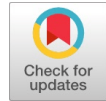


A Novel Implementation of Variable Step Size Constant Modulus Algorithm with LMS update

Jaswant, Sanjeev Kumar Dhull



Abstract: This paper shows novel implementation of Constant Modulus Algorithm (CMA) using LMS update with variable step size (VSS). Fast convergence and good quality reception of 4-QAM has been achieved.

Index Terms: Adaptive, Blind, CMA LMS, Algorithm.

I. INTRODUCTION

After training or supervised algorithm, blind algorithm or data unaided is the new arena of research. In blind equalization family Constant Modulus Algorithm (CMA) is widely implemented and used. In supervised or data aided algorithms, LMS algorithms is time tested and most widely used. CMA is complex to implement but it saves precious bandwidth while LMS, on the other hand, has robustness in its implementation. In this text, strong points of both algorithms will be used. To make the convergence of algorithm faster, a variable step size LMS will be used to update CMA algorithm.

II. LEAST MEAN SQUARE (LMS)

LMS is a non-blind or data aided adaptive algorithm. To set the co-efficient weights of weight vector, known training sequence is required.

Mathematics Analysis:

$i(n)$: zero-mean ($\mu_i=0$), WSS input signal

v_N : N-tap FIR-filter v_1, v_2, \dots, v_N

$\Psi(n)$: zero-mean ($\mu_\Psi=0$), WSS desired signal

$\hat{e}(n)$: error signal

Moreover, $i(n)$ and $\Psi(n)$ are assumed to be jointly WSS.

Input data matrix $i(n)$: $i(n) = [i_1 \ i_2 \ \dots \ i_N]^T$

Weight co-efficient matrix $v(n)$: $v(n) = [v_1 \ v_2 \ \dots \ v_N]^T$

$\gamma(n)$: output signal given by

$$\gamma(n) = v^H(n)i(n) = i^H(n)v(n) \quad (1)$$

Here $(.)^H$ represents Hermitian Transpose.

$$\hat{e}(n) = \Psi(n) - \gamma(n) = \Psi(n) - i^H(n)v(n) \quad (2)$$

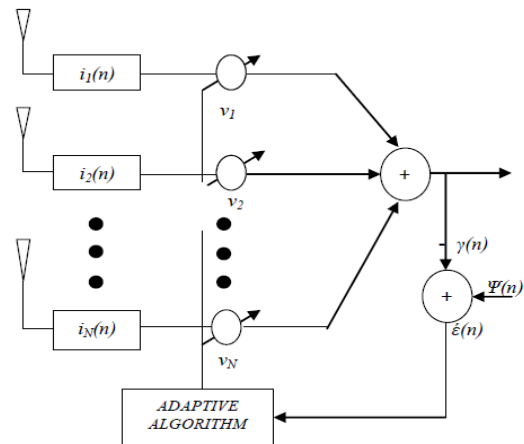


Figure 1: ADAPTIVE BEAMFORMING STRUCTURE

Filter weight co-efficient update rule of LMS:

$$v(n+1) = v(n) + \mu i(n) \hat{e}^*(n) \quad (3)$$

μ is step-size. It is constant and has to be chosen carefully.

For universal bound:

$$0 < \mu < 2/\lambda_{\max} \quad (4)$$

Solution of eqn. (3) for μ provides the stability of Steepest Decent procedure. λ_{\max} is the eigen value of correlation matrix R of input data matrix such that $R = E[i(n)i^H(n)]$.

LMS ALGORITHM:

Initiation: $v(0) = v_{\text{initial}}$

Start:

For: $n=0, 1, 2, \dots, N$.

$\gamma(n) = v^H(n)i(n)$

$\hat{e}(n) = \Psi(n) - \gamma(n)$

$v(n+1) = v(n) + \mu i(n) \hat{e}^*(n)$

END

Stop.

III. CONSTANT MODULUS ALGORITHM (CMA)

The CMA [1-5], proposed by D. N. God. [2], is the most widely implemented technique for data unaided equalization. By circuit design, its implementation is easy. Considering a base-band model of a digital communication channel characterized by finite impulse response (FIR) filter along with AWGN. The cost function of CMA is described as [6-7]:

$$J_{CMA}(n) = E\{|i_k|^2 - R_2\}^2 \quad (5)$$

In eqn. (5) R_2 is positive real constant. R_2 depends on statistical properties of input signal i_k . It is defined as:

$$R_2 = E\{|s(n)|^4\} / E\{|s(n)|^2\}^2 \quad (6)$$

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*Correspondence Author(s)

Jaswant, ¹PhD Scholar, Deptt. of Electronics & Communication GJU S&T, HSR (email id: jaswantee@gmail.com)

Sanjeev Kumar Dhull, Professor, Deptt. of Electronics & Communication GJU S&T, HSR

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Stochastic gradient approach is used like in LMS, update equation is obtained of CMA as:

$$v(n+1) = v(n) + \mu i(n) \hat{e}^*(n) \quad (7)$$

Where μ is the step-size parameter and it is constant. The asterisk (*) denotes complex conjugation. Error signal of CMA is given by:

$$e_k = y_k / |y_k|^2 - R_2 \quad (8)$$

CMA has advantage of decoupling of Intersymbol Interference and recovery of carrier phase from each other.

IV. PROPOSED ALGORITHM

In previous sections we investigated two most widely considered adaptive algorithms. CMA exhibits slow convergence speed when it compared with data aided algorithms. Generally, due to stability considerations, the values of step parameter that can be used in the data unaided algorithms are comparatively smaller than that of values of μ used in the LMS algorithm.

Since rate of convergence is determined by μ in these types of algorithms, data unaided equalizers in general do not exhibit fast convergence rates. Moreover, considering a constellation of data and a data unaided equalization technique for which upon convergence, the error term e_k does not converge to zero. In this situation, for the same steady state mean square error (MSE) [8-10], the value of μ that is utilized in the data unaided algorithm has to be significantly lower than that of LMS algorithm. This causes slow convergence of data unaided algorithms.

The proposed adaptive algorithm is based on Variable Step Size (VSS) CMA with LMS update. A VSS is used to overcome the slow convergence problem.

The benefits of two different algorithms are combined to gain the fast convergence speed:

- The convergence speed is more for large value of step size μ .
- In the steady state, mean square error is less for small values of μ .

$$v(n+1) = v(n) + \mu(n) i(n) \hat{e}^*(n) \quad (9)$$

If consecutive signs of the gradient estimate, $-i(n)\hat{e}(n)$, are found to be identical, then variable step size $\mu(n)$ is increased to $\mu(n) = \alpha\mu(n)$, here ($\alpha > 1$) ($\mu(n)$ is away from the optimal value, it is better to speed up the process by increasing step size).

If continuous changes in the sign of gradient estimate, $-i(n)\hat{e}(n)$, are found, then $\mu(n)$ is decreased $\mu(n) = \mu(n)/\alpha$ ($\alpha > 1$) ($\mu(n)$ is close to optimal value, it is advisable to slow down the process by decreasing step size to improve the steady state response). Using this technique convergence rate is improved significantly and less steady state error is observed.

V. RESULTS OF SIMULATION

Performance of the proposed algorithm has been demonstrated. Convergence speed and 4-QAM constellation reception have been observed using computer simulations of LMS, CMA and VSS CMA with LMS update.

4-QAM constellation has been considered in all computer simulations. The results demonstrated are for the case of Additive White Gaussian Noise (AWGN) with a signal-to-noise ratio (SNR) of 25dB at the input end of the equalizer circuit.

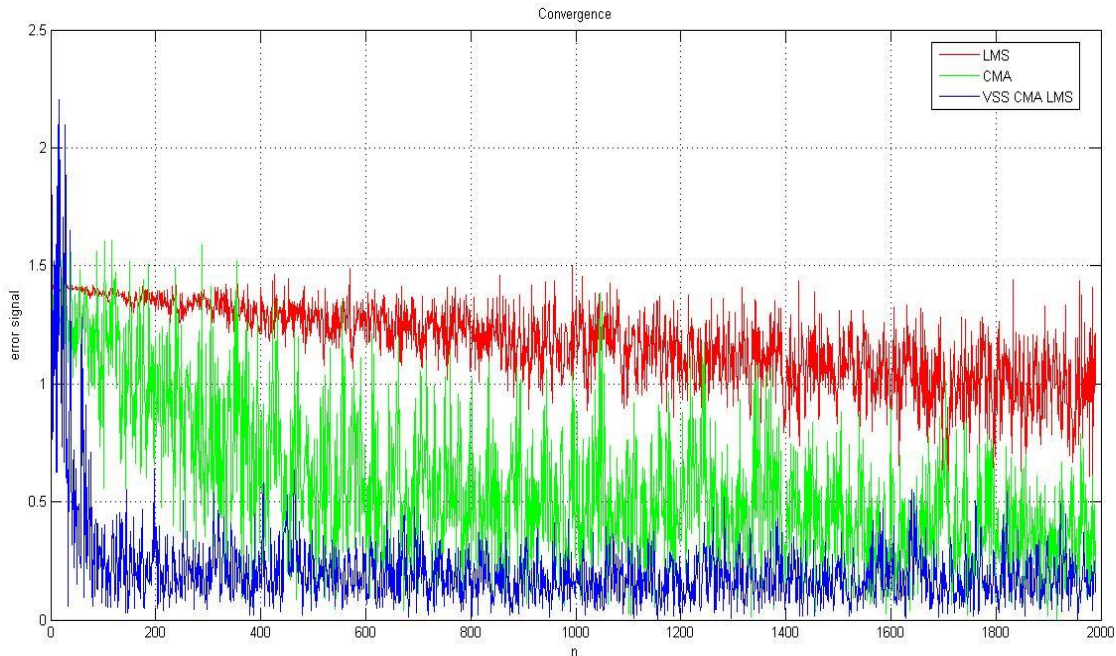


Figure 2. Comparison of convergence speed of LMS, CMA & VSS CMA with LMS update algorithms

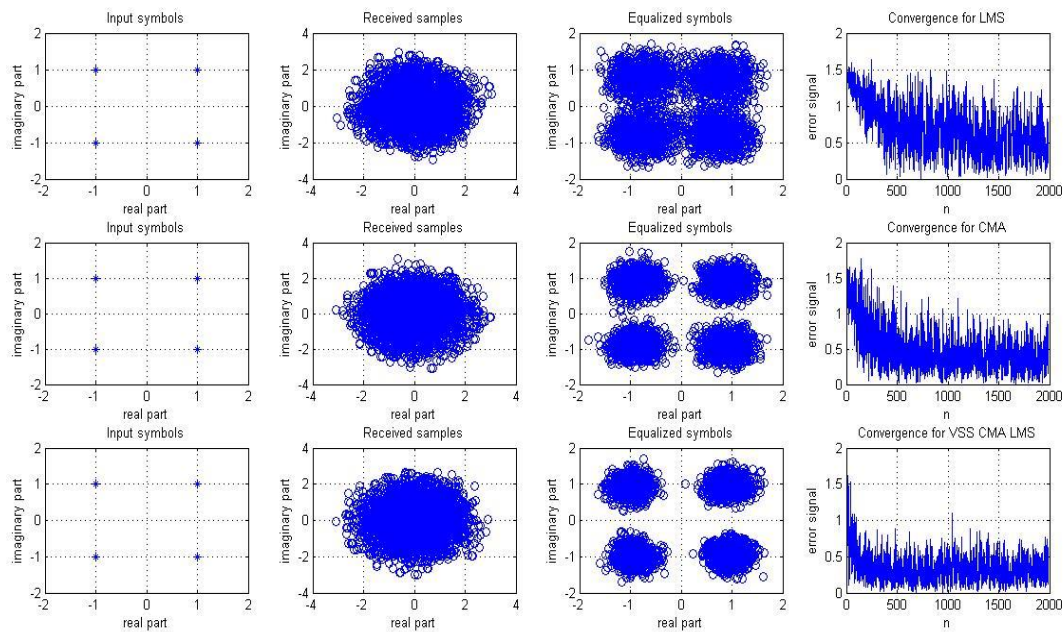


Figure 3. 4-QAM reception using LMS, CMA & VSS CMA with LMS update algorithms

VI. CONCLUSION

We proposed a variable step size CMA with LMS update algorithms. Convergence speed shows significant improvement as depicted in Figure 2. 4-QAM reception is improved because spread around actual signal is less. From above results it can be concluded that VSS CMA with LMS update improves the convergence speed and reception of signal but at the cost of more complexity and computation.

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AUTHORS PROFILE



jaswantec@gmail.com
Mob: 7065508710 or 9306452820

Jaswant, PhD Scholar from Electronics & Communication (ECE) Engineering, is from GJU S&T, HSR-125001. He received his B.Tech. & M.Tech. Degrees from GJU S&T In year 2010 & 2013 respectively. His research area includes Digital Signal Processing, RADAR. Email ID:

Dr. Sanjeev Kumar Dhull is a Professor in GJU S&T in Electronics & Communication Deptt.