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Convergence Speeds of the Weight Vectors Based on Adaptive Beam Forming

G. Vijay Babu[1], M. Sreedhar Reddy[2*]
[1]Student, Department of ECE, Malla Reddy College of Engineering & Technology, Hyderabad, Telangana, India. Email: vijay12345rvb@gmail.com
[2]Associate Professor, Department of ECE, Malla Reddy College of Engineering & Technology, Hyderabad, Telangana, India. Email: maale.sreedharreddy@gmail.com
*Corresponding Author

Abstract: The paper presents the faster convergence speeds of the weight vectors based on adaptive beam forming. The adaptive beam forming has faster convergence speeds of the weight vectors and much larger output SINRs. The step size of the adaptive algorithm is adjusted between the noise-free a posteriori and a priori errors to get the faster convergence rate and less misadjustment than the CLMS algorithm. On the other hand, minimizing the square of the augmented noise-free based on variable step size, the adaptive algorithm better improvements in the output SINR and accuracy. The results shows, comparison of different adaptive algorithms of MSE and output SINR.

Keywords: Complex-valued Least Mean Squares (CLMS), Convergence speed, Shrinkage, Steady-state, Variable step size, Widely linear.

I. Introduction

A smart antenna system combines multiple antenna elements with a signal-processing capability to optimize its radiation pattern automatically in response to the signal environment. In recent years, smart antennas have been considered to be one of the most expected technologies, which are adapted to the demanding high bit-rate or high-quality in broadband commercial wireless communication such as mobile internet or multi-media services [1] [2]. In wireless communications, smart antenna systems (or antenna arrays) can be used to suppress multipath fading with antenna diversity and to increase the system capacity by supporting multiple co-channel users in reception and transmission [3]. Adaptive beam forming is the main technique of smart antenna system in which an array of antennas is exploited to achieve maximum reception in a specified direction by estimating the signal arrival from a desired direction (in the presence of noise) while signals of the same frequency from other directions are rejected. Adaptive beam forming has found numerous applications in radar, sonar, seismology, microphone array speech processing [4]-[8] and in wireless communications. Adaptive beam forming algorithms can be classified into two categories: non-blind adaptive algorithms and blind adaptive algorithms. In this paper, we consider the Non-blind algorithms, Least Mean Square (LMS) and Normalized Least Mean Square (NLMS), and study their performance. Here we propose a new schema called adaptive Normalized Least Mean Square (A-NLMS) to overcome the shortcomings of LMS and NLMS. Simulation shows ANLMS has fastest convergence rate as it can detect the active taps and update the weights of those active elements only. And A-NLMS has narrower beam width with higher gain towards the desired direction compare to other two algorithms.

II. Adaptive Beamforming Algorithm

Most of the adaptive beam forming algorithms can be divided into two types according to whether a training signal is used or not: Non-Blind Adaptive algorithm and Blind Adaptive algorithm. In the paper, we consider non blind adaptive algorithm. Blind adaptive algorithm can require training signal, a training signal is sent from the transmitter to the receiver during the training period. Different types of Least-Mean Square (LMS), Recursive Least Square (RLS) algorithms, etc. [16-18] are some examples of non-blind algorithm.

A. SL-CLMS Algorithm

The choice of μ in the update of tap weights vector is very critical for SL-CLMS. A small μ will ensure lower steady state MSE, but the algorithm will converge slowly; a large μ can provide faster convergence rate at the cost of higher steady state MSE. Any selection must be a compromise between convergence rate and steady state MSE.

The error signal of SL-CLMS is given by:

$$\begin{aligned} e(k) &= s_0(k) - \boldsymbol{w}^H(k)\boldsymbol{x}(k) \\ &= \epsilon_{\text{opt}}(k) + \boldsymbol{w}_{\text{opt}}^H\boldsymbol{x}(k) - \boldsymbol{w}^H(k)\boldsymbol{x}(k) \\ &= \epsilon_{\text{opt}}(k) + e_f(k) \end{aligned}$$

$$e_f(k) = \boldsymbol{w}_{\text{opt}}^H \boldsymbol{x}(k) - \boldsymbol{w}^H(k)\boldsymbol{x}(k) = -\boldsymbol{v}^H(k)\boldsymbol{x}(k)$$

the update weight vk is given by:

$$\boldsymbol{v}(k+1) = [\boldsymbol{I}_M - \mu_k \boldsymbol{x}(k)\boldsymbol{x}^H(k)]\boldsymbol{v}(k) + \mu_k \epsilon_{\text{opt}}^*(k)\boldsymbol{x}(k)$$

where xk is the transmit data sequence.

B. SWL-CLMS Algorithm

It uses the steepest-descent method and recursively computes and updates the weight vector. Due to the steepest-descend the updated vector will propagate to the vector which causes the least Mean Square Error (MSE) between the beam former output and the reference signal. The following derivation for the LMS algorithm. The MSE is defined by:

$$\begin{aligned}\tilde{e}_f(k) &= [\boldsymbol{w}_{1,\text{opt}} - \boldsymbol{w}_1(k)]^H \boldsymbol{x}(k) \\ &\quad + [\boldsymbol{w}_{2,\text{opt}} - \boldsymbol{w}_2(k)]^H \boldsymbol{x}^*(k) \\ &= -\boldsymbol{v}_1^H(k)\boldsymbol{x}(k) - \boldsymbol{v}_2^H(k)\boldsymbol{x}^*(k)\end{aligned}$$

where

$X^*(t)$ = complex conjugate of the desired signal.

X(t) = received signal from the antenna elements.

w^H = output of the beam form antenna.

$(.)^H$ = Hermetian operator.

The LMS algorithm converges to this optimum Wiener solution. The basic iteration is based on the following simple recursive relation:

$$W(n+1) = w(n) + \mu x(n)\, e(n)$$

By decreasing μ the precision will improve but it will decrease the adaptation rate. An adaptive μ could solve this issue by starting with a large μ and decrease the factor when the vector converges.

C. RLS

The convergence speed of the LMS algorithm depends n the Eigen values of array correlation matrix. In an environment yielding an array correlation matrix with large eigen value spread algorithm converges with a slow speed. This problem is solved with the RLS algorithm by replacing the gradient step size μ with a gain matrix $R^{-1}(n)$ at the n^{th} iteration, producing the weight update equation.

$W(n) = W(n-1) - R^{-1}(n)\, X(n)\, €^*(W(n-1))$ Where $R^{-1}(n)$ is given by:

$$R^{-1}(n) = \delta 0\ R^{-1}(n-1) + X(n)^* X^H(n)$$

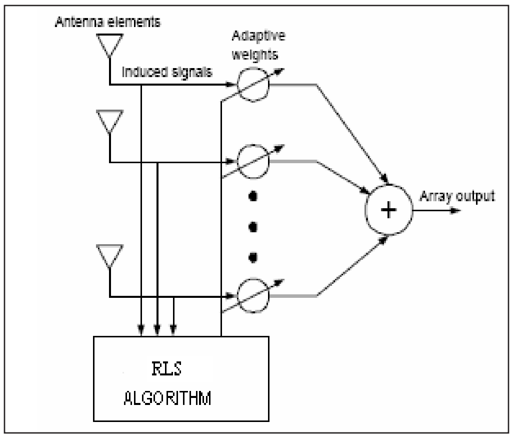

Fig. 1: RLS Adaptive Beam Forming Network

Where δ0 denoting a real scalar less than but close to 1, The δ0 is needed for exponential weight of post data and is referred to as the forgetting factor as the update equation leads to de-emphasize the old sample. The quantity 1/(δ0-1) is normally referred to us the algorithm memory, Thus for δ0=0.99 the algorithm memory is close to 100 samples.

The algorithm of RLS algorithm is given by:

Step 1) set the initial guess as w (0).

Step 2) Calculate error signal is generated by comparing original unknown signal u (t).

$$e(t) = x(t) - u(t)$$

Step 3) Update the weight vector by:

$$W(n) = W(n-1) - R^{-1}(n)\, X(n)\, €^*(W(n-1))$$

Where $R^{-1}(n)$ is given by $R^{-1}(n) = \delta 0\ R^{-1}(n-1) + X(n)^* X^H(n)$

Step 4) Go back to <step2> if the procedure is to be continued.

Step 5) Array output $Y(n) = W^h X(n)$.

Where $X(n) = S(t)a(\Theta 0) + \sum Ut(t)a(\Theta t) + n(t)$

III. Results

We have implemented the adaptive algorithm by using the MATLAB environment.

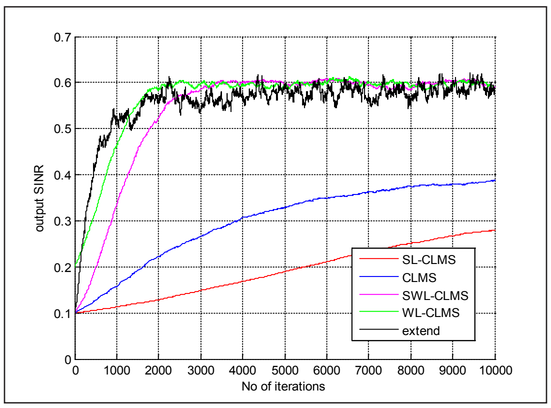

Fig. 2: Output SINRs of SL-CLMS, SWL-CLMS, CNLMS, WL-CNLMS, VSS and WL-VSS Algorithms

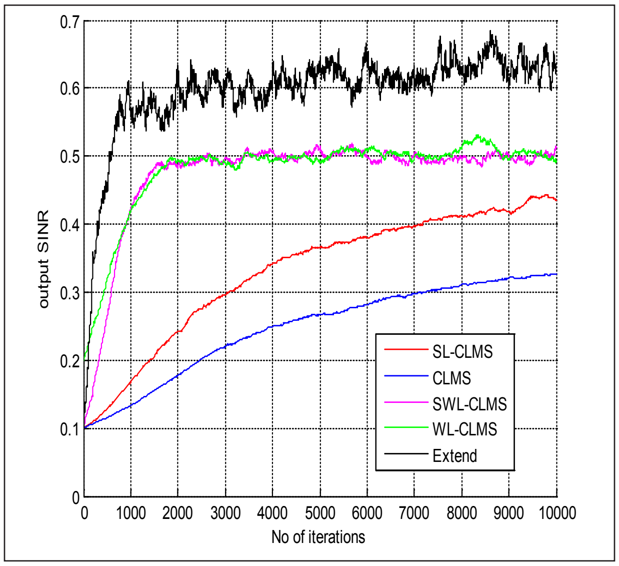

Fig. 3: Output SINRs of SL-CLMS, SWL-CLMS, CLMS, WL-CLMS Algorithms for Different µ

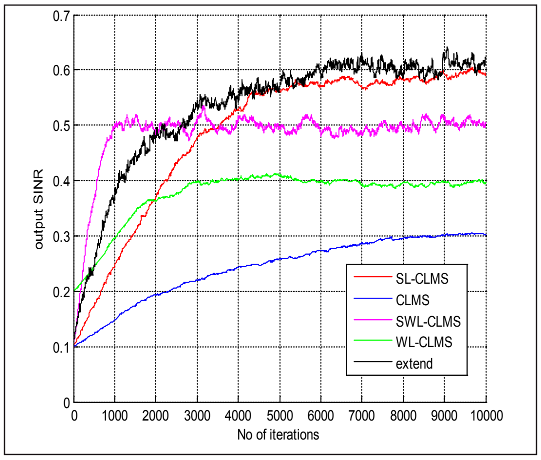

Fig. 4: Output SINRs of SL-CLMS, SWL-CLMS, CLMS, WL-CLMS Algorithms for Different

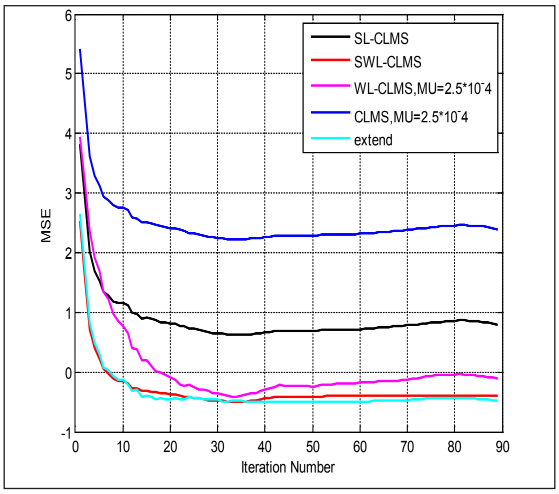

Fig. 5: Learning Curves: MSEs of SL-CLMS, SWL-CLMS, CLMS and WL-CLMS Algorithms Q=1

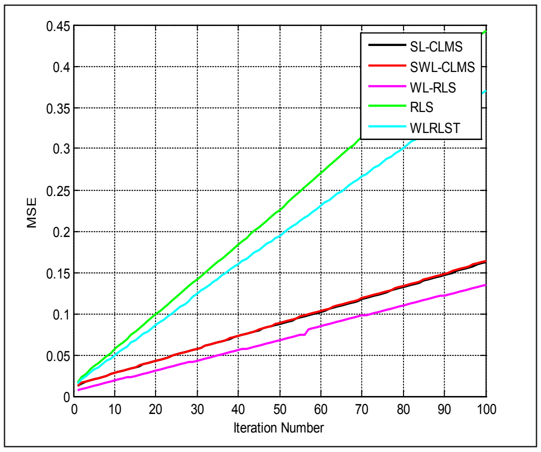

Fig. 6: MSE of SL-CLMS, SWL-CLMS, RLS and WL-RLS Algorithms Versus Number of Sensors Q=2

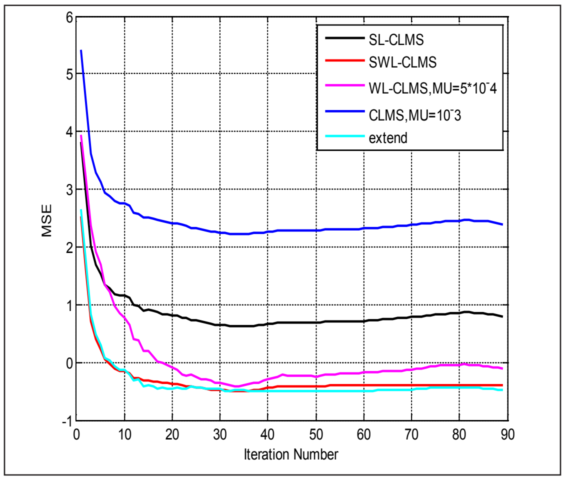

Fig.7: MSE of SL-CLMS, SWL-CLMS, RLS and WL-RLS Algorithms Versus Number of Sensors Q=1

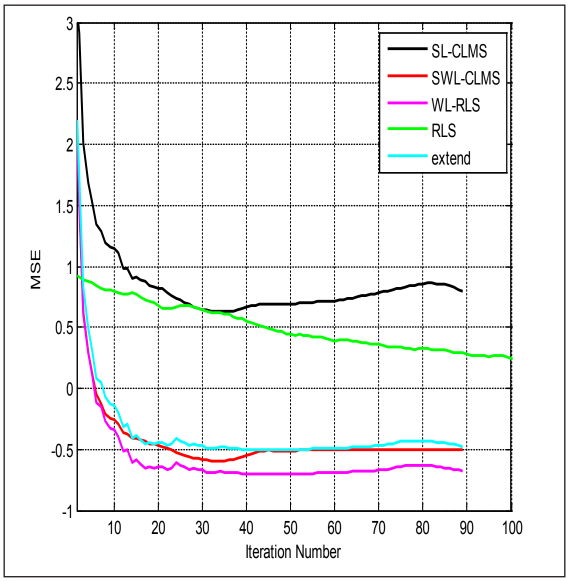

Fig. 8: Computational Times of SL-CLMS, SWL-CLMS, RLS and WL-RLS Algorithms Versus Number of Sensors Q=3

IV. Conclusion

This paper discussed various adaptive beam forming algorithms like SL-CLMS, RLS, SWL-CLMS etc. used in smart antennas. The result obtained from the simulations showed that the adaptive algorithm had better convergence compared to LMS, and most efficient algorithm. It can suppress interference and increase the user capacity of a CDMA cellular system. Further through adaptive beam forming, the base station can form narrower beams towards the desired user and nulls towards interfering users, considerably improving the signal-to-interference-plus-noise ratio. Such smart antennas also can be used to achieve different benefits.

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