. 2. then (21) becomes with input signal as given by

$$e_{k(BBB)} = \mathbf{W}_{CMA}\mathbf{X}_k - \mathbf{W}_{BLMS}\mathbf{X}_k \quad (22)$$

$$e_{k(BBB)} = \mathbf{X}_k(\mathbf{W}_{CMA} - \mathbf{W}_{BLMS}) \quad (23)$$

Correspondingly, the weight vectors are also treated as single entity for proposed method therefore (23) implies that as the adaptation progresses, the adaptive process will finally converge to mean square error. Thus the overall error signal of the blind Bessel beamformer (BBB) becomes as given by

$$e_{k(BBB)} = \mathbf{X}_k \hat{\mathbf{W}}^T_{k(BBB)} \quad (24)$$

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

Differentiate (24) w.r.t. weight vector $\mathbf{W}$, where subscript k is dropped for simplicity and then we have

$$\frac{\partial e_{k(BBB)}}{\partial \mathbf{W}_{BBB}} = J_v(N)\mathbf{X}_k(1) + 0 = J_v(N)\mathbf{X}_k \quad (25)$$

Therefore, simply putting value of (25) in the gradient estimate of the form [16] given by

$$\hat{\nabla}_k = 2e_k \begin{bmatrix} \frac{\partial e_k}{\partial \mathbf{W}_0} \\ . \\ . \\ \frac{\partial e_k}{\partial \mathbf{W}_L} \end{bmatrix} = 2e_k\{J_v(N)\mathbf{X}_k\} \quad (26)$$

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

For developing and analyzing a variety of adaptive algorithms, we have steepest decent method [Widrow *et al*., chap 2 (2.35) at reference[17] [Haykin, (4.36) at reference[18,19]. Using this method as described by

$$\mathbf{W}_{k+1} = \mathbf{W}_k - \mu\hat{\nabla}_k \quad (27)$$

Putting (26) into (27), then we have the required weight vector

$$\mathbf{W}_{k+1(BBB)} = \mathbf{W}_{k(BBB)} + 2\mu e_{k(BBB)} J_v(N)\mathbf{X}_k \quad (28)$$

where μ is a variable step-size as defined in (17) and depends on signal array vector. Equation (28) is the required weight vector to update the beamformer in accordance with the adaptive environment.

Simulation Results of Proposed Method

In this section, a strategy is adopted that an incoming signal(s) is at a certain angle {angle of arrivals (AOAs) are indicated in the given **Figure 1** and 3} using N (here N=10) antennas and suppressing all other incoming signals at the same time, in order to evaluate the performance of proposed method developed in the previous section. This assumption is fulfilled while the given results were discussed. Comparison is also made with BLMS, CMA and LMS algorithms for further evaluation.

Desired user is placed at –30 degrees AOA along with interferers coming from other than desired AOA as shown in **Figure 3** for proposed algorithm and subsequent MSE is obtained as shown in **Figure 4**. Optimum array gain towards desired user is achieved. 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 & security by suppressing interference. Due to optimum array gain (in terms of focusing energy), range is also be increases. Results obtained are summarized in **Table 1**.

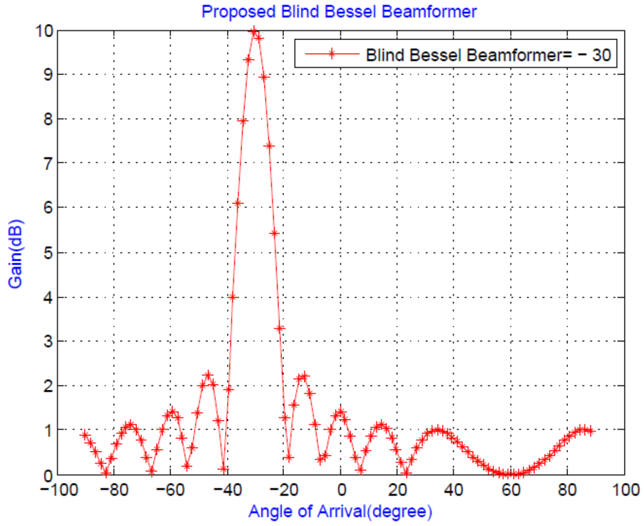

Figure 3; Radiation pattern of blind bessel beamformer.

Input Parameter			Output Parameter	
AOA (degree)	No. of Samples	Element Spacing	SLL (dB)	Gain (dB)
- 30	500	0.5 λ	2.1	10.0

Table 1. Input and output estimates.

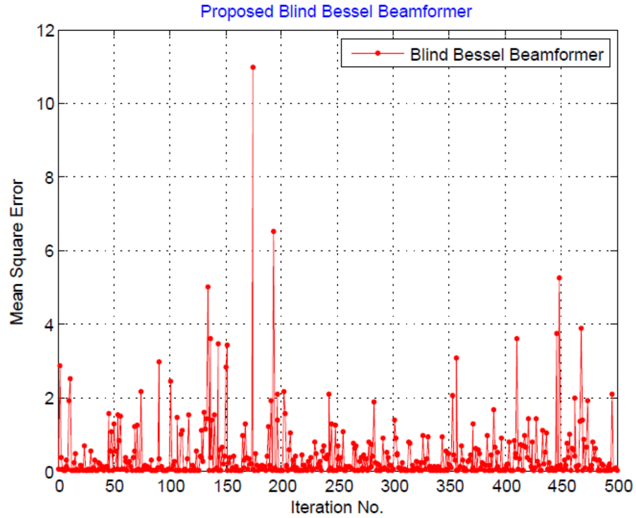

Figure 4; System performance w.r.t. MSE.

The performance curve as shown in **Figure 4** indicates that MSE behaviour of proposed algorithm is like CMA and does not follow steady path, however its convergence is satisfactory which is observed from frequent optimum array gain. 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.

Performance Comparison

Performance w.r.t. Array Gain

Comparison of proposed method is also made with BLMS, CMA and LMS algorithms for further evaluation as shown in **Figure 5**. In **Figure 5**, a strategy with 04 desired users is adopted that are coming at different AOAs as 0, -20, 20 and -40 degrees which are picked up by smart antenna equipped with proposed method, BLMS, CMA and LMS beamformers respectively in order to assess its performance in terms of array gain.

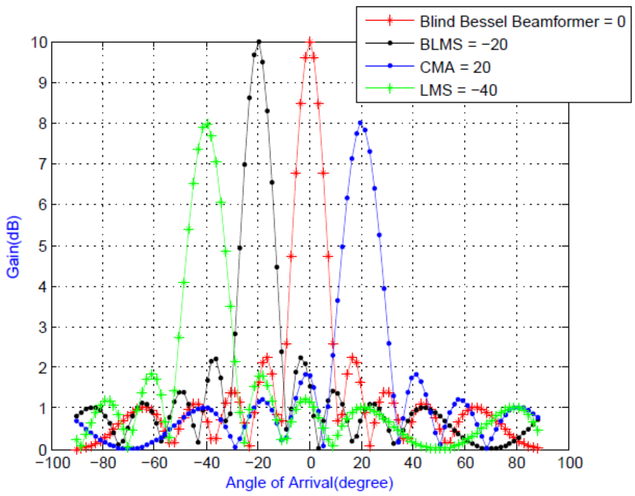

Figure 5; Radiation patterns achieved by blind bessel beamformer, BLMS, CMA and LMS algorithms.

You can see that proposed method and BLMS have optimum array gain with slightly greater SLL as compared to CMA and LMS beamformers. This improvement comes in both proposed method and BLMS beamformers 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 CMA and LMS beamformers are adjusted (set at 0.00001) 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.

Algorithms under testing	**Input Parameter**	**Output Parameter**	
	AOA (degree)	SLL (dB)	Gain (dB)
Blind Bessel beamformer	0	2.1	10.0
BLMS	- 20	2.1	10.0
CMA	20	1.9	8.0
LMS	- 40	1.9	8.0

Table 2. Performance analysis.

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.

The performance parameters as shown in **Table 2** are extracted from **Figure 5.**

Performance w.r.t. Convergence

If we compare and observe the performance curve for steady state MSE as shown in **Figure 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 large fluctuation except the proposed one. Due to large fluctuation, their performance are worst than the performance of the proposed method.

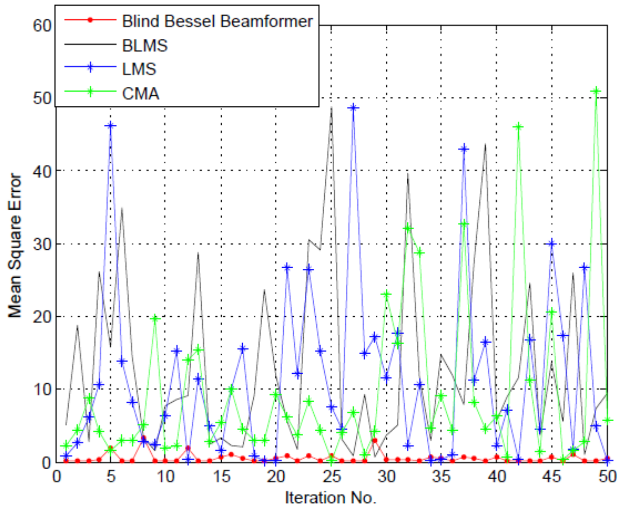

Figure 6; System Performance w.r.t. MSE of Blind Bessel Beamformer, BLMS, CMA and LMS algorithms.

The proposed technique has a clear performance advantages (i.e. large array gain 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.

Discussion On Results

Salient Aspects:

Salient aspects of the results are concluded as follows:

5.1.1. 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 of 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 as shown in [3] still requires training, but just to open the eye at start or whenever the blind algorithm fails.

5.1.2. The proposed method has achieved similar beam patterns and array gain with same SLL as obtained with BLMS but proposed scheme has an advantage that it does not need an external reference signal for its adaptation whereas the latter requires training/ external reference signal to update its complex weight vector. Though both of them are based on variable step size which is estimated by (17) and depends on signal array vector.

5.1.3. 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.

5.1.4. The proposed method has achieved optimum array gain as compared to CMA and LMS with slightly higher SLL but this may be compromised while keeping in mind that proposed method is blind and having self adjustment property where no operator involvement exists. Whereas LMS needs both these parameters for its operation and CMA also requires a step size by trial-and-error method but within range as specified in (17) at[3] for its optimum performance.

5.1.5. The MSE of proposed method is found most favorable 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.

5.1.6. The proposed method is also not following steady state path for MSE. However, the proposed method has achieved minimum MSE as compared to BLMS, CMA and LMS algorithms which are exhibiting large fluctuation. Due to large fluctuation, their performance are worst than the performance of the proposed method. Therefore, its application in wireless cellular communication is important for enhancing quality and capacity of the system by minimizing MSE & suppressing interference.

5.1.7. 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 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 robustness towards noise and interference. Therefore stability in the system is achieved because of self adjustment property of AGC.

5.1.8. It may also be added 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 are met by the proposed method. So it is better to use proposed method for getting aforesaid advantages for smart antenna.

5.1.9. The proposed method has a clear performance advantages (i.e. large array gain, lower MSE and self gain control) over other CMA and LMS algorithms. It in turn may reduce interference, enhance range, provide quality signal to desired users and increase capacity of the system. Because of this, it may be more useful where signal statistics vary rapidly with time. Therefore its application may provide cost effective solution for wireless cellular communication companies.

Generalized aspects:

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

5.2.1. The proposed method enhances range and security due to optimum array gain.

5.2.2. 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.

5.2.3. 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.

5.2.4. 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.

5.2.5. 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 new blind concept with AGC for adaptive beamforming which may provide cost effective solution for wireless cellular communication companies if this breakthrough design may apply at BTS for enhancing range, provide quality & secure signal and increase capacity of system with aforesaid benefits.

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