Implementation of Variable Step-size LMS algorithm to track the frequencies of FSK

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Abstract— This paper deals with the implementation of Least Mean Square (LMS) algorithm and Variable Step-size LMS algorithm in Decision Feedback Equalizer (DFE) for removal of noisy signal at the receiver efficiently. The channel disrupts the transmitted signal by spreading it in time. Although, the LMS algorithm is robust and reliable, it is slow in convergence. In order to increase the speed of convergence, modifications have been made in the algorithm where the weights get updated depending on the Step-size parameter. Simulation results for the VSS is compared with the Conventional LMS and Performance is analysed.

Index Terms—Decision Feedback Equalizer, noisy signal, Variable Step-size, LMS.

I. Introduction

The field of digital communication is increasing day by day. There have been vast changes going on. Digital communication has proved itself to be more reliable and to have advantages over the analogue communication system. The achievements made by digital communication are robust and reliable. However, this field suffers from a major problem at the receiving end, which is known as Inter Symbol Interference (ISI) due to which one symbol overlaps with the subsequent symbols. A very common approach to overcome this problem is by using Decision Feedback Equalizer (DFE). The filters used here are adaptive filters where the coefficients get updated with the help of Least Mean Square (LMS) algorithm. The LMS algorithm is convenient due to its computational simplicity. However, it has very low convergence speed.

The main aim of this paper is to improve the existing algorithm in a way that would converge faster and produce a better mean square error. This is done by implementing some constrains in the filter coefficients updating criteria. According to simulation results, the improvements provide fast convergence of the algorithm and low mean square error. One of the first solutions to the elimination of ISI was to build a linear equalizer which mainly consists of linear filter and a threshold device.

To optimize the transmitter and receiver, the mean square error between the input and the output of the equalizer was minimized. To simplify the mathematical problem, zero forcing conditions and mean square error were used extensively. Basically the approach was to minimize noise variance using zero forcing constraint, minimize the mean square error and also minimize the probability of error [2].Nonlinear equalizers have also been used and have proven to have better performance over the simple linear types.

DFE is a non-linear equalizer. The feedback filter uses linear combination of previous outputs and uses them to minimize the mean square error. For simplification, it is assumed that the outputs which are used in the feedback part are correct [2] [1].An improvement to DFE was made by using BLMS (Block implementation of LMS) where a block adaptive filter was used instead of the sample by sample DFE. A problem in DFE is the huge computation complexity which is due to the long feedback part of the DFE. In this solution the signal is divided into blocks. To get small delays, the length of the block can be much smaller than the filter's order.

The block LMS based DFE is mathematically equal to the sample by sample version and at the same time offers a significant computational saving [3]. Decision feedback equalizers are very useful as sub-optimal solutions when the constellation size is large

and the channel memory is long, which is true in many current and next-generation communications systems. That decision feedback equalizers are implemented as FIR filters makes them especially attractive for processors such as the SC140 core, which have multiple ALUs, because multi-sampling can be used to implement FIR filters very efficiently.

II. LMS algorithm

Least mean squares (LMS) algorithms are a class of adaptive filter used to mimic a desired filter by finding the filter coefficients that relate to producing the least mean squares of the error signal (difference between the desired and the actual signal). It is a stochastic gradient descent method in that the filter is only adapted based on the error at the current time. convergence and mean in least mean square algorithm .

As the LMS algorithm does not use the exact values of the expectations, the weights would never reach the optimal weights in the absolute sense, but a convergence is possible in mean. That is, even though the weights may change by small amounts,changes about the optimal weights. However, if the variance with which the weights change, is large, convergence in mean would be misleading. This problem may occur, if the value of step-size μ is not chosen properly.

If μ is chosen to be large, the amount with which the weights change depends heavily on the gradient estimate, and so the weights may change by a large value so that gradient which was negative at the first instant may now become positive. And at the second instant, the weightmay change in the opposite direction by a large amount because of the negative gradient and would thus keep oscillating with a large variance about the optimal weights. On the other hand if μ is chosen to be too small, time to converge to the optimal weights will be too large. The block diagram for the LMS

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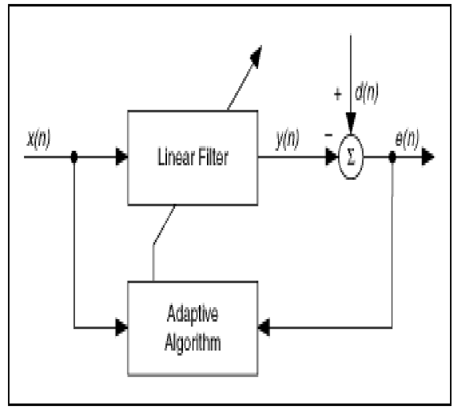


Fig 1: Block diagram of LMS

algorithm is given above, x(n) is the desired signal where d(n) is the received signal, e(n) is the error value obtained, w(k) is the weight updation value. the design of the algorithm is given as follows in the flowchart

III.VARIABLE STEP-SIZE LMS ALGORITHM

This algorithm is a modified form of LMS algorithm. Based on the step-size value the convergence and stability of the algorithm is determined. Hence this mu value plays an important role, the update equation varies in VSS-LMS.

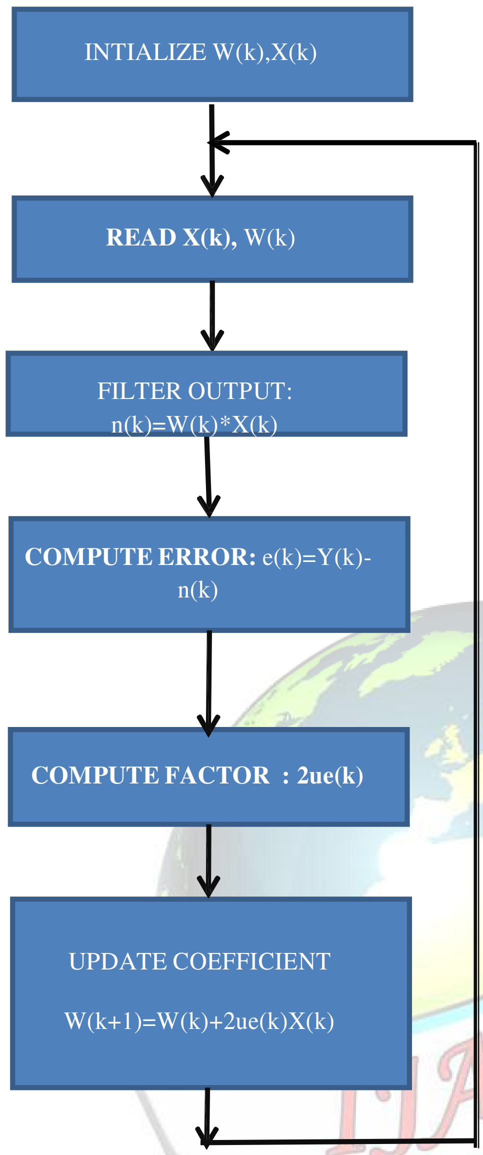


Fig 2. Flow chart for LMS

IV.Results and Discussion

Performance of the algorithm used in the decision feedback equalizer is compared, the simulations results are given which is discussed as follow. In fig.3 the output of the LMS algorithm is discussed

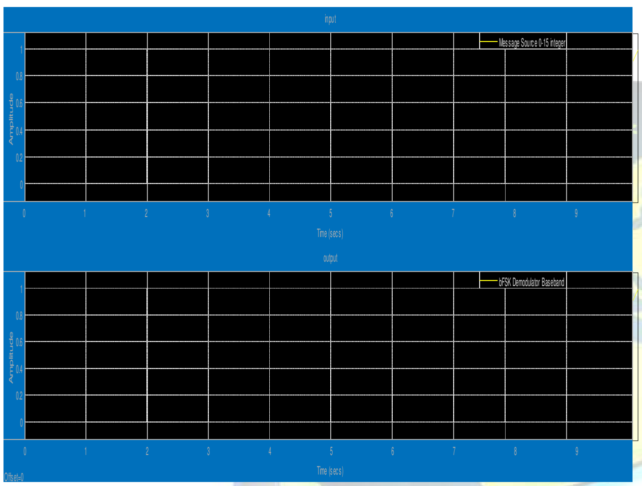
a)The input and output waveform is shown for the Conventional LMS algorithm whose step-size μ value is 0.3,here two signals are tracked by using DFE where the separation of frequency is 10,To obtain a less error value the step-size value has to be adjusted for this assumed value the output signal is received with noise, the amount of error can be reduced by setting an appropriate steep-size. However adjusted manually is a tedious process in many applications.

b)This plot shows the weight updation values of the algorithm for the received input signals, it shows how the weight values varies according to each adjustments in the adaptive algorithm, at the initial stage the values are equal to zero and the updation takes place after sometime it is shown

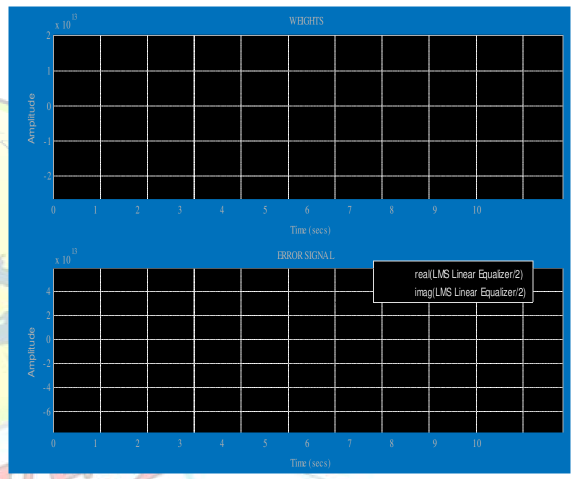
c) It shows the adaptive frequency response. **Frequency Response** of an electric or electronics circuit allows us to see exactly how the output gain (known as the magnitude response) and the phase (known as the phase response) changes at a particular single frequency, or over a whole range of different frequencies from 0Hz, (d.c.) to many thousands of mega-hertz, (MHz) depending upon the design characteristics of the circuit. Two applications of frequency response analysis are related but have different objectives. For an audio system, the objective may be to reproduce the input signal with no distortion. That would require a uniform (flat) magnitude of response up to the bandwidth limitation of the system, with the signal delayed by precisely the same amount of time at all frequencies. That amount of time could be seconds, or weeks or months in the case of recorded media. In contrast, for a feedback apparatus used to control a dynamic system, the objective is to give the closed-loop system improved response as compared to the uncompensated system. The feedback generally needs to respond to system dynamics within a very small number of cycles of oscillation (usually less than one full cycle), and with a definite phase angle relative to the commanded control input. For feedback of sufficient amplification, getting the phase angle wrong can lead to instability for an open-loop stable system, or failure to stabilize a system that is open-loop unstable. Digital filters may be used for both audio systems and feedback control systems, but since the objectives are different, generally the phase characteristics of the filters will be significantly different for the two applications.

d) It shows the filter tapping points while the coefficients of the weight values are changing. here the Frequency separation value is 10,step-size=0.3

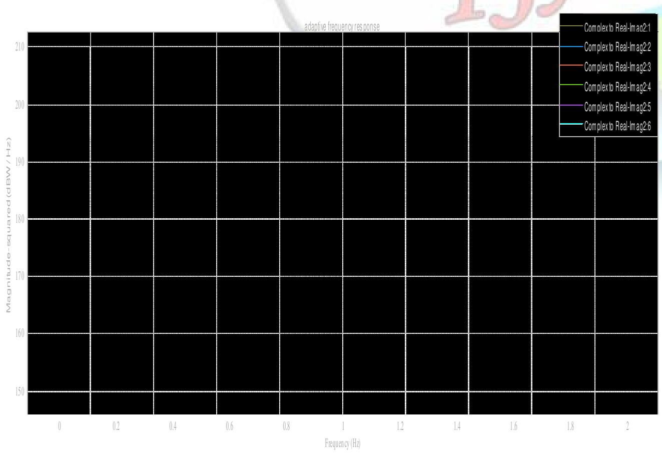
e)this fig shows the scatter plot of the BFSK signal, A scatter plot can be used either when one continuous variable that is under the control of the experiment and the other depends on it or when both continuous variables are independent. If a parameter exists that is systematically incremented and/or decremented by the other, it is called the control parameter or independent variable and is customarily plotted along the horizontal axis. The measured or dependent variable is customarily plotted along the vertical axis. If no dependent variable exists, either type of variable can be plotted on either axis and a scatter plot will illustrate only the degree of correlation between two variables



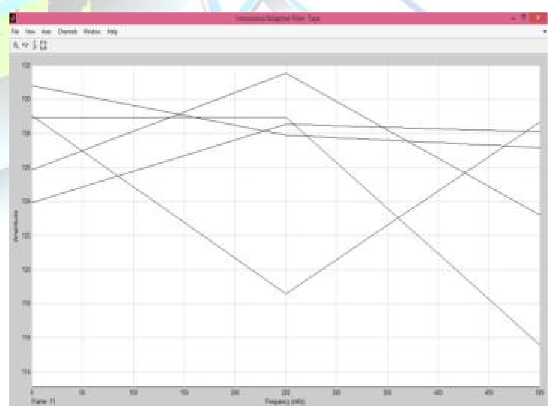
a. Input and output waveform



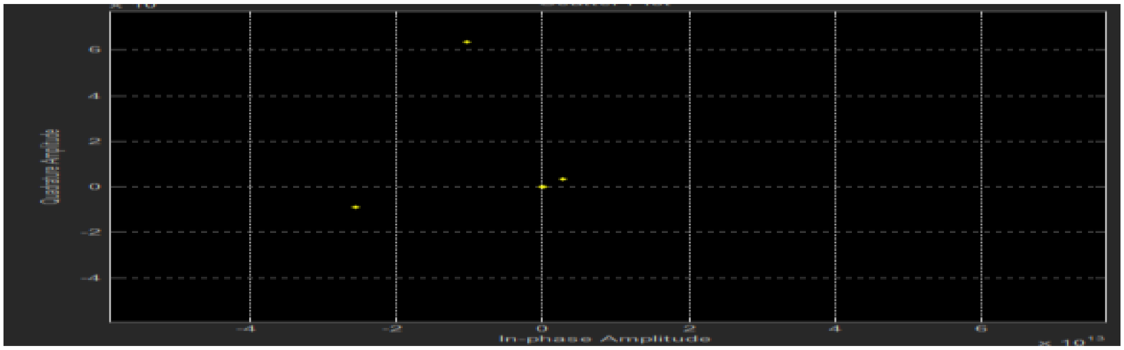
b. weight updation graph



c. Adaptive frequency response

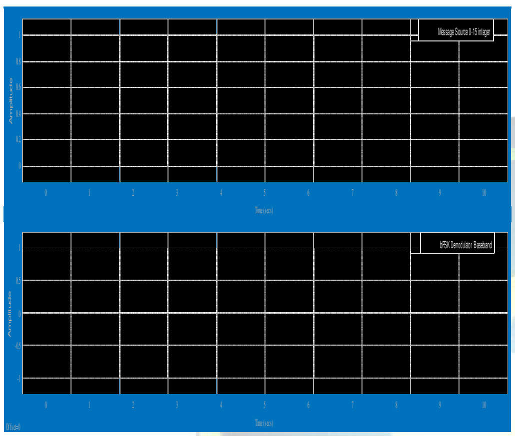


d. Adaptive filter taps

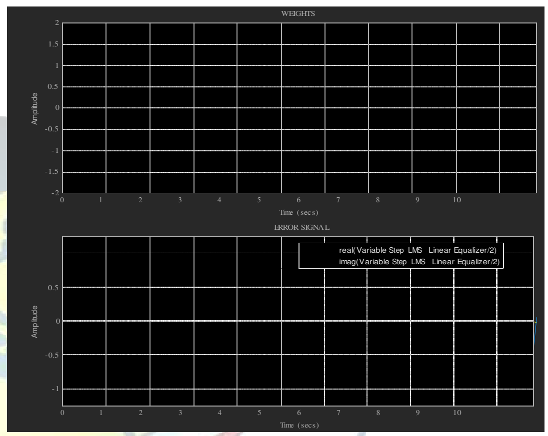


e. Scatter plot

Fig 3 LMS Algorithm Simulation results

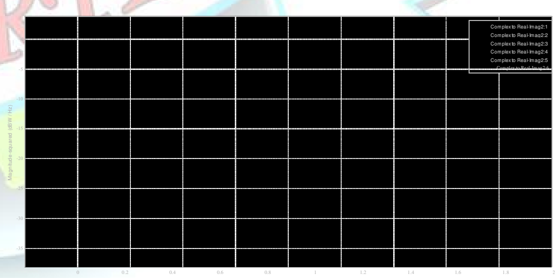


a. input and output waveform



b. weight updation waveform

C. Adaptive filter taps



d. Adaptive frequency response

e Scatter Plot

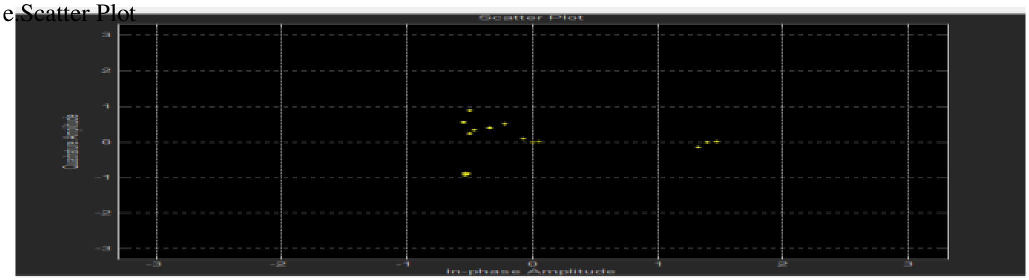


Fig 4 VSS-LMS Algorithm Simulation results

In the figure 4 the VSS-LMS output waveform is discussed, the error value obtained in LMS algorithm is more compared to VSS-LMS algorithm

a)The input and output waveform is shown for the VSS-LMS algorithm whose step-size μ value is varies between 0 t0 1,here two signals are tracked by using DFE where the separation of frequency is 10,To obtain a less error value the step-size value has to be adjusted for this assumed value the output signal is received with noise, the amount of error can be reduced because of the variable step-size.

b)This plot shows the weight updation values of the algorithm for the received input signals, it shows how the weight values varies according to each adjustments in the adaptive algorithm, at the initial stage the values are equal to zero and the updation takes place after sometime it is shown

c) It shows the adaptive frequency response, better response is obtained when compared to the above plot

d) It shows the filter tapping points while the coefficients of the weight values are changing. here the Frequency separation value is 10,step-size is variable

e) This fig shows the scatter plot of the BFSK signal, is used to visualize the constellation of a digital modulated signal.

V. Conclusion

In this paper performance of an improved LMS based DFE is compared with conventional LMS algorithm. Based on the results, we have shown that our improved method has higher convergence speed and less error in comparison with the existing LMS based DFE. Due to the improvements made, the new method can be useful in various applications specially those which include very long stream of transmitted data. The study can be further extended by applying more constraints in step size or combining the current approach with the block implementation of LMS based DFE.

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