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Two Channel Estimation Methods for MIMO-OFDM System

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Abstract

Adaptive Filter is a part of the modern communication system. The applications of the adaptive filters are channel equalization, noise cancellation, system identification and adaptive beam forming. So the proper implementation of adaptive filter is a great deal. The intersymbol interference (ISI) caused by the multipath in band limited frequency selective time dispersion channel distort the transmitted signal. In this paper, we have concentrated on modifying the algorithm for the adaptive filter. The proposed VSS-LLMS and Modified Variable Step Size Leaky LMS (MVSS-LLMS) which improves the channel estimation in the noisy environment. Also we compared the results of our proposed algorithms with the LMS, RLS and VLLMS and observed that it improves in computational complexity and Bit Error Rate (BER) performance.

Keywords: Adaptive Channel Estimation, Adaptive filter, LMS, RLS, VLLMS and MVSS-LLMS

1. Introduction

Modern wireless communication systems require higher data rate technologies to meet the demand for high data rate services such as multimedia, VOIP etc. In order to meet this enormous demand of higher data rate and better coverage of wireless network the channel bandwidth is increased. But this approach is not practical as the frequency spectrum is very expensive, even though by increasing the more complex modulation scheme for improving the throughput it is not used due to increased complexity of radio systems and therefore its cost. For transmitting large amount of data various modulation schemes are employed. Recent approach is to employ Orthogonal Frequency Division Multiplexing (OFDM) [2-9,11]. OFDM modulation turns the frequency-selective channel into a set of parallel flat fading channels to overcome the ISI.

Least mean square (LMS), Kalman filter, Normalized Least mean square (NLMS)[4] and variable step size LMS (VSSLMS) [1] are some of the numerical computational techniques that have been applied for channel estimation in wireless communication. Along with it, fuzzy logic, neural networks, simulated annealing are also some of the new techniques used for frequency estimation. The LMS algorithm is mostly used conventional algorithm for the designing of adaptive filters due to its computational simplicity, ease of implementation and unbiased convergence [10]. In this paper, we have given more emphasis on the LMS algorithm. We have modified the LMS algorithm and proposed new VSS-LLMS and Modified Variable Step Size Leaky LMS (MVSS-LLMS) algorithms for channel estimation in noisy environment. The remaining portion of this paper is organized as follows; M.M. Mushrif[3] Section II describes the generalized adaptive channel estimation method. Section III describes proposed VSS-LLMS and MVSS-LLMS algorithms. The performance analysis is represented in section IV and in section V gives the conclusion that we have derived from the results.

2. Adaptive Channel Estimation Method

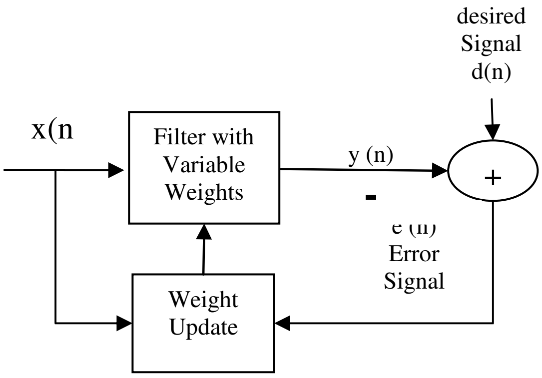

Figure.1 Adaptive Channel Estimation Method

Adaptive channel estimation shown in Fig. 1 is process with a linear filter that has a transfer function controlled by variable parameters .The parameters of the estimator are adjusted according to an optimization algorithm. Because of the complexity of the optimization algorithms, most adaptive estimators are digital filters. Adaptive estimators are required because some parameters of the desired processing operation are not known in advance or are changing. The closed loop adaptive estimator uses feedback in the form of an error signal to refine its transfer function. For the optimum performance of the filter the closed loop estimation process use cost function. To minimize the cost on the next iteration. The most common cost function is the mean square of the error signal.

3. Proposed Algorithms

3.1 Variable Step-Size Leaky Least Mean Square (VSS-LLMS) Algorithm

According to the previous algorithm, we are considering the Leaky LMS with cost function as

$$Jn = e^2(n) + y(n)w^T(n)w(n) \quad (1)$$

Therefore the equation of weight updating becomes

$$w(n+1) = e^2(n) - \frac{\mu(n)\partial Jn}{\partial w(n)} \quad (2)$$

Where *a* variable step size parameter *is* μ *(n)* and may be updated as the following equation explain in the previous algorithm

$$\mu(n+1) = \lambda\mu(n) + \gamma(\mathrm{n})\,\mathrm{p}^2(\mathrm{n}) \quad (3)$$

Where, $\lambda = 1/n$

Where p(n) is the autocorrelation of error e(n) and can be computed as

$$\mathrm{p}(n+1) = \beta p(\mathrm{n}) + (1-\beta)\,\mathrm{e(n)\,e(n-1)} \quad (4)$$

In the VLLMS [1] algorithm the designer choose the forgotten parameter β in between 0 and 1. But choosing the value of β puts some weights on the convergence of the algorithm and gives large BER. Therefore, to overcome from this here it is used variable forgotten parameter β(n) which is updated as

$$\beta(n+1) = \beta(\mathrm{n}) - \frac{\log\beta(\mathrm{n})}{N} \quad (5)$$

Where N-is the Filter tap value

So the equation (4), autocorrelation of error is modified as

$$p(n+1) = \beta(\mathrm{n})\,\mathrm{p(n)} + (1-\beta(\mathrm{n})\,\mathrm{e(n)\,e(n-1)}) \quad (6)$$

Finally, the updated leakage factor γ(n) given as

$$\gamma(n+1) = \gamma(\mathrm{n}) - 4\mu(\mathrm{n})\,\mathrm{ne(n)}\,\mathrm{x}^T(n)w(n-1) \quad (7)$$

Where constant ρ, ρ>1And finally weight is updated as

$$\mathrm{w}(n+1)=((1-2\mu(n)\gamma(n))\,\mathrm{w(n)}+2\mu(n)\,\mathrm{e(n)\,x(n)} \qquad (8)$$

3.2 Modified Variable Step-Size Leaky Least Mean Square (MVSS-LLMS) Algorithm

We know that, at a time n the error signal is given by

$$e(n)=d(\mathrm{n})-\mathrm{y(n)} \qquad (9)$$

As it is already discussed in the LMS algorithm [15]. The output of the linear filter is given by

$$y(n)=w^T(n)*\mathrm{x(n)} \qquad (10)$$

Where x (n) is the input to the filter which is

$$\mathrm{x}(n)=[\mathrm{x(n)\,x(n-1)\,x(n-2).....x(n-L+1)}]^T \qquad (11)$$

And w (n) is the filter gain

$$w(n)=[w(0)w(1)w(2).....w(\mathrm{n-L+1})]^T \qquad (12)$$

Updating the weight as

$$w(n+1)=w(n)+\textbf{\textit{Some increment vector}} \qquad (13)$$

Where this increment vector is taken as derivative of cost function which result in the weight update as

$$w(n+1)=w(n)-\mu\nabla(\mathrm{e}^2(\mathrm{n})) \qquad (14)$$

On solving the derivative,

$$\frac{\partial\,\mathrm{e}^2(\mathrm{n})}{\partial w}=\frac{2e(n)\partial e(n)}{\partial w}$$

$$\frac{\partial\,\mathrm{e}^2(\mathrm{n})}{\partial w}=\frac{2e(n)\partial y(n)}{\partial w}$$

$$=-2(e(n)x(n) \qquad (15)$$

So the updated weight equation is given by,

$$w(n+1)=w(n)+2\mu(e(n)x(n) \qquad (16)$$

The cost function of Leaky LMS algorithm is given by

$$J(n)=e^2(n)\gamma w(\mathrm{n})^T w(n) \qquad (17)$$

To avoid the parameter drifting [13, 14] constant leakage factor γ should be chosen between 0 and 1. But constant γ gives over/under parameterization. By using the variable leakage factor, we can avoid the over/under parameterization. Then the modified cost function is as

$$J(n)=e^2(n)\gamma(\mathrm{n})\,\mathrm{w(n)}^T w(n) \qquad (18)$$

In order to update the leakage factor [12] we can use the same steepest decent rule, but here the variable leakage factor is updated as

$$\gamma(n+1)=\gamma(n)-2\mu(n)\rho e(n)\,\mathrm{x}^T(\mathrm{n})\gamma w(\mathrm{n})^T w(n) \qquad (19)$$

Where ρ is variable must be greater than 1.

In the proposed algorithm MVSS-LLMS, we have considered variable step size. If we take the large value of step size it will reduce the transient time, but on the contrary it increases the misadjustment [11]. So to ensure the step size parameter does not become too large and too small, upper and lower limit are specified say μmax and μmin.Therefore, the step size can be updated as

$$\mu(n+1) = \mu(n) + \frac{(\mu_{\max} - \mu_{\min})i}{N} \quad (20)$$

The weight and the leakage factor are updated similar to Leaky LMS

$$w(n+1) = (1 - 2\mu(n)\gamma(\mathrm{n}))\,\mathrm{w(n)} + 2\mu(n)e(n)x(n) \quad (21)$$

$$\lambda(n+1) = \lambda(n)2\mu(n)\,pe(n)x^{T}(n)w(n) \quad (22)$$

Where p is variable must be greater than 1.

4. Performance Analysis

4.1 Computational Complexity

Here we have considered N iteration. So the inner product requires N complex multiplications and N complex additions. The multiplication of any scalar with vector requires N complex multiplication. In the Table no.1 below shows the computational complexity of conventional LMS, RLS[5], Variable Leaky LMS (VLLMS) and our proposed algorithms VSS-LLMS. MVSS-LLMS. We observe that modified variable step size leaky LMS is less complex than compared to the variable Leaky LMS.

Table-I Computational Complexity

Algorithms	Multiplication	Addition	Division
LMS[6]	2N+1	2N	-
RLS[5]	N^2+5N+1	N^2+3N	1
VLLMS[1]	N^2+7N+3	5N	-
VSS-LLMS	N^2+5N+3	6N	2
MVSS-LLMS	N^2+5N+3	6N	1

4.2 Bit Error Rate(BER)

In this section we have described the comparison of the proposed modified Leaky LMS algorithm with the other existing channel estimation algorithms. The input Signal added to adaptive white Gaussian noise is used to study the performances of the algorithms in the presence of noise. The five different cases of noises with signal-to-noise ratios (SNRs) of 10, 20, 30, 40 and 50 dB are considered. The parameters used in the VSS-LLMS. and MVSS-LLMS are μ_{max}=0.1, μ_{min}=0.1x 10^{-4},γ=1.1 and β =0.97.the initial value of ρ=0 , γ=0 , μ=0 and initial weight w=0.The bit error rate performance of LMS, RLS, VLLMS, VSS-LLMS. and MVSS-LMS are shown in fig 2,fig 3,fig 4, fig 5 and fig 6. Table II gives the comparison of VLLMS and MVSS-LMS. Comparison results shows that the performance of the proposed modified MVSS-LLMS is better than the other channel estimation schemes. Among the LMS-based algorithms, the simple LMS perform poorly compared to the RLS and VLLMS because of having larger errors and inconsistent dynamic behavior with respect to SNR variations. The dynamic behavior of VLLMS and MVSS-LLMS are almost similar; however, the error in estimation in the former case is larger compared to the latter one. Therefore it is evident that MVSS-LLMS performs better compared to the others.

Table-II BER Comparison of VLLMS and MVSS-LLMS

SNR	BER		
	VLLLMS	VSS-LLMS	MVSS-LLMS
5	0.0004429	0.0001269	5.57e^{-006}
10	0.0003937	0.0001123	4.95e^{-006}
15	0.0003444	9.822e-005	4.33e^{-006}
20	0.0002952	8.419e-005	3.17e^{-006}
25	0.0002460	7.016e-005	3.097e^{-006}
30	0.0001968	5.613e-005	2.47e^{-006}
35	0.0001476	4.21e-005	1.85e^{-006}
40	0.0000984	2.80e-005	1.23e^{-006}
45	0.0000492	1.403e-005	6.17e^{-007}
50	0.0000098	2.806e-006	1.27e^{-007}

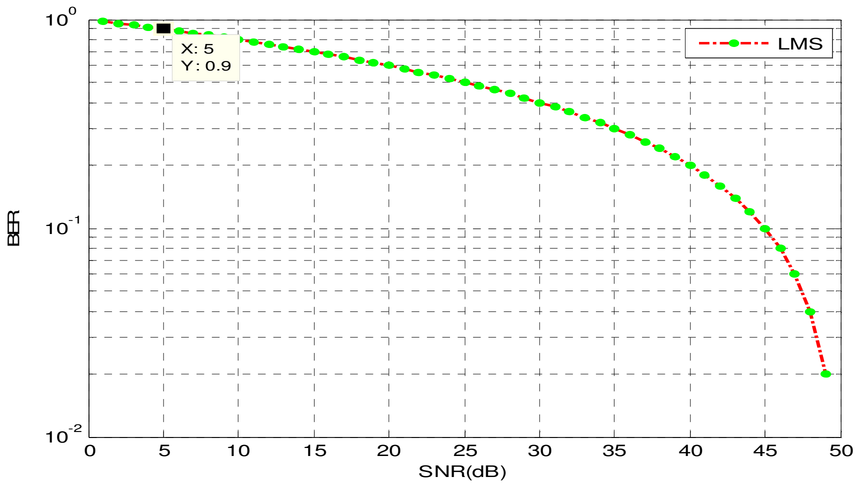

Figure- 2 BER of LMS

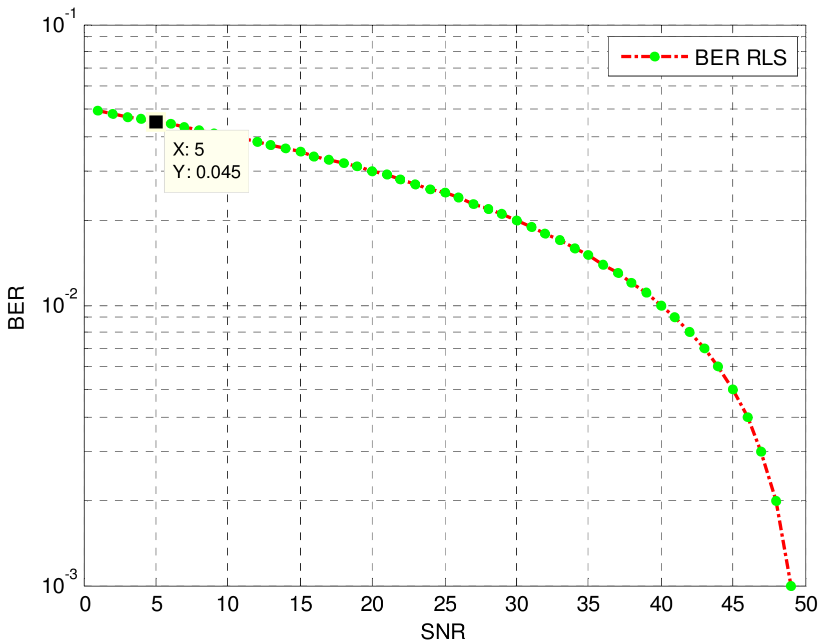

Figure- 3 BER of RLS

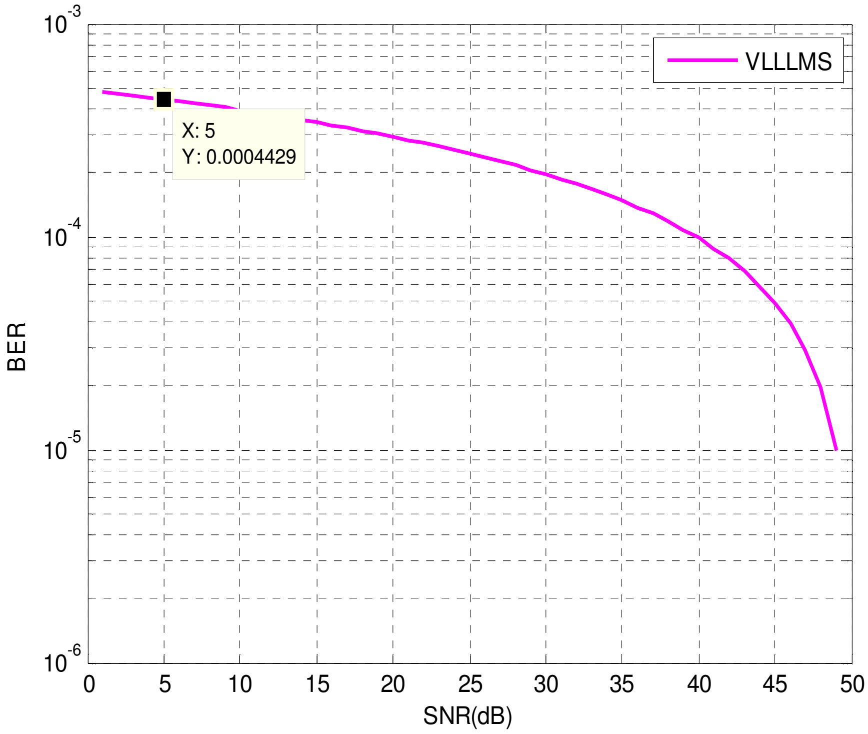

Figure- 4 BER of VLLMS

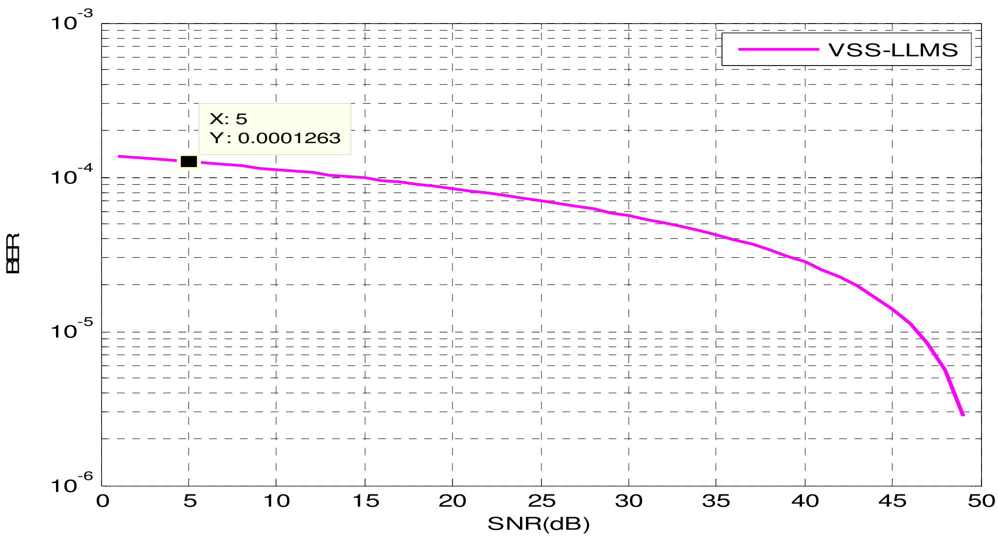

Fig- 5 BER of VSS-LMS

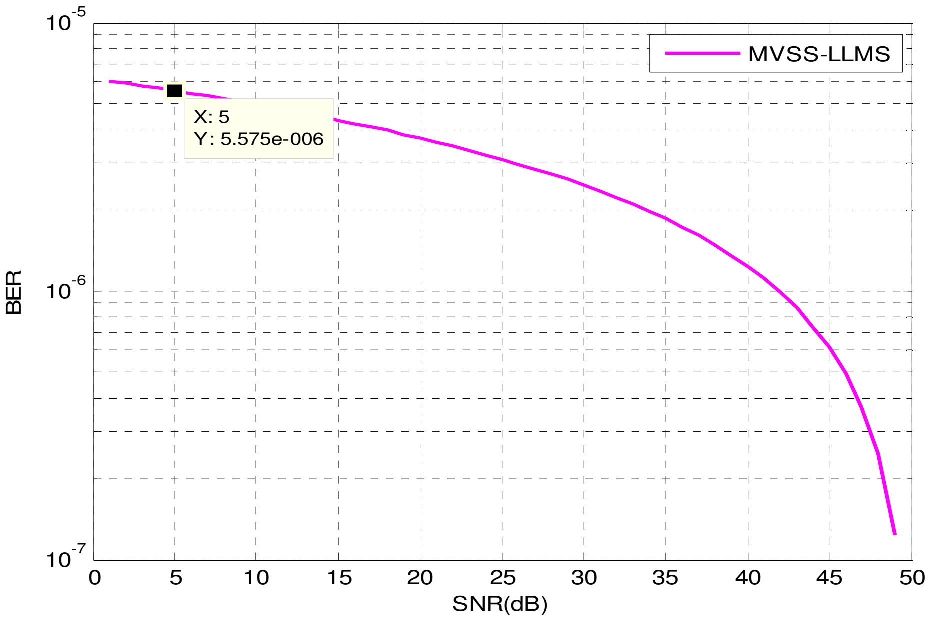

Fig- 6 BER of MVSS-LLMS

CONCLUSION

VSS-LMS and MVSS-LMS algorithm have been introduced which uses a variable step size and variable leakage factor to improve the bit error rate and the convergence ability of the fixed step size LMS algorithm. The proposed algorithm is compared with the fixed step size algorithm and other variable step size algorithms. VSS-LMS and MVSS-LMS algorithm have superior performance to the fixed step size algorithm, lesser complex than the VLLMS algorithm and it improves the BER performance.

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