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# Improvement in convergence rate and stability: ICMA for Smart antenna system

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**Abstract**

Smart antenna attracts immense attention while implementing it in the wideband wireless communication systems, highlighting the importance of these techniques in Wireless Interoperability Microwave Access (WiMAX), which consists of Orthogonal Frequency Division Multiplexing (OFDM)-based system. Nonblind adaptive beamforming algorithms such as Least Mean Square (LMS), Improved Least Mean Square (ILMS), LLMS and blind algorithms such as Constant Modulation Algorithm (CMA), newly developed Improved CMA formulated for Smart Antenna (SA) which will be applied in wideband wireless networks are analysed. Simulation of LMS, LLMS, ILMS, CM and ICMA adaptive beamforming algorithms is carried out to calculate the error by using MATLAB. The error curve shows that the ILMS and ICMA converge faster than traditional LMS and CMA. The error for ICMA is least as compared to other algorithms because of variable step size. The error of newly developed ICMA algorithms were compared with the errors presented in previously presented papers.

***Keywords***: *Smart Antenna, LMS, CMA, ICMA, adaptive algorithm.*

## 1. Introduction

Wireless Telecommunication technology has changed the lives during the past few decades. In the homes, offices and Educational institution the mobile portable devices gives more freedom such that the communication with each other at any time and in any place is possible. Today there are many application of wireless communication in almost in every area such as Personal Communications Services (PCS), Wireless Personal Area Networks (WPAN), Wireless Local Area Networks (WLAN) and many other Telecommunication systems, which provides reliable wireless connections between computers, portable devices and consumer electronics within a short range.

As the growing demand for mobile communications is constantly increasing, the need for better coverage, improved capacity and higher transmission quality arises. Thus, more efficient use of the radio spectrum is required. Smart Antenna Systems (SAS) are capable of efficiently utilizing the radio spectrum and assure a successful solution to the present wireless system problems while accomplishing reliable and robust high-data-rate transmission. Smart antenna systems comprise several critical areas such as individual antenna array design, signal processing algorithms, space-time processing, wireless channel modeling and coding and network performance. A Smart Antenna (SA) is a digital wireless communications antenna system that takes advantage of diversity effect at the source (transmitter), the destination (receiver), or both. Diversity effect involves the transmission and/or reception of multiple radio frequency (RF) waves to increase data speed and reduce the error rate.

The use of smart antennas can cut down the difficulty caused by multipath wave propagation. Smart antennas fall into three major categories: SIMO (single input, multiple output), MISO (multiple input, single output), and MIMO (multiple input, multiple output). In SIMO technology, one antenna is used at the source, and two or more antennas are used at the destination. In MISO technology, two or more antennas are used at the source, and one antenna is used at the destination. In MIMO technology, multiple antennas are employed at both the source and the destination. MIMO has attracted the most attention recently because it can not only eliminate the adverse effects of multipath propagation, but in some cases can turn it into an advantage.

## 2. Adaptive Beam forming Algorithms

For the time-varying signal propagation environment, a recursive update of the weight vector is needed to track a moving user so that the spatial filtering beam will adaptively steer to the target user's time-varying DOA, thus resulting in optimal transmission/reception of the desired signal [1]. To solve the problem of time-varying statistics, weight vectors are typically determined by adaptive algorithms which adapt to the changing environment. Figure 1 shows a generic adaptive antenna array system consisting of an N-element antenna array with a real time adaptive array signal processor containing an update control algorithm.

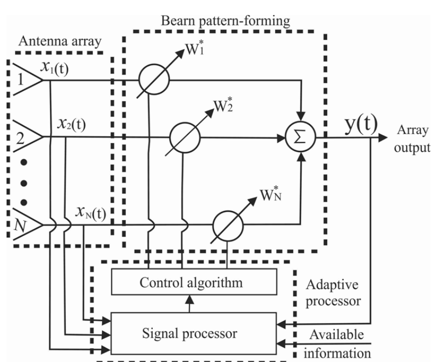


**Fig. 1 Functional diagram of an *N*-element adaptive array**

The data samples collected by the antenna array are fed into the signal processing unit which computes the weight vector according to a specific control algorithm. Steady-state and transient-state are the two classifications of the requirement of an adaptive antenna array. These two classifications depend on whether the array weights have reached their steady-state values in a stationary environment or are being adjusted in response to alterations in the signal environment. If the reference signal for the adaptive algorithm is obtained by temporal reference, *a priori* known at the receiver during the actual data transmission can either continue to update the weights adaptively via a decision directed feedback or use those obtained at the end of the training period. Several adaptive algorithms can be used such that the weight vector adapts to the time-varying environment at each sample.

## 2.1 LMS Algorithm:

The LMS algorithm can be easily realized with the advantage of simple, less operations and robust for signal statistical characteristic. Then the convergence rate and steady state error of LMS algorithm is analyzed and in order to achieve faster convergence rate and less state error a new variable step size LMS algorithm is proposed [2]. By combining the signals incident on the linear antenna array and by knowing their DOA, a set of weights can be adjusted to optimize the radiation pattern. The application of the LMS algorithm to estimate the optimum weights of an antenna array is widespread. Some of the parameters are related to the array structure in terms of its size and element spacing. Others are related to the incident signals including their number and angular separation. Moreover, the SNR has an effect on the performance of the LMS beam former. The LMS algorithm involves the adjustment of a set of weights to minimize the difference between a reference signal and the antenna array output. The reference signal is used by the array to distinguish between the desired and interfering signals at the receiver. A block diagram of an adaptive beam former (LMS) is shown in Figure 2 [3]. The output of the array is given by,

$$y(t) = \boldsymbol{w}^H x(t) \qquad (1)$$

Therefore the LMS algorithm can be summarized in following equations;

Output $y(n) = w^H x(n)$ (2)

Error $e(n) = b(n) - y(n)$ (3)

Weight $\boldsymbol{w}(n+1) = \boldsymbol{w}(n) + \mu x(n) e^*(n)$ (4)

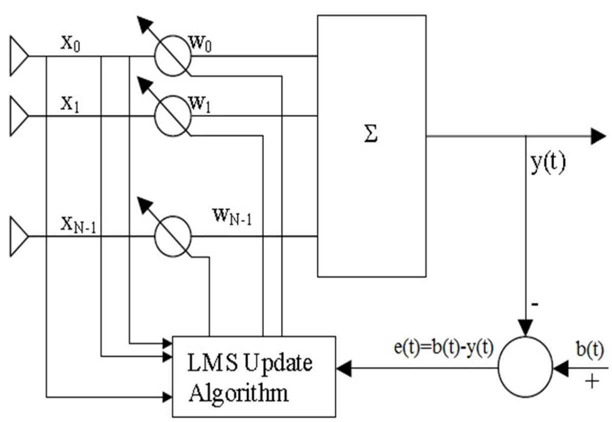


**Fig .2 Block diagram of LMS algorithm**

### 2.2 The Constant-Modulus Algorithm (CMA)

Many communication signals, frequency or phase modulated, such as FM, CPFSK modulation, and square pulse-shaped complex pulse amplitude modulation (PAM) has a constant complex envelope [88]. This property is usually referred to as the *constant modulus* (CM) signal property. For these types of communication signals, one can take advantage of the prior knowledge of this characteristic and specify the adaptation algorithm to achieve a desired steady state response from the array. The CMA is the most wellknown algorithm of this kind. It is suitable for the transmission of a modulated signal over the wireless channel, since noise and interference corrupt the CM property of the desired signal [4]. Thus, the CM provides an indirect measure of the quality of the filtered signal. It adjusts the weight vector of the adaptive array so as to minimize the variation of the desired signal at the array. After the algorithm converges, a beam is steered in the direction of the signal of interests, whereas nulls are placed in the direction of interference. In general, the CM algorithm seeks a beamformer weight vector that minimizes a cost function of the form

$$\boldsymbol{J}_{p,q} = E\left\{\left|\left|y(k)\right|^{p} - 1\right|^{q}\right\} \tag{5}$$

Equation (5) describes a family of cost functions. The convergence of the algorithm depends on the coefficients $p$ and $q$ in (5). A particular choice of $p$ and $q$ yields a specific cost function called the *(p, q) CM cost function*. The (1, 2) and (2, 2) CM cost functions are the most popular. The objective of CM beamforming is to restore the array output $y(k)$ to a constant envelope signal. Using the method of steepest descent, the weight vector is updated using the following recursive equation,

$$\boldsymbol{w}(k+1) = \boldsymbol{w}(k) - \mu \nabla_{\boldsymbol{w},\boldsymbol{w}^*}(\boldsymbol{J}_{p,q}) \tag{6}$$

When the (1, 2) CM function is used, the gradient vector is given by [5]

$$\nabla_{\boldsymbol{w},\boldsymbol{w}^*}(\boldsymbol{J}_{1,2}) = \frac{\partial \boldsymbol{J}_{1,2}}{\partial \boldsymbol{w}^*} = E\left[\boldsymbol{X}(k)\left(y(k) - \frac{y(k)}{|y(k)|}\right)^*\right] \tag{7}$$

Ignoring the expectation operation in (7), the instantaneous estimate of the gradient vector can be written as

$$\nabla_{\boldsymbol{w},\boldsymbol{w}^*}(\boldsymbol{J}_{1,2}(k)) = \boldsymbol{X}(k)\left[y(k) - \frac{y(k)}{|y(k)|}\right]^* \tag{8}$$

Therefore, using (8), the resulting weight vector is given by

$$\boldsymbol{w}(k+1) = \boldsymbol{w}(k) - \mu\left[y(k) - \frac{y(k)}{|y(k)|}\right]^* \boldsymbol{X}(k) \tag{9}$$

$$= \boldsymbol{w}(k) + \mu e^*(k)\boldsymbol{X}(k)$$

Where,

$$e(k) = \frac{y(k)}{|y(k)|} - y(k) \tag{10}$$

Comparing the CM and the LMS algorithms, we notice that they are very similar to each other. The term $y(k)$ $|y(k)|$ in CM plays the same role as the desired signal in the LMS. However, the references signal $b(k)$ must be sent from the transmitter to the receiver and must be known for both the transmitter and receiver if the LMS algorithm is used. The CM algorithm does not require a reference signal to generate the error signal at the receiver [5]. Several other properties of the constant modulus algorithm are discussed in [6].

**2.2 Improved CMA:**

CMA has the disadvantages of the slow convergence rate and large steady state MSE. The objective of this work is to improve the convergence properties of the CM schemes. The convergence properties of any adaptive algorithm depend on the cost function, which is subject to minimization during the adaptation process. The cost function is a function of the equation for the error, defined as the difference between the present and the desired value of any property of the signal that is to be restored. Therefore, the cost function of an adaptive algorithm can be changed either by changing the function itself or by changing the error equation. The most commonly used definition of the cost function is the mean squared value of the error. Changing the definition of the cost function provides a lot of advantages. For example, a non-MSE criterion improves the performance of the adaptive algorithm when the interfering noise distribution is non-Gaussian. In this work, instead of changing the definition of the cost function, step size is varied to improve the performance the CM algorithm. It is shown that the performance of CMA can be improved by only changing the equation for the error signal. Some error equations provide better convergence rate, while other error equations improve performance by eliminating the probability of converging to local minima. Convergence to global minima can be confirmed by following some steps and checks during the initialization and adaptation respectively.

Several new algorithms have been introduced to overcome the disadvantages of CMA. A variable step size Improved CMA (ICMA) is proposed to improve the stability of the system and convergence speed. ICMA is CMA, but the step size is changed as the correlation matrix is changed to avoid unstable system. ICMA shows the performance improvement in convergence behaviour.

The variable step CMA is proposed based on the relationship between the performance and step $\mu$. The basic principle of Improved CMA is that at the stage of beginning to converge or change of system parameter for the weight of adaptive algorithm is far away from the optimal weight; choose a large value for $\mu$ to ensure it has faster convergence rate and tracing rate. When the weight of algorithm is near to the optimal value, in order to reduce the steady state error, choose a smaller value for $\mu$ therefore $\mu$ becomes scaling independent as given in the following equation (11)

$$\boldsymbol{w}^{(k+1)} = \boldsymbol{w}^{k} - \frac{\mu}{\|\boldsymbol{x}_k\|^2}\boldsymbol{x}_k\left(y_k - \frac{y_k}{|y_k|}\right) \qquad (11)$$

As can be seen from Equation (11), the algorithm reduces the step size $\mu$ to make the changes large. As a result, the step size $\mu$ varies adaptively by following the changes in the input signal level. This prevents the update weights from diverging and makes the algorithm more stable and faster converging than when a fixed step size is used. In addition, the ICMA algorithm is used as the MMSE method needs to cope with the large changes in the signal levels of wireless communication systems, the new optimum ICMA algorithm update the weight vectors according to the following equations

$$R_{rr} = \sum_{1-N_1}^{N_2} x(n)x^H(n) \quad r = \sum_{1-N_1}^{N_2} b^*(n)x(n) \qquad (12)$$

$$w_0 = R^{-1}r \qquad (13)$$

$$y(n) = w^H x(n) \qquad (14)$$

$$e(n) = y(n)\left[1 - \frac{1}{|y(n)|}\right] \qquad (15)$$

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n)x(n)\mu e^*(n) \qquad (16)$$

$$= \boldsymbol{w}(n) + \frac{\mu}{\|x(n)\|^2}x(n)e*(n) \qquad (17)$$

The final weight vector of the ICMA algorithm is estimated from equation (11). In the ICMA algorithm, advantages of both the block adaptive and sample by sample techniques are employed. In this algorithm, the initial weight vector is obtained by matrix inversion through Sample Matrix Inversion (SMI) algorithm, only for the first few samples or for a small block of incoming data instead of arbitrary value before calculating the final weight vector. The final weight vector is updated by using the ICMA algorithm.

## 3. Simulation Results of different beamforming algorithm for Error plot:

Simulation of LMS, LLMS, ILMS, CM and ICMA adaptive beamforming algorithms is carried out to calculate the error by using MATLAB. The error curve shows that the ILMS and ICMA converge faster than traditional LMS and CMA.

The error of newly developed ICMA algorithms were compared with the errors presented in [9].

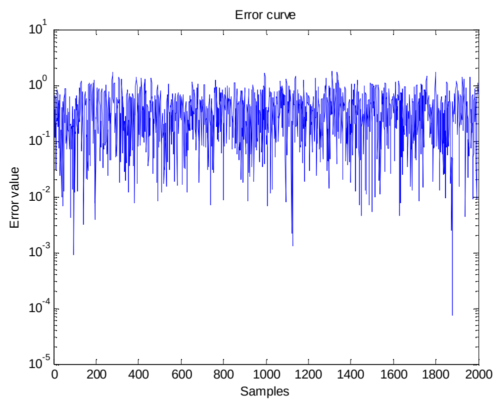


Figure .3: Error plot of traditional LMS

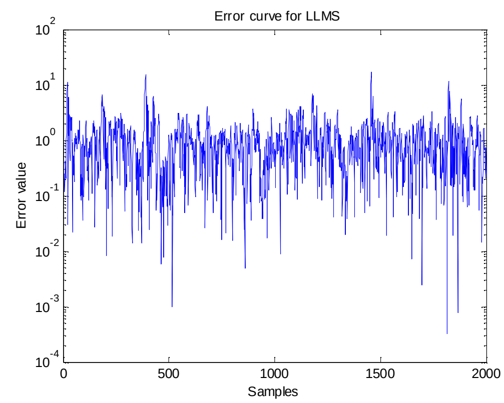


Figure.5. Error plot of LLMS algorithm

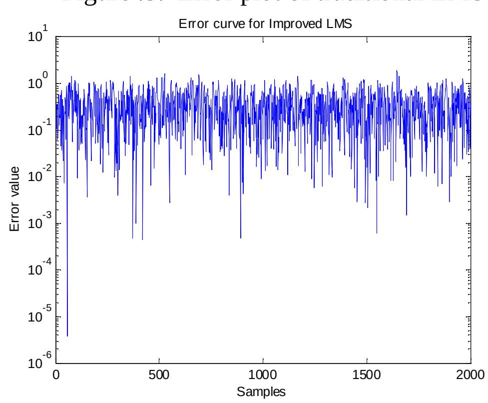


Figure.4. Error plot of improved LMS algorithm

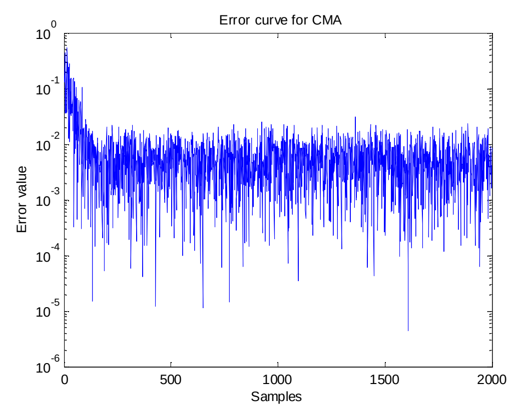


Figure.6. Error plot of CMA

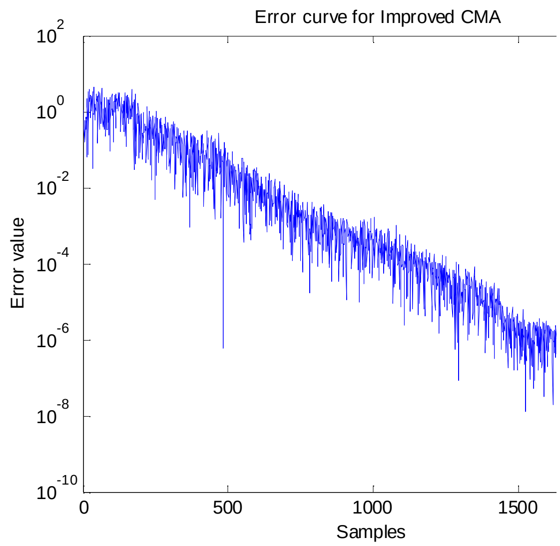


Figure.7. (a) Error plot of improved CMA

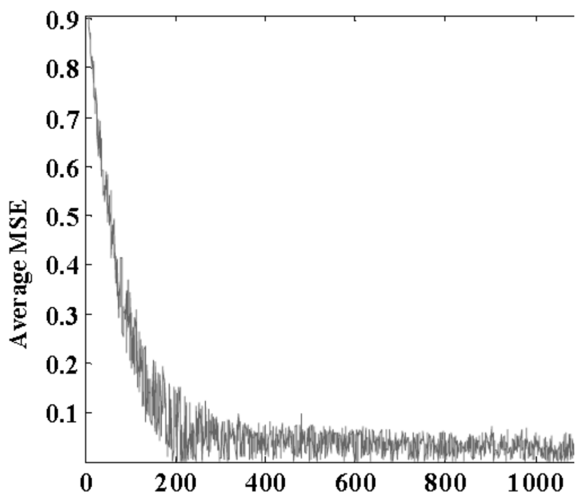


Figure.8. Mean square error plot for the NCMA algorithm[9]

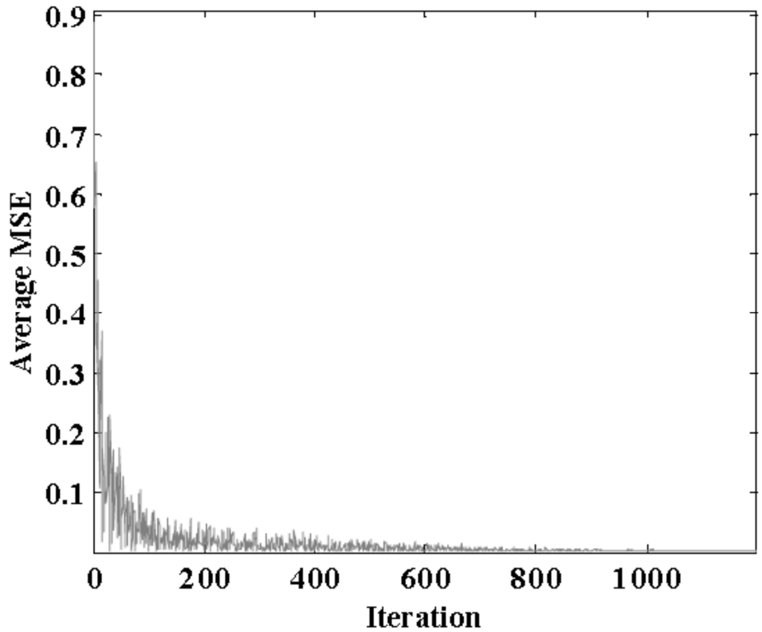


Figure.9 Mean square error plot for the SMI-NCMA algorithm [9]

From Figures 7 to 9 it is clear that the convergence of proposed ICMA is faster than the typically NCMA algorithm and SMI-NCMA algorithms published in [9]. The NCMA algorithm starts to converge from iteration number 200 whereas SMI-NCMA and ICMA algorithm starts to converge from the initial iteration. It is observed that at around 100 iterations the NCMA error is almost 0.2591, SMI-NCMA error is 0.0568 and ICMA error is 0.03981. Consequently there is 30% decrement in the error at around 100 iterations with the proposed ICMA algorithm as compared to SMI-NMCA of [9].

## 7. Conclusion

The error for Traditional LMS algorithm is maximum 3.1 and minimum 0.0001 for 300 and 1800 samples respectively. For ILMS the maximum error is 1 and minimum error is $10^{-6}$ it remains between 1 and .001 till the end (2000 samples). The minimum error for LLMS is $10^{-4}$ and maximum error is 31 and it keeps on changing between 3 and 0.01till the end (2000 samples). The least error is 0.000001 and the maximum error is 0.31 for CMA and it remains between 0.01 and 0.0001 towards the end for 2000 samples. Similarly the minimum and maximum errors for ICMA are $10^{-10}$ and 1 respectively. Therefore it is concluded that there is minimum 40% improvement in the error for the newly developed ICMA algorithm as compared to other algorithms. Hence it is resolved that ICMA starts to converge from the beginning itself.

The proposed ICMA attain more flying convergence than the typical NCMA and SMI-NCMA algorithms. Also the NCMA algorithm starts to converge from the iteration number 200 whereas the SMI-NCMA and ICMA algorithm starts to converge from the initial iteration. In this case, the NCMA error is almost 0.2591, the SMI-NCMA error is 0.0568 and the ICMA error is 0.03981 at around 100 iterations. Hence there is 30% decrement in the error at around 100 iterations with the proposed ICMA algorithm as compared to SMI-NMCA.

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