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Performance Enhancements of MIMO-OFDM System Using Various Adaptive Receiver Structures

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Abstract— **In wireless communications, multi-channel transmission is utilized to obtain high capacity and better throughput efficiency. Multiple-Input Multiple-Output (MIMO) Orthogonal Frequency Division Multiplexing (OFDM) is considered as spectrally efficient system to achieve high throughput communications. This paper investigates the performance enhancement of MIMO-OFDM system using NLMS, variable step-size NLMS and RLS adaptive receivers. The performances of using fixed step-sizes were investigated and an optimum value was chosen, based on a trade-off between the convergence speed and the steady state noise floor for NLMS algorithm and was compared with the variable step-size NLMS. The mean-square-error (MSE) performance of the proposed variable step-size approach was compared with that of fixed step-size, which shows an excellent convergence speed and steady state performance. In addition to that, the RLS algorithm was compared with the NLMS and variable step-size NLMS. Also, the bit-error-rate (BER) of the proposed receivers was compared with that of the conventional receiver.**

I. INTRODUCTION

In a multi-channel system, frequency selective fading or narrowband interference affects small percentage of sub-channels whereas in a single channel system, a single fade or interference might cause the entire channel to fail. To realize OFDM, we have to maintain orthogonality between sub-channels (i.e., reducing crosstalk between them). Orthogonality can be maintained using cyclic prefix which is the copy of the last part of an OFDM symbol. Cyclic prefix will be appended to the transmitted symbol [1]. This introduces a loss in the signal to noise ratio (SNR). However, the zero inter symbol interference (ISI) mitigates the loss. Inter Symbol Interference (ISI) can be avoided using pulse shaping. Raised cosine windowing of the transmitted pulses will result into a sinc shaped frequency response of each sub-channel where the roll off region acts as a guard interval. Thus, the frequency spectrum of each sub-channel falls much more quickly and therefore reduces the interference to the adjacent frequency bands. In a discrete time model of an OFDM system, the modulation and the demodulation are substituted with inverse FFT and FFT, thereby achieving frequency division multiplexing by baseband filtering process. Furthermore, it will eliminate the banks of sub-channels oscillators and coherent demodulators required by frequency division multiplexing [2]. One of the simplest, yet robust adaptive filter algorithms is the normalized least mean square (NLMS). The weight vector of NLMS can be changed automatically, while that of LMS cannot [3]. If the rate of convergence is fast, the filter will be adapted quickly to a stationary environment of unknown statistics. The most important parameter that dominates the NLMS algorithm is the step size. If the step size is set to a large value, the convergence rate of NLMS algorithm will be fast. However, the steady state MSE will increase. On the other hand, if the step size is set to small value, the convergence rate will be slow but the steady state MSE will decrease [4]. Recent related work is given in [5] and [6]. In [5], only the MMSE performances of using the NLMS adaptive algorithm for different MIMO systems have been investigated. While in [6], a new channel estimation method for OFDM by combining LS and MMSE using Evolutionary Programming was proposed. In this paper, we evaluated the performance of the NLMS algorithm for MIMO-OFDM system using various fixed and variable step-sizes. An optimum step-size value is chosen based on a trade-off between the convergence speed and the steady state MSE. Then, the bit error rate (BER) performance of the proposed NLMS adaptive receiver is compared with that of the conventional one. The investigation is also extended to Variable Step Size NLMS (VSNLMS) and the Recursive Least Square (RLS) algorithms. In VSNLMS, the algorithm will have to make a large step size during the initial part and a small step- size when the system nearly reaches to a steady-state MSE. RLS is an adaptive filtering algorithm derived from the Wiener and Kalman filters. It is based on classical method of least square, which involves the use of time average. A distinctive feature of the RLS algorithm is that its derivation is relied on a basic result in linear algebra known as the matrix-inversion. Another important feature of the RLS algorithm is that it utilizes information contained in the input data, extending back to the instant of time when the algorithm is initiated. The resulting rate of convergence is therefore faster than simple LMS algorithm. Adaptive filters have been used for various objectives and wide range of applications such as adaptive equalization, adaptive noise-cancellation and adaptive beam forming. The NLMS algorithm uses the instantaneous squared error to estimate the Mean Square Error (MSE) and the filter is subjected to slow adaptation to permit the necessary linear operations in its derivation [7].

The paper is organized as follows. Section I gives an introduction and theoretical background of MIMO-OFDM and adaptive filter algorithms. Section II introduces the system overview. Sections III and IV describe the system's model and simulation results, respectively. Finally, Section V concludes the paper.

II. SYSTEM OVERVIEW

A. NLMS Adaptive equalizer

Typical block diagram of NLMS adaptive filter is shown in Fig. 1 The input *x(n)* produces an output *u(n)*, the output will be subtracted from the desired signal *d(n)* to produce an error signal *e(n)*. The input signal and error signal are combined together in the NLMS algorithm where the algorithm manipulates the transversal filter to minimize the MSE. The filter will repeat this process for a number of iteration until it reaches the steady state.

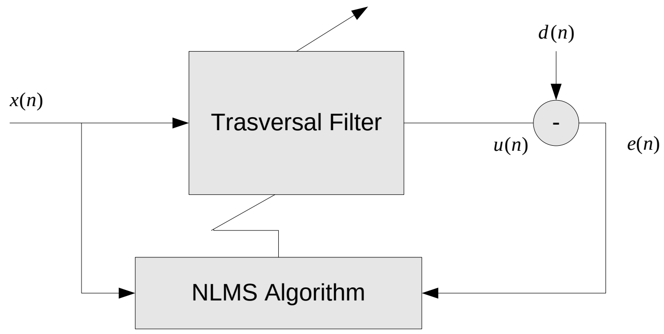

Fig. 1: Block diagram of an NLMS adaptive equalizer

B. NLMS Algorithm

The weight vector of an adaptive filter should be changed in a minimal mechanism, subject to a constraint imposed on the updated filter's output. The NLMS algorithm is based on the principal of minimal disturbance from one iteration to the heading iteration [1]. Let the received symbol vector at time associating to the n^{th} OFDM symbol be

$$\boldsymbol{y(n) = [y_o(n), y_1(n), \cdots, y_{L-1}(n)]^T} \quad (1)$$

The weight vector for the i^{th} sub-channels, $i = 0,1,..,N - 1$ is

$$\boldsymbol{w_i(n) = [w_{i,0}(n), w_{i,1}(n), \cdots, w_{i,L-1}(n)]^T} \quad (2)$$

The desired response is

$$\boldsymbol{d(n) = w^H(n+1)y(n)} \quad (3)$$

According to the NLMS algorithm, the update procedure for the weight vector $w_i(n)$ is characterized as

$$\boldsymbol{w_i(n+1) = w_i(n) + \mu\, y(n)\, e_i^*} \quad (4)$$

Where $e_i(n)$ is the error for the i^{th} sub-channels, $i = 0,1,...,N-1$, μ is the step size parameter.

$$\boldsymbol{e_i(n) = d_i(n) - w_i^H(n)y(n)} \quad (5)$$

The optimal value of the incremental change is obtained by

$$\boldsymbol{e_i(n) = d_i(n) - w_i^H(n)y(n)\frac{e(n)\, y(n)}{\|y(n)\|^2}} \quad (6)$$

$$\boldsymbol{w_i(n+1) - w_i(n) = \frac{\mu\, e(n)y(n)}{\|y(n)\|^2}} \quad (7)$$

A constant value σ is appended to the denominator to avoid *w(n+1)* to be unbounded when the tap-input vector *y(v)* becomes too small, hence the NLMS can be written as

$$\boldsymbol{w_i(n+1) - w_i(n) = \frac{\mu\, e(n)y(n)}{\sigma + \|y(n)\|^2}} \quad (8)$$

C. Step-size Control Mechanism

The stability of the NLMS filter depends on the step size parameter. Therefore, we have to find the optimum step size for the adaptive filter. The desired response is set as follows

$$\boldsymbol{d(n) = w^H(n)y(n+1) + u(n)} \quad (9)$$

Where *u(n)* is an unknown disturbance. An estimate of the unknown parameter *w* is calculated from the tap-weight vector *w(n)*. The weight error vector is

By substituting (9) into (8), we obtain

$$\boldsymbol{\varepsilon(n+1) - \varepsilon(n) = -\frac{\mu\, e(n) y(n)}{\sigma + \|y(n)\|^2}} \qquad (10)$$

The stability of adaptive filter can be studied by identifying the mean square deviation, denoting E as the expected value

$$\boldsymbol{\mathcal{D}(n) = E\Big[[|\varepsilon(n)|^2]\Big]} \qquad (11)$$

By substituting (10) into (11), we obtain

$$\boldsymbol{\mathcal{D}(n+1) - \mathcal{D}(n) = \mu^2 E\left[\frac{|e(n)|^2}{\|y(n)\|^2}\right] - 2\mu E\ Re\left[\frac{\xi(n)e(n)}{\|y(n)\|^2}\right]} \qquad (12)$$

Where $\xi(n)$ is the undisturbed error signal that can be written as follows

$$\boldsymbol{\xi(n) = \varepsilon^H(n) y(n)} \qquad (13)$$

$$\boldsymbol{\varepsilon(n)} = w - \boldsymbol{w}(n) \qquad (14)$$

The bounded range for the normalized step size can be obtained from (12) as follows

$$\mathbf{0} < \mu < 2\frac{\boldsymbol{Re[\xi(n)e(n)/\|y(n)\|^2]}}{\boldsymbol{E[|e(n)|^2/\|y(n)\|^2]}} \qquad (15)$$

For real valued data input, we can use the following equation

$$\boldsymbol{E\Big[[|\xi(n)|^2]\Big] = E\Big[[|y(n)|^2]\Big]\,\mathcal{D}(n)} \qquad (16)$$

By substituting (16) into (15)

$$\mathbf{0} < \mu < 2\frac{\boldsymbol{E\Big[[|y(n)|^2]\Big]\,\mathcal{D}(n)}}{\boldsymbol{E[|e(n)|^2]}} \qquad (17)$$

$$\mathbf{0} < \mu < 2\boldsymbol{\mu_{optimum}} \qquad (18)$$

Where $E[|e(n)|^2]$ is the estimation of the error signal power. $E[|y(n)|^2]$ is the estimation of the input signal power, $\mathcal{D}(v)$ is the estimation of the mean-square deviation, σ is the stable parameter and $\mu_{optimum}$ is the optimum step size parameter [8], [9].

D. Variable Step-size NLMS Algorithm

The notion behind the variable step-size algorithm is to make a large step size during the initial part and a small step- size when the system nearly reaches to a steady-state MSE. In the proposed method, the step-size for the NLMS algorithm is changed into a variable one, where the fixed step-size μ is multiplied by $PR(n)$ being a selection from random numbers of uniform distribution [0 1] at each iteration time and then multiplied further by a curve function to control the value of the variable step-size. The curve function is given by

$$\boldsymbol{\zeta(n)} = \begin{cases} \boldsymbol{\left(\left(\frac{6}{N}\right)^2\left(n - \left(\frac{N}{6}\right)\right)^2\right) + 0.001} & \boldsymbol{1 \le n \le \frac{N}{6}} \\ \mathbf{0.001} & \boldsymbol{\frac{N}{6} \le n \le N} \end{cases} \qquad (19)$$

where N represents the number of iterations.

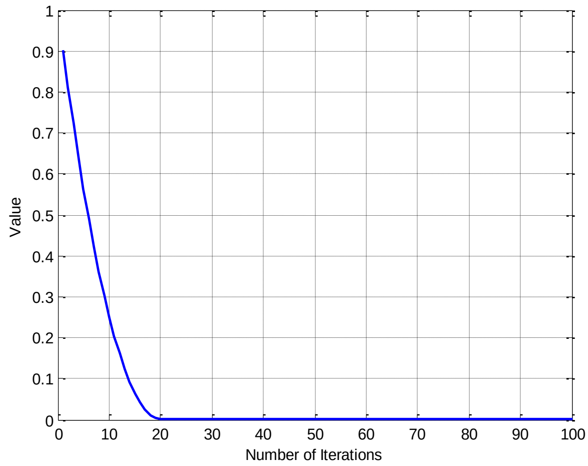

Fig. 2: Curve of $\zeta(n)$ in case of N=100

Fig. 2 shows $\zeta(n)$, given in (19), against the number of iterations. It can be seen that during the initial part of the curve, it rapidly decreased from 1 to 0.001. In this period, the system needs large values of step-size to make the system converge to the steady-state as fast as possible and needs small values of step-size when getting close to the steady-state. The slope of this curve should not be too steep; otherwise we will get small values of step-size while the system still needs large values. In a steady-state period, the system needs the step-size to maintain a small value but should not be down to zero to decrease the steady-state MSE. Therefore, we generated the curve to maintain a small value (0.001) in the steady-state. Multiplying (19) by both the random numbers, $PR(n)$, and the normalized step-size parameter, μ, the variable step-size expression becomes [9]

$$\boldsymbol{\mu(n) = PR(n).\zeta(n)\mu} \qquad (20)$$

By substituting the variable step-size in (20) into the standard fixed step-size NLMS algorithm in (8), the proposed algorithm is obtained as below.

$$w_i(n+1) = w_i(n) + \frac{\mu(n)\, e(n) y(n)}{\sigma + \|y(n)\|^2} \quad (21)$$

Fig. 3 shows an example of the proposed variable step-size, where the number of iterations N =100 and the normalized step size $\mu=1$.

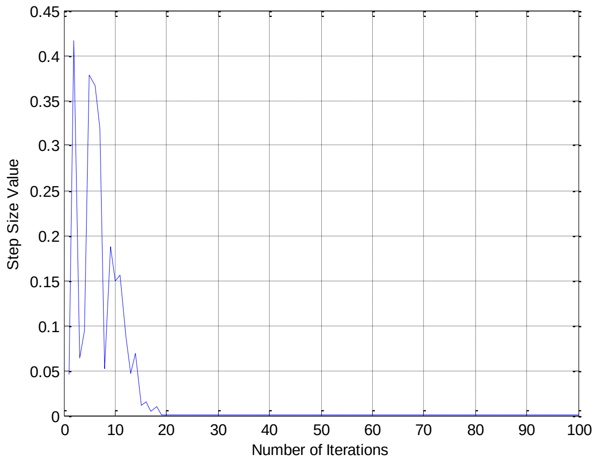

Fig. 3: Variable step size for $\mu=1$

E. RLS Adaptive Equalizer

Typical block diagram of RLS adaptive filter is shown in Fig. 4. The input *x(n)* produces an output *y(n)*, the output will be subtracted from the desired signal *d(n)* to produce an error signal *e(n)*. The filter utilizes information contained in the input data, extending back to the instant of time when the algorithm is initiated. The RLS algorithm minimizes the sum of squares of its output at every time interval. The filter coefficients will be updated while using the information contained in the current set of coefficient. The current set of coefficient *w(n)* will be calculated based on the previous set and control parameter *c(n)* which is used to apply correction on the coefficient weights [10].

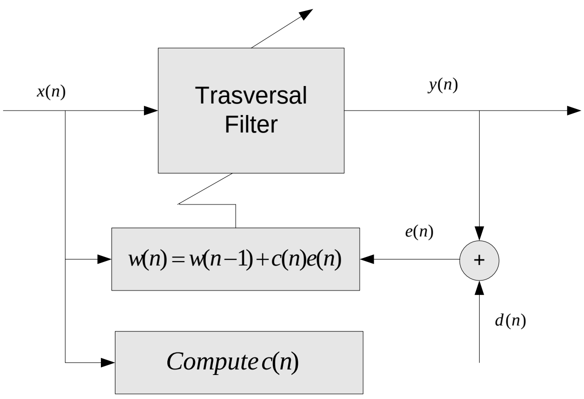

Fig. 4: Block diagram of an RLS adaptive equalizer

F. RLS Algorithm

The other class of adaptive filter algorithm is the Recursive Least Square (RLS). The algorithm relies on minimizing the cost function

$$J(n) = \sum_{k=1}^{n} \sigma^{n-k} + e_n^2(k) \quad (22)$$

Where $k=1$ is the time at which the RLS algorithm initiates, a constant small positive value σ very close to, yet less than 1. When $\lambda<1$, more attention is given to the most error estimates and thereby more updated input samples that result into more utilization of the current samples of the input data and tends to forget the past [10]. The RLS takes into account the previous values of error estimations. Excellent performance in a time varying channel can be achieved using RLS algorithm with the expense of more computational complexity and stabilization problems. The RLS cost function shows at a time n, all the past error estimation values after the initialization of the algorithm. As the time proceeds, the amount needed to process the algorithm increases. The limited memory and computational capabilities hinder the implementation of the algorithm in it is pure form since the algorithm assumes all data will be processed. Therefore, in practical, the algorithm takes into account only a finite number of previous error estimation values which correspond to the RLS FIR order (i.e. number of tap weights.). Let the output of the FIR filter at n, using the current weight vector and the input of a previous time k (i.e. the received OFDM symbol) for $k=1, 2, ...n$:

$$y_n(k) = w^T(n)x(k) \quad (23)$$

$$y_n(k) = [y_n(1), y_n(2), \cdots, y_n(n)]^T \quad (24)$$

The estimation error value $e_n(k)$ is the difference between the desired output value at time k and the corresponding value $y_n(k)$

$$e_n(k) = d(k) - y_n(k) \quad (25)$$

$$e(n) = [e_n(1), e_n(2), \cdots, e_n(n)]^T \quad (26)$$

$$e(n) = d(n) - y(n) \quad (27)$$

The desired response is

$$d(n) = [d(1), d(2), \cdots, d(n)]^T \quad (28)$$

Assuming *x(n)* as a matrix consisting of *n* previous input column vector up to the current time, *y(n)* can be expressed as There are two main components in the RLS adaptive filter.

$$\boldsymbol{x(n) = [x(1), x(2), \cdots, x(n)]} \quad (29)$$

$$\boldsymbol{y(n) = x^T(n)w(n)} \quad (30)$$

FIR filter and adaptive weight control mechanism

$$\boldsymbol{y(n) = w(n-1)x(n)} \quad (31)$$

The inner product ***w****(n-1)****x****(n)* indicates an estimate of the desired signal *y(n)*, based on the old least squares estimate of the tap weight vector that was made at time *(n-1)*. As a consequence, the error is fed back to the adaptive weight control mechanism in order to update the processor weighting parameter. (31) describes the adaptive operation of the RLS algorithm, whereby the tap weight vector is updated by incrementing its old value by an amount equal to the e*(n)* times the time-varying gain vector *c(n)* which is an important parameter used to control the correction applied to the tap weight. It is defined as the tap input vector *x(n)* multiplied by the inverse of the estimate of error variance $\sigma^2(n)$,

$$\boldsymbol{c(n) = x(n)/\sigma^2(n)} \quad (32)$$

The estimate of the error variance $\sigma^2(n)$ is computed using the following equation:

$$\boldsymbol{\sigma^2(n) = \lambda\sigma^2(n-1) + |x(n)^2|} \quad (33)$$

i.e. by adding to the previous estimate of error variance that is multiplied by the exponential weighting factor λ the sum of square tap-input. λ is a positive constant close to but less than 1. The inverse of $1\text{-}\lambda$ is a measure of the memory of the RLS algorithm. Hence, the tap weight vector can be *w* [10].

$$\boldsymbol{w(n) = w(n-1) + k(n)e(n)} \quad (34)$$

III. SYSTEM MODEL

The MIMO-OFDM system was implemented with the aid of MATLAB/SIMULINK. The execution process is binary data that is modulated using BPSK and mapped into the constellation points. The digital modulation scheme will transmit the data in parallel by assigning symbols to each sub-channel and the modulation scheme will determine the phase mapping of sub-channels by a complex I-Q mapping vector [11]. The complex parallel data stream has to be converted into an analogue signal that is suited to the transmission channel. This is performed by the Inverse Fast Fourier Transform (IFFT). IFFT converts the signal to the time domain since OFDM treats the transmitted symbols as they are in the frequency domain. Assuming that the sub-channels number is *N*, the transmitted symbol *X(k)* is transformed to *x(n)* by IFFF as following:

$$\boldsymbol{x(n) = IFFT(X(k)) = \sum_{k=0}^{N-1} X(k) e^{\frac{2\pi nk}{N}} \quad n = 0, \ldots, N-1} \quad (35)$$

Each OFDM symbol is appended by a copy of 0.25% of IFFT size to the original OFDM symbol resulting in making the transmitted signal periodic, which plays a major role in avoiding ISI and ICI.

The transmitted symbol after adding the cyclic prefix is given in (26) below:

$$x_t(n) = \begin{cases} x(n) & n = 1,2 \ldots N \\ x(N+n) & n = -N_t, -N_t+1, ..1 \end{cases} \quad (136)$$

These symbols will be transmitted through the fading channel with impulse response *h(n)* that has additive noise *n*. The MIMO-OFDM system with A_t transmit and A_r receive antennas can be described as:

$$\boldsymbol{\begin{bmatrix} y_{t1}(n) \\ \vdots \\ y_{tA_r}(n) \end{bmatrix} = \left[\begin{bmatrix} h_{t11}(n) & \cdots & h_{t1\,At}(n) \\ \vdots & \ddots & \vdots \\ h_{tA_{r}1}(n) & \cdots & h_{tAr\,At}(n) \end{bmatrix}\right] \begin{bmatrix} x_{t1}(n) \\ \vdots \\ x_{tA_t}(n) \end{bmatrix} + \begin{bmatrix} n_1 \\ \vdots \\ n_{Ar} \end{bmatrix}} \quad (37)$$

The wireless fading channel consists of many parallel Gaussian sub-channels; hence it can be expressed as following:

$$\boldsymbol{h(n) = \sum_{q=0}^{Z-1} h_q\, e^{j\left(\frac{2\pi}{N}\right) f_{Dq} T_n} \delta(\tau - \tau_q) \quad n = 0, \ldots, N-1} \quad (38)$$

Z is the number of paths for the signal propagation, h_q is the amplitude response of path *q*, f_{Dq} is the Doppler shift of path *q*, τ_q is the delay of path *q*. Single path fading will omit the summation operator from the previous expression. At the receiver side, the received symbol $y_t(n)$ will be transformed back to the frequency domain *Y(k)* by FFT after omitting the cyclic prefix [10].

$$\boldsymbol{Y(k) = FFT(y(n)) = \sum_{n=0}^{N-1} y(n)\, e^{-j\left(\frac{2\pi kn}{N}\right)} \quad n = 0, \ldots, N} \quad (39)$$

The simulation model of the MIMO-OFDM used in the tests is shown in Fig. 5

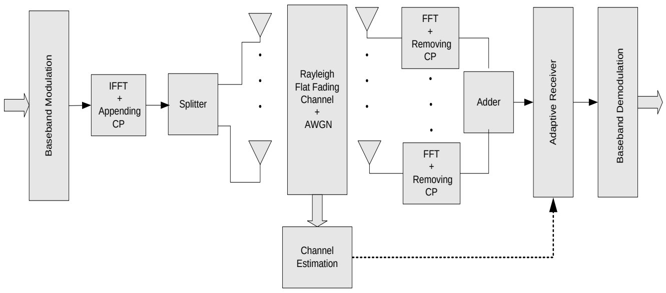

Fig. 5: 2x2 MIMO-OFDM system model with adaptive filter based on NLMS algorithm

The generated sub-channels will be modulated using BPSK, the number of sub-channels is 64, and the number of cyclic prefix is 16 sub-channels. The transmitted symbols will be sent by two antennas at the transmitter side and received by two antennas at the receiver side. The symbols will pass through Rayleigh fading channel. The sampling time is 10^{-6} sec. The power will be divided evenly among the two antennas at the transmitter. The NLMS adaptive filter at the receiver will compensate the effect of the communication channel on the transmitted symbols. The adaptive NLMS receiver subsystem is shown in Fig. 6. It comprises the OFDM demodulation, the NLMS adaptive filter, and then the received symbols were demodulated and I-Q de-mapped to obtain the original transmitted symbols.

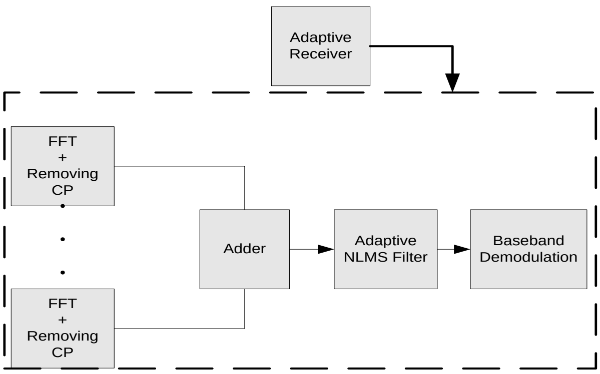

Fig. 6: Adaptive filter Receiver Structure

IV. SIMULATION RESULTS

The BER and MSE performances of the aforementioned NLMS adaptive receiver are explored by performing extensive computer simulations. In these simulations, we considered 2x2 MIMO-OFDM system. The data symbol is based on BPSK modulation. Various values of the NLMS algorithm's step-size have been used. The signal to noise ratio is 15 dB. First the BER performance of using different fixed step-sizes has been investigated and the results are shown in Fig. 7. It is clear that the step-sizes with values 0.3 - 0.6 give less bit-error-rate. Also the MSE performances, shown in Fig. 8, for various step-sizes have been investigated to measure the convergence speed of the NLMS algorithm. It is clear that both step-sizes of 0.3 and 0.4 give fast convergence while the step-size of 0.3 gives lowest MSE level. Hence the step-size of 0.3 was chosen as the best step-size since it provides a trade off between the convergence speed and the steady sate noise floor. Fig. 9 displays the performances of using the variable step-size approach in (20) for $\mu=1.99$ and $\mu=1$. When the unknown disturbance is zero, the optimal step-size in (18) will be 1 [9]. Therefore, the step-size parameter μ cannot be bounded over $\mu= 2$ [12]. Hence $\mu=1.99$ was selected as the highest value that can be bounded. The step-size $\mu=1$ results in the fastest convergence speed for the NLMS algorithm at the expense of a higher steady-state MSE.

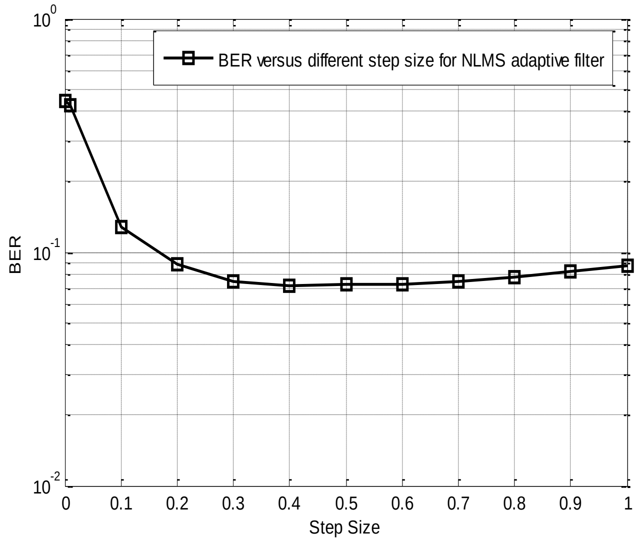

Fig. 7: BER versus different step-sizes

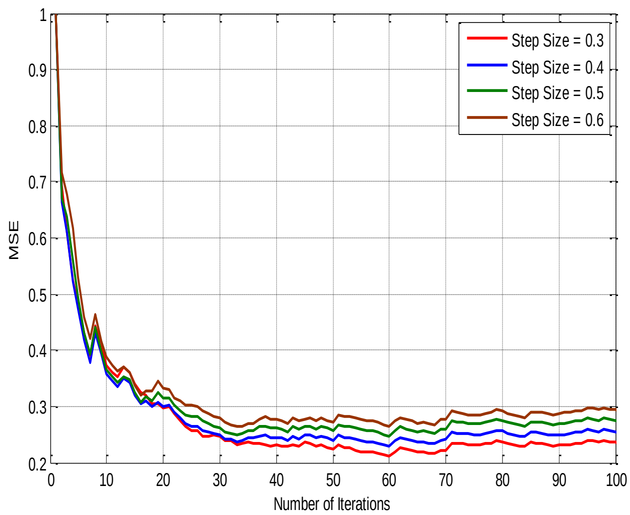

Fig. 8: Performances of NLMS for various fixed step-sizes

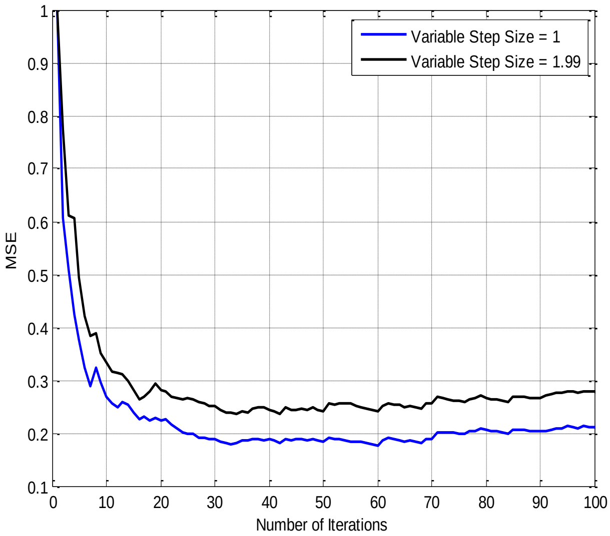

Fig. 9: Performances of variable step-size NLMS algorithm

From the results shown in Fig. 9, the step size $\mu = 1$ was chosen to compare the performance between the variable step-size and the fixed step-size. Simulation results in Fig. 10 have shown that the steady state MSE noise floor level of the proposed receiver is much lower than that of the conventional fixed step-size receiver.

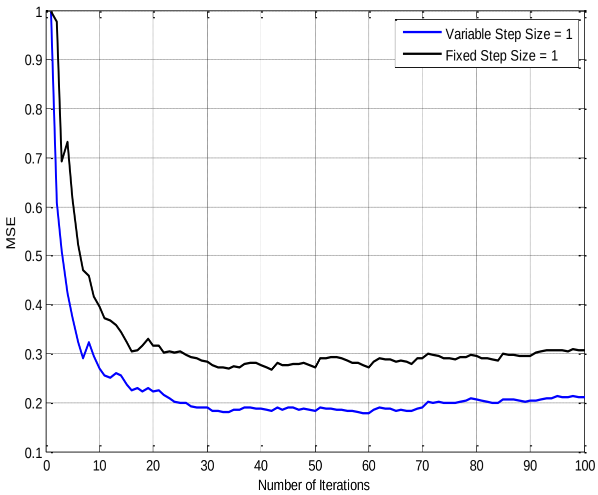

Fig. 10: Comparison of fixed and variable step-sizes in case of $\mu = 1$

Also to accurately highlight the superiority of the proposed receiver in terms of its convergence speed compared with the conventional receiver, a comparison between both receivers has been made at nearly the same noise floor level. The results in Fig. 11 clearly show that the convergence rate of the proposed method is faster than that of the conventional fixed step size NLMS algorithm.

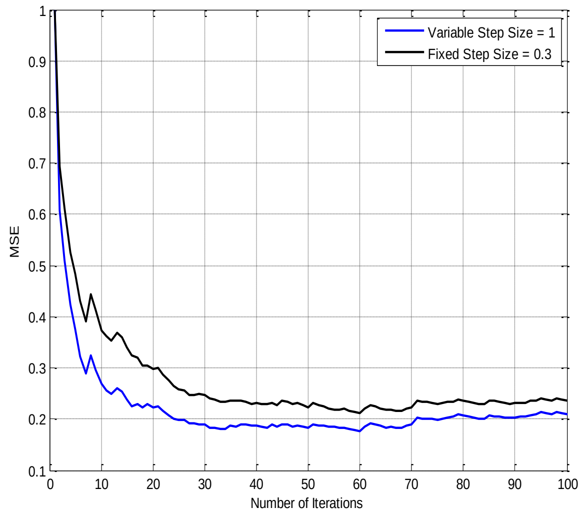

Fig. 11: Comparison of fixed step-size of $\mu = 0.3$ and variable Step-size of $\mu = 1$

The BER performances versus E_b/N_0 for the step-sizes of 0.3, 0.4, 0.5, and 0.6 and the variable step-size receiver with $\mu = 1$ have been investigated and compared with that of the conventional MIMO-OFDM receiver. It is clear that using the conventional receiver (i.e., without using the NLMS adaptive filter) the BER is almost 50% because the channel state information is not known at the receiver.

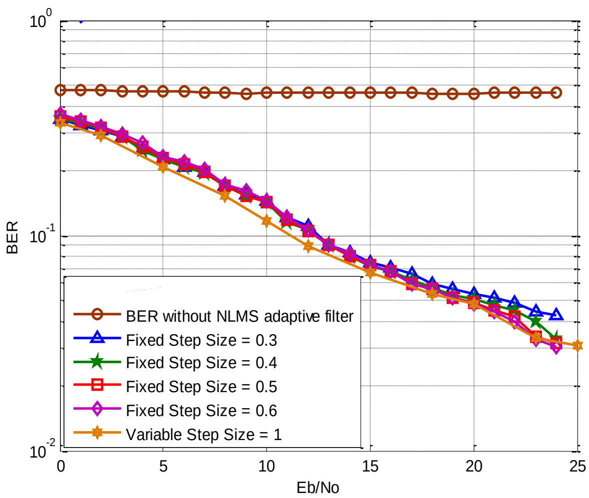

Fig. 12: BER performance versus E_b/N_0 for NLMS and VSNLMS

Also the MSE and BER performances of utilizing the RLS algorithm have been tested and compared with both the NLMS with fixed step-size and variable step-sizes algorithms. The results of the MSE performance are presented in Fig. 13, which show that the RLS convergence speed is faster with lower steady state noise level compared with the variable step-size NLMS algorithm. On the other hand, the performance of using the fixed step-size NLMS shows slow convergence speed and higher MSE steady state level. For the BER performance, Fig. 14 shows that utilizing the variable step-size NLMS provides better performance compared to that of the fixed step-size. Also the results show that using the RLS algorithm outperforms the other two algorithms at high SNR.

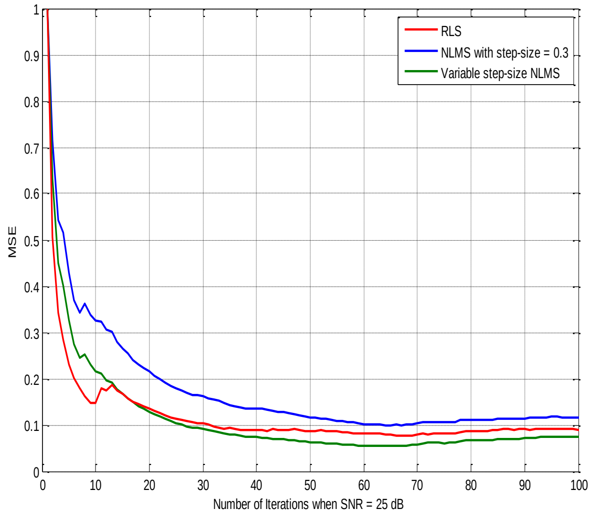

Fig. 13: MSE Performances of using different algorithms

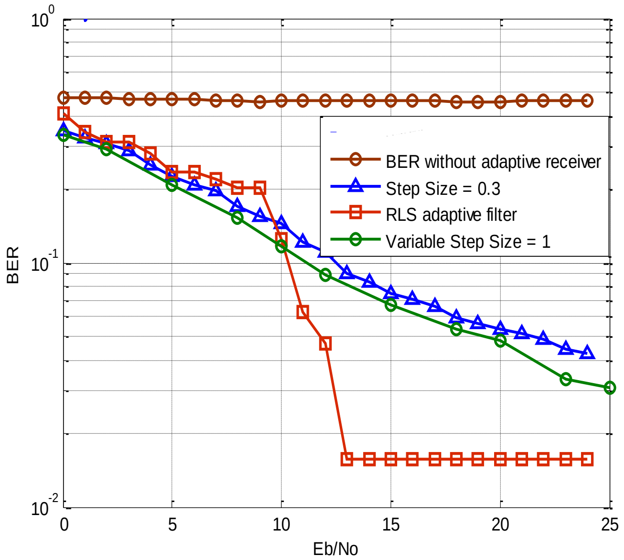

Fig. 14: BER performances versus E_b/N_0 for optimum fixed step-size NLMS, VSNLMS and RLS algorithms

V. Conclusion

The MIMO-OFDM has been simulated and tested, using MSE and BER performances, over fading channels. Three various adaptive algorithms in the adaptive receiver structure have been used. The MSE and BER performances of the proposed receiver structures against the conventional receiver have been investigated and extensive computer simulations results were presented. It can be concluded that the proposed receiver adopting the variable step-size NLMS achieved faster convergence are and lower BER in comparison with the fixed step-size NLMS algorithm. Also adopting the RLS algorithm provides fast convergence but higher MSE compared to the variable step-size NLMS. In terms of BER, the performance of using the RLS provides better performance at high SNR.

Future Work

The next direction is to tackle the simulations under multipath fading channels for the MIMO-OFDM communication system to extensively address the performance of the system under more realistic transmission mediums. It is possible to formulate a higher order MIMO-OFDM communication system to investigate the diversity gain and the system performance. The estimation based adaptive equalizer algorithm can be compared to the singular value decomposition in which, the MIMO channels can be decomposed into parallel channels with a prior knowledge of the channel gain matrix, adopting this approach could therefore be the main subject of the continuing research. The applications of the adaptive equalizer in other fields such as noise cancellation would be another extension to the work in this project.

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