A Novel Implementation of Multi-Modulus Algorithm Blind Equalization Based on Recursive Least Square Algorithm

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Abstract: **A Multi-Modulus algorithm based on adaptive blind equalization removes the unwanted effects of ISI and improves the phase issues, saving the cost of rotator at the receiver end. In this paper a new algorithm combination of Recursive Least Square (RLS) and Multi-Modulus Algorithm (MMA) named as RLS-MMA is proposed by providing few assumption, fast convergence and minimum Mean Square Error (MSE) is achieved. Excellence of this technique is shown in the simulations presenting MSE plots and the resulting filter results.**

Index Terms: **Blind Equalization, RLS, CMA, MMA, RLS-CMA, RLS-MMA, Cost function.**

1. INTRODUCTION

Equalization is the basic building block of modern digital communication system. Equalization is defined as the process which helps to retrieve the transmitted signal free from the undesirable channel effects at the receiver end. Undesirable effect can be classified as (linear) channel distortion and additive noise commonly known as (ISI) that corrupts the transmitted signal making it cumbersome for the receiver end to recover the transmitted data directly. Equalization can be categorized into two major categories the Non-Blind equalization and the Blind equalization. Non blind equalization is a technique which equalizes the received signal by the help of training bit to update the weights. Training bits are embedded with the transmitted signal and repeated every time, information about the training bits are pre known at the receiver so thereby the received training bits are analyzed and the channel response is calculated accordingly to match the equalizer output minimizing some criterion typically MSE(Mean Square Error). Non blind equalization gives a better performance but the main disadvantage is the wastage of bandwidth about 25% bandwidth consumption in GSM (global system for mobile communication) [1]. Blind Equalization or self-recovering algorithm defines an equalization without the use of training bits [3], [9]. Blind equalization has been a hot area of research from the last few decades. Constant Modulus Algorithm is considered as one of the famous algorithms of blind equalization proposed by Godard [1], [2], [3]. CMA utilizes method of steepest descent to equalize the signal. CMA due to its increased bandwidth efficiency which increases bits rate [1], and its simplicity like LMS makes it very popular but its major weakness is that it has slow convergence seemingly its cost function is also dependent on the amplitude of the signal thus resulting lack of knowledge about the constellation, hence the overall performance suffers when using higher order QAM schemes [4], [5]. A replacement of CMA was proposed called as MMA [6], [7]. MMA despite of just minimizing the magnitude of equalizer's output y(n), it considers both the real $y_R(n)$ and $y_I(n)$ individually[8]. MMA achieves better convergence and the cost of rotator at the receiver end is also nullified.

In this research work a new MMA based algorithm has been proposed by having some enhancement to the Multi-Modulus Algorithm results are quite considerable for the QAM constellations. In section 2 the existing algorithms are discussed which contains the brief description about CMA, RLS-CMA and MMA. In section 3, a new algorithm is proposed, followed by the simulation comparison included in section 4 and in section 5 the final work is concluded.

2. THE EXISTING BLIND ALGOTHMS

2.1 Constant Modulus Algorithm

CMA [2],[5] has the assumptions that input to the channel is a modulated signal which has constant amplitude at every instant in time. The advantage of the blind equalization is the bandwidth is high because of there is no training of the pulses. In the conventional equalization process needs the training of the pulse. CM is used for QAM signals where the amplitude of the modulated signal is not the same at every instant. The error e(n) is then determined by considering the nearest valid amplitude level of the modulated signal as the desired value[1].

Adaptive channel equalization without a training sequence is known as blind equalization. A baseband model with a channel impulse response, channel input, additive white Gaussian noise (AWGN), and equalizer input are denoted by c(n),s(n), w(n), and u(n) respectively. The data symbols transmitted s(n) , are assumed to consist of stationary independently and identically distributed (i.i.d.), real or complex non-Gaussian random variables.

The equalizer input,

$$u(n)=s(n)*c(n)+w(n) \qquad (1)$$

is then sent to a tap-delay-line blind equalizer with impulse response , intended to equalize the distortion caused by Inter-Symbol Interference (ISI) without a training signal.

The output of the blind equalizer

$$y(n)=u(n)*f(n) \\ = s(n)*h(n)+w(n)*f(n) \\ = \sum_i h(i)s(n-i) + \sum_i f(i)w(n-i) \quad (2)$$

It can be used to recover the data transmitted symbol s(n)
where

$$h(n)=c(n)*f(n)$$

The cost function of the constant modulus algorithm is

$$J_{CMA}(n)=E\{[|y(n)|^2 - R2]^2\} \quad (3)$$

where

$$R2 = E\{|s(n)|^4\} / E\{|s(n)|^2\} \quad (4)$$

Depending on the cost function only the blind equalization was determined [2].

2.2 Multi-Modulus Algorithm [7]

The tap weight vectors are the co-efficients of the equalizers which is by determining the transfer function of the equalizer. The tap weights are frequently updated to minimize error at the output of the equalizer. It is used to measure of the deviation in the output which provides difference between the actual values. There are two ways of acquiring new tap weights for the equalizer. One is to transmit a training sequence known by both transmitter and receiver at the beginning of the communication. The receiver then detects the impulse response of the channel from the training sequence, and obtains the tap weights by computing the inverse transfer function of the channel. The other way is to predetermine an initial value for each of the tap weights, and design a cost function according to the characteristics of the received signal. The tap weights are continually adjusted by reducing the cost of the cost function until the error is minimized.
The cost function of Multi Modulus Algorithm was

$$J_{MMA} = J_R(n)+J_I(n) \\ = E\{[|y_R(n)|^2 - R_{2,R}]^2\} + E\{[|y_I(n)|^2 - R_{2,I}]^2\} \quad (5)$$

where

$$R_{2,R} = E\{|s_R(n)|^4\} / E\{|s_R(n)|^2\} \text{ and } R_{2,I} = E\{|s_I(n)|^4\} / E\{|s_I(n)|^2\} \quad (6)$$

It allows the both blind equalization and carrier phase recovery.

Decomposing the cost function of MMA [10] into the real and imaginary parts thus allows both the modulus and the phase of the equalizer output to be considered; therefore, joint blind equalization and carrier-phase recovery may be simultaneously accomplished, eliminating the need for a rotator to perform separate constellation-phase recovery in steady-state operation.
The tap-weight vector of the MMA is updated according to

$$f(n+1)=f(n)-\mu.e^*(n)u(n)$$

Where

$$e(n)= e_R(n)+je_I(n) \quad (7)$$

$$e_R(n)= y_R(n)(y_R(n)^2 - R_{2,R}) \quad (8)$$

$$e_I(n)= y_I(n)(y_I(n)^2 - R_{2,I}) \quad (9)$$

The results of the analysis indicate that the MMA alone can remove ISI and simultaneously correct the phase error, because it implicitly incorporates a phase- racking loop, which automatically recovers the carrier phase[8].

2.3 Recursive Least Square Constant Modulus Algorithm

Due to slow convergence and adaptation of CMA algorithm, Nassar Amin and NahalWaleed introduced a modification of CMA algorithm and used Method of Least square over Method of steepest descent algorithm for CMA [11]. RLS-CMA outperform CMA in term of MSE [11], [12].

Cost function of RLSCMA for the fast convergence is specified by:

$$J(w)=E[(|y(n)|^2 - 1)^2] \quad (10)$$

$$J(w) = \sum_{k=1}^{n} \lambda^{n-k}(|y(n)|2 - 1)\,2 \quad (11)$$

is the forgetting factor and valued between $0<\lambda<1$. RLS-CMA is derived from standard Recursive Least Square algorithm except it considers an input signal z(n) [11], rest of algorithm is concluded as:

$$z(n)=x(n)x^H(n)w(n-1) \quad (12)$$

$$h(n)=p(n-1) * z(n) \quad (13)$$

p(n-1) is the inverse correlation matrix and Kalman gain is calculated as follow:

$$k(n)= h(n)/(\lambda+Z^H(n)h(n)) \quad (14)$$

$$e(n)=1 - w^H(n-1)z(n) \quad (15)$$

e(n) is the error term equation.
Weight update equation is as follow:

$$w(n)=w(n-1)+k(n)e^*(n) \quad (16)$$

p(n) inverse correlation matrix update is as follow:

$$p(n)=p(n-1)/\lambda-k(n)Z^H(n)p(n-1)/\lambda \quad (17)$$

initial conditions are specified as w(0)=[1,1x(k-1)] ,$p(0)=\delta^{-1}I_{kxk}$ delta δ is assumed small positive constant like 10^{-3}.

3 NEW BLIND ALGORITHM

A new blind algorithm Recursive Least Square Multi-Modulus Algorithm (RLS-MMA) is proposed in this section. Combining the work done by S.Makino and Y.Kaneda for Recursive Least Square [13], [14], [15], [16]. Chen and et.al and for Recursive Least Square Constant Modulus Algorithm [17], [18] and various links for CMA and MMA convergence and MSE optimization a new algorithm is developed. Performance of the equalizers is analyzed by the MSE plots. Cost function of the algorithm is defined as:

$$J(w)=E[((y^2R(k)-1)^2]+E[((y^2I(k)-1)^2] \quad (18)$$

$$J(w)=\Sigma^n{}_{k=1}(y^2{}_R(k)-1)^2+\Sigma^n{}_{k=1}((y^2I(k)-1)^2 \quad (19)$$

where$y_I(k)$ and $y_R(k)$ are the imaginary and real terms of equalizer's output and is the forgetting factor valued between. .
Algorithm of RLS-MMA is as follow, z(n) is the input of the equalizer:

$$z(n) = x(n)x^H(n)w(n-1) \quad (20)$$

$$h(n) = p(n-1)z(n) \quad (21)$$

p(n-1) is defined as inverse correlation matrix. Kalman gain is as follow:

$$k(n)= h(n)/(\lambda+Z^H(n)h(n)) \quad (22)$$

$$e_R(n) = y_R(n)(y_R{}^2(n)-R_{2,R}) \quad (23)$$

$$e_I(n) = y_I(n)(y_I{}^2(n)-R_{2,I}) \quad (24)$$

$$e(n)= e_R(n)+ e_I(n) \quad (25)$$

$$R2,R = E\{|s_R(n)|^4\}/ E\{|s_R(n)|^2\} \text{ and } R2,I = E\{|s_I(n)|^4\}/ E\{|s_I(n)|^2\} \quad (26)$$

Where $s_I(n)$ and $s_R(n)$ are the imaginary and real part of the transmitted source signal.
Weight update equation is given as:

$$w(n)=w(n-1)+k(n)e^*(n) \quad (27)$$

p(n) inverse correlation matrix update is as follow:

$$p(n)=p(n-1)/\lambda-k(n)Z^H(n)p(n-1)/\lambda \quad (28)$$

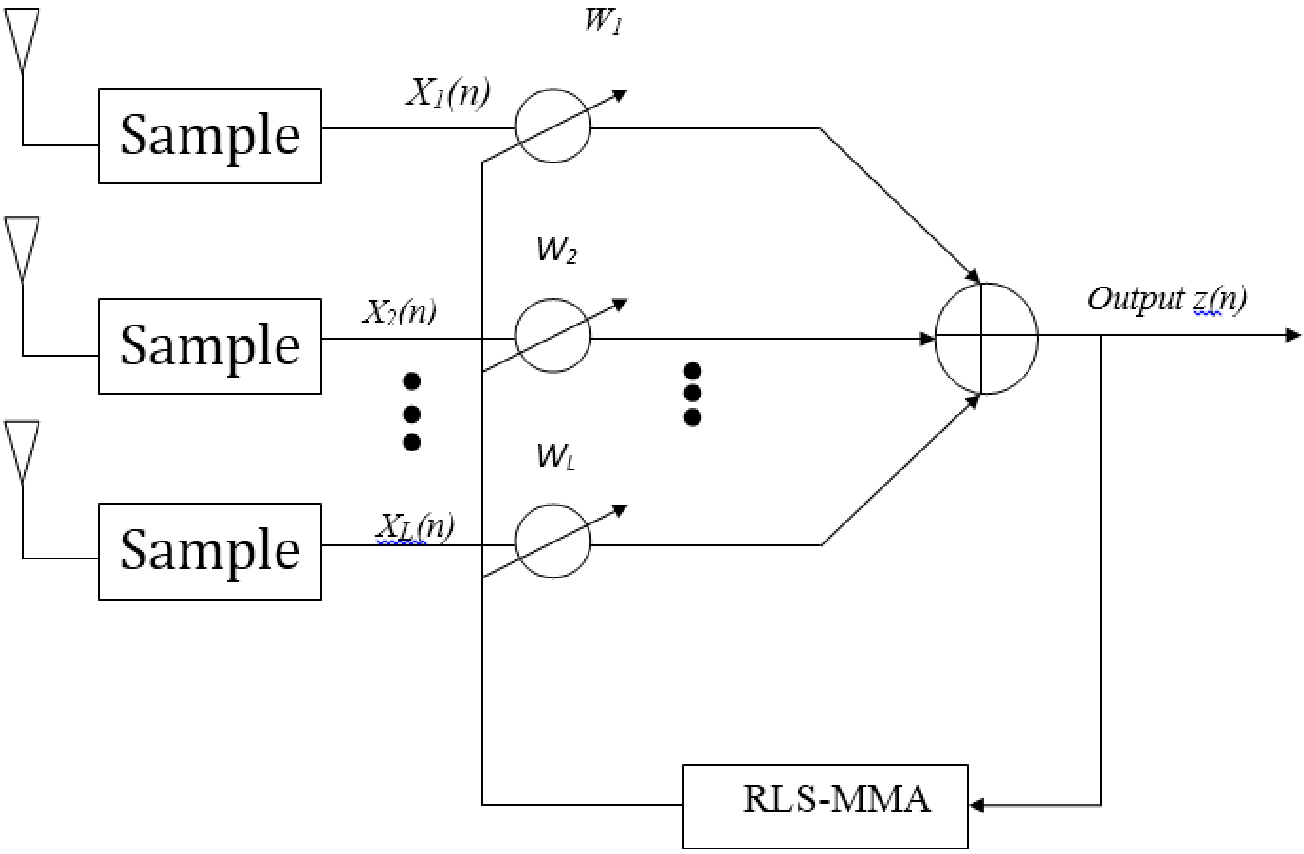

Fig: Adaptive beamforming structure.

4. SIMULATION RESULTS

The following section evaluates the performance of the entire algorithm mentioned where the main parameter focused was lay on the Mean Square Error (MSE). Performance of CMA and RLS-CMA was compared further MMA performance was compared with the proposed algorithm RLSMMA. In the simulations s(n) was the QAM signal, SNR is 25db. CMA and MMA simulations used a step size µ of value 0.09 while forgetting factor is considered 0.99 for RLS-CMA and RLS-MMA. Results are shown as follow:

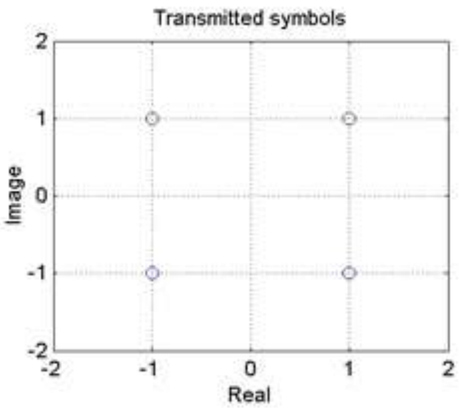

Fig 1. Transmitted Symbols

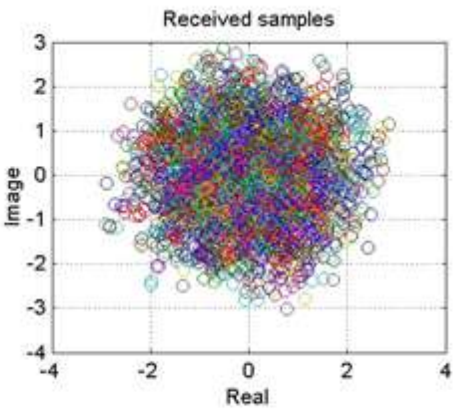

Fig 2. Received Symbols without Equalization

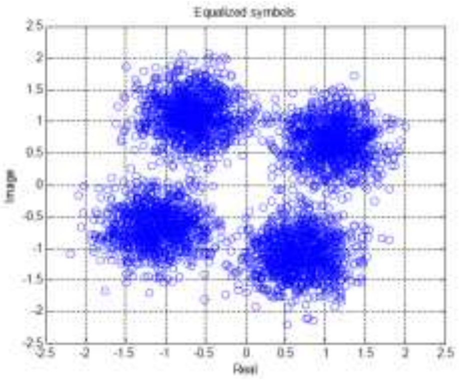

Fig 3. Received Symbols with RLS

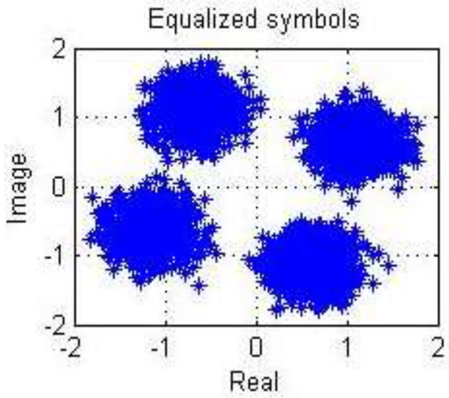

Fig 4. Received Symbols with CMA

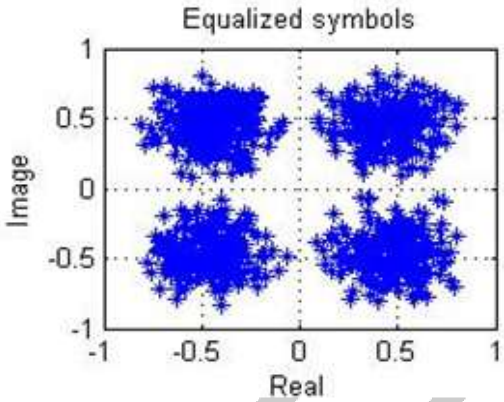

Fig 5. Received Symbols with MMA

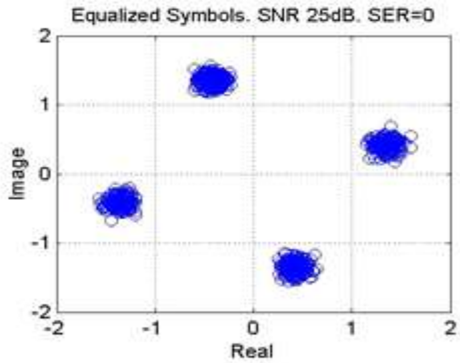

Fig 6. Received Symbols with RLS-MMA

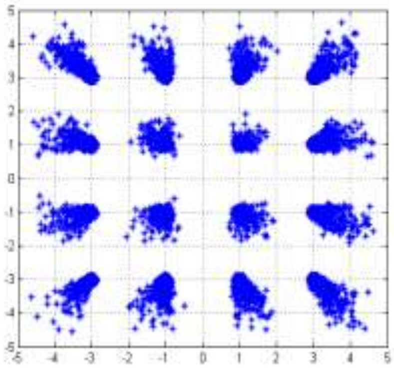

Fig 7. Received Symbols with MMA(16-QAM)

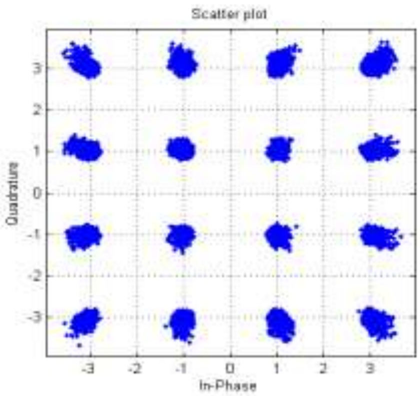

Fig 8. Received Symbols with RLS-MMA

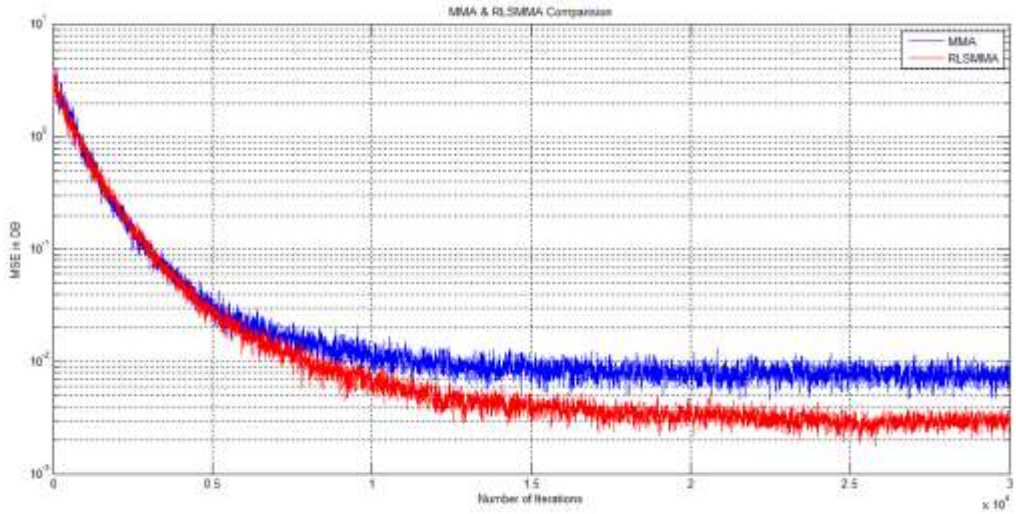

Fig 9. Comparison of MMA and RLS-MMA

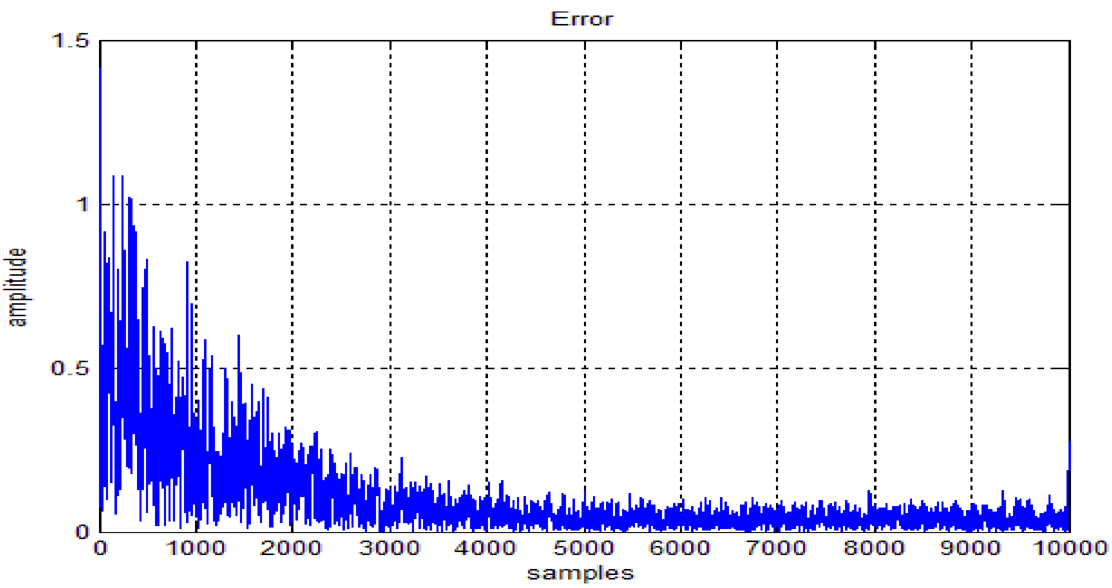

Fig 10. Error results of RLS-MMA

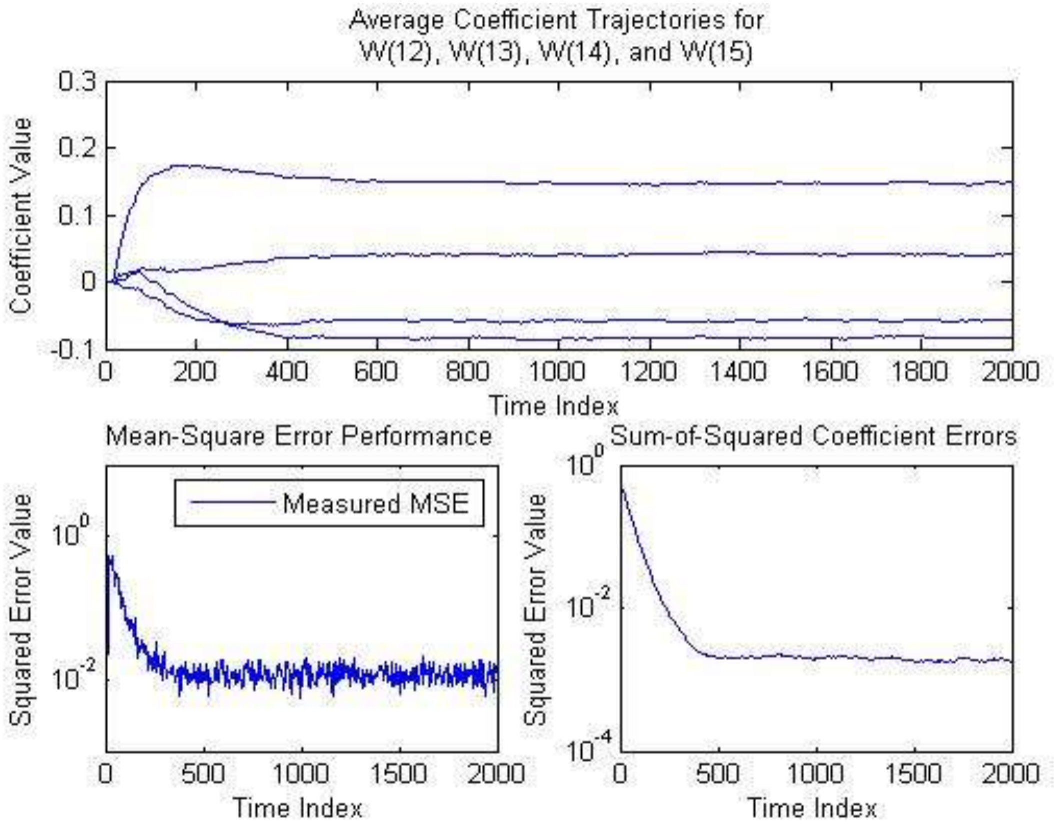

Fig 11. Co-efficient Trajectories with MSE vs Time Index of RLS-MMA

Fig 1. shows the transmitted signal (4-QAM), Fig 2. shows received symbols with using any adaptive technique, Fig 3. depicts received symbols with RLS whereas Fig 4. Represents received symbols with CMA. Fig 5. shows received symbols with MMA, Fig 6. depicts received symbols with RLS-MMA. A combination of RLS & MMA algorithms brings out improvement in the overall performance of algorithms. Fig 7. shows received symbols with MMA(16-QAM) while Fig 8. represents received symbols with RLS-MMA with improvement in noise cancellation. Fig 9. reflects the improvement of RLS-MMA over MMA in terms of MSE (Mean Squared Error). Fig 10. shows error results of RLS-MMA. Fig 11. depicts Co-efficient Trajectories with MSE vs Time Index of RLS-MMA

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