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Comparative analysis of Adaptive Algorithms for Estimation of Unknown System Characteristics

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Abstract: This paper aims the method of estimating unknown system characteristics (desired signal) by using the system identification method. The design of such system belongs to the optimal filtering domain, which is originated from the work of Wiener. In such applications fixed or adaptive Filters can be used. Fixed filters designed based on system prior knowledge, but adaptive algorithm based filters consists the ability to adjust their own parameters automatically and can match their (unknown system) characteristics with desired system (known system) characteristics. Design of these adaptive systems not required any prior knowledge of system characteristics. In the proposed system parameters were estimated using various least square adaptive algorithms. Since a finite impulse response(FIR) filter only has zeros, is stable irrespective of the filter coefficients, this work selects a FIR filter as the base filter. The adaptive algorithm used is Least Mean Square (LMS) and various LMS algorithms like Normalized-LMS, Signed-LMS, Signed–Signed LMS, Signed data, Signed error etc. The proposed work used C software to develop System identification with adaptive FIR filter using various LMS algorithms and also implemented this model by using TMS320C6713 DSK for Real Time Applications. Texas Instrument (TI) assembly language can be obtained by using 3.1V Code Composer Studio (CCS).

Keywords: Adaptive algorithms, estimation of unknown characteristics, LMS, NLMS, signed error LMS, signed-data LMS, sign-sign LMS algorithm.

I. INTRODUCTION

Methods of Adaptive filtering are used in a various signal processing applications like echo cancellation, adaptive noise cancellation, adaptive equalization, system identification etc. An adaptive filter is a self-correcting filter that uses an adaptive based algorithm to “design itself”. In the proposed work an algorithm called LMS algorithm is used to develop an Adaptive system to estimate or identifies the unknown characteristics of the system, which includes a filter, called adaptive filter [1].

Adaptive filter output should be zero or less i.e. an adaptive filter has to minimize “error function” itself by using error correcting algorithms. This can be demonstrated by using FIR fixed system as unknown system shown in Figure.1 [2].

The adaptive system estimates the characteristics of unknown system and obtains same frequency responses as the given desired filter response like low pass filter or the given band pass filter. Bernard Windrow and Ted Hoff first proposed (LMS) adaptive algorithm in 1960 by its originators [3], [4].

LMS algorithm is the most widely used in various adaptive filtering algorithms due to its simplicity [5] i.e. robustness, low computational complexity and reliability to signal statistics. Unlike other adaptive algorithms, it doesn’t require complex computation like measurements of the pertinent correlation functions and matrix inversion. Adaptive filtering is more effective than linear filtering in cases where the signal information is not known (either statistically or exactly) or the conditions change with time. This is because adaptive filters are time varying and non-linear, with characteristics dependant on input, output, and/or environmental values.

The adaptation is brought about by altering the values of an array of adjustable weight elements at the input. The closed-loop adaptation is necessary as no prior knowledge of the input signal is available and it is required to track the error. Closed-loop adaptation is also more stable so, if part of the system fails then the adaptive filter will work around that part to keep the filter working as efficiently as possible.

A closed-loop system can be potentially troublesome where a performance surface has non-unique optima, as this introduces uncertainty as to the outcome. When designing a closed-loop system it is also important to keep the system stable by keeping the speed of the algorithm down far enough so that the output will not grow and diverge instead of converging on the minimum as it is supposed to.

The proposed system is application of System identification which uses an adaptive filter and shown in Figure.2. The Signal is corrupted by additive Noise, and a distorted but correlated version of the noise, is also available. The goal of the adaptive processor in this case is to produce an output y (n) that closely estimates the desired signal using various LMS algorithms[2], [3] which is known system, so that the overall output of adaptive filter will closely matches reference signal as Error will be minimized to zero [3], [5].

II. SYSTEM DESIGNING AND SOFTWARE

In the statistical approach to the solution of the linear filtering problem, we assume the availability of certain statistical parameters (i.e. mean and correlation functions) of the useful signal and unwanted additive noise and the requirement is to design a linear filter with the noisy data as input so as to minimize the effects of noise at the filter output according to some statistical criterion. A useful approach to this filter-optimization problem is to minimize the mean square value of the error signal defined as the difference between some desired response and the actual filter output For stationary inputs, the resulting solution is commonly known as the Wiener filter, which is said to be optimum in the mean-square error sense. Least Mean-Square algorithm (LMS) is the most used technique concerning adaptive filtering. The LMS algorithm updates the adaptive filter coefficients from sample to sample as expressed in the equation (1):

$$W_{k+1}=W_k+2\mu e_k X_k \quad (1)$$

Where, X and W is the input vector and coefficient vector of adaptive filter. μ is called step size parameter, which controls the convergence of the algorithm. e_k is the difference or error between the adaptive desired output and the actual output, it is used to adjust the filter coefficients. This work implements the LMS algorithm to design an adaptive filter for System Identification approach using a Texas Instrument digital signal processing (DSP) board. An adaptive filter is a nonlinear, Time varying, self-adjusting system. It is more complex and difficult to analyze compared to a fixed coefficient filter, but it offers substantially increased system performanc**e** when input signal characteristics are unknown or time varying. Adaptive filters are widely used in adaptive signal processing applications. Fixed filters are not suitable for such applications because the design of fixed filters must be based on prior knowledge of both the signal and the noise. While, adaptive filters have the ability to adjust their own parameters automatically, and there design requires little or no prior knowledge of signal or noise characteristics. An adaptive filter is composed of two important parts: a base filter and an adaptive algorithm. Since a finite impulse response (FIR) filter only has zeros, is stable irrespective of the filter coefficients, in the proposed work selected a FIR filter as the base filter. The adaptive algorithm used is the LMS algorithm, and the programming language used is C/C++ language. For real time implementation Texas Instrument (TI) TMS320C6713 assembly language can be obtained by using Code Composer Studio (CCS) [1], [6].

The General form of Adaptive filter structure is shown below in figure.1 and the algorithm used to update the filter coefficients is expressed in equation.2.[2]

$$W[n+1,k]=W[n,k]+2\mu\, e[n]\, X[n-k],\ k=0, 1,..., N-1 \quad (2)$$

Where, N is the number of taps (coefficients) of the adaptive filter. X[n-k] is the kth delay of the system input signal. W[n,k] is the kth filter coefficient at time n (at each time, there are N coefficients to be updated). Step size parameter μ is selected by trial. e[n] is the error signal shown in equation.3.

$$e[n]=d[n]-y[n] \quad (3)$$

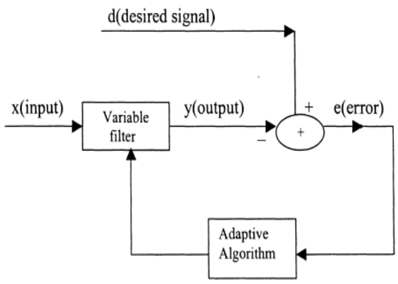

Figure (1): A General form of Adaptive filter

Here, d[n] is the output of unknown system i.e. desired system output; y[n] is the identified system output i.e. actual output of adaptive filter. e[n] is error between desired output and actual out of the systems shown in figure.1 used to estimate the characteristics of unknown system by update the coefficients of the adaptive filter. The most recent N input signals are stored in a consecutive memory location, and at each time, when a new signal comes in, the oldest signal will be shifted out from this part of memory, and the new signal will be shifted in. The adaptive filter actual output y (n) is the convolution of the adjustable filter impulse response h(n) and input signal x(n), which is expressed in equation.4.[3]

$$y(n)=\sum_{k=0}^{N-1} h(k)x(n-k) \quad (4)$$

The implementation is verified by a given finite impulse response(FIR) low pass filter and a band pass filter as "unknown" systems, using the adaptive filter to identify these “unknown" systems. So the desired system output d[n] shown in equation.5. [3]

$$d(n)=\sum_{k=0}^{M-1} h_d(k)x(n-k) \quad (5)$$

Where, $h_d(k)$ represents the desired system impulse response sequence. M is the number of taps of the desired system. The LMS algorithm is used to minimize the mean square error $E[e^2(n)]$. If the adaptive filter has the same frequency response as the given low pass filter or the given band pass filter, it will demonstrate that the adaptive filter is functionally adaptive to the "unknown" system. Algorithm implementation is correct if adaptive algorithm estimates the characteristics of unknown system shown in figure.2. [2]

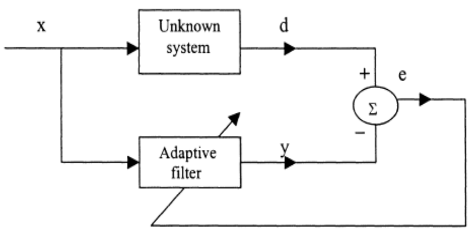

Figure (2): Estimation of unknown characteristics of an adaptive filter. A System Identification application

A. Mean-Square Error Criterion

Figure.2 illustrates a linear filter with the aim of estimating the desired signal d(n) from input x(n). Assume that d(n) and x(n) are samples of infinite length,

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random processes. The filter output is y(n) and the estimation error is given by e(n). The performance of the filter is determined by the size of the estimation error, that is, a smaller estimation error indicates a better filter performance. As the estimation error approaches zero, the filter output y(n) approaches the desired signal d(t) and coefficients of adaptive filter are matched with coefficients of unknown system and hence characteristics of the unknown system is estimated. Clearly, it is required that estimation error to be as small as possible. In simple words, in the design of the filter parameters, we choose an appropriate function of this estimation error as a performance or cost function and select the set of filter parameters, which optimizes the cost function [3]. In Wiener filters, the **cost function** [4] chosen shown in equation.6.

$$\xi = E[e(n)^2] \qquad (6)$$

Where, E [.] denotes expectation or ensemble average since both d(n) and x(n) are random processes shown in figure.3.

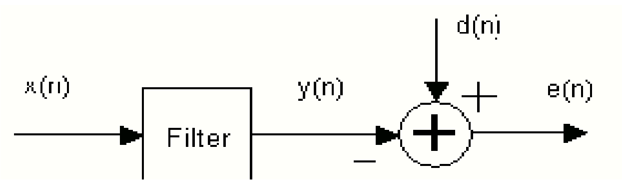

Figure.3: A linear adaptive filter used for estimating desired signal d(n).

B. Wiener Filter: Transversal, Real-Valued Case

Consider an adaptive transversal filter as shown in Figure.4. Assume that the filter input and the desired output are real-valued stationary processes [4], [9]. The filter tap weights $w_0, w_1, w_2 \ldots w_{N-1}$ are also assumed to be real-valued, where N equals the number of delay units or tap weights we can define the filer input x(n) and tap-weight vectors, w, as column vectors.[2]

$$X(n)=[x(n)x(n-1)x(n-2) \ldots x(n-N+1)]' \qquad (7)$$

$$W = [w_0 w_1 \ldots w_{N-1}]' \qquad (8)$$

The filter output is defined as,

$$y(n)=\sum_{i=0}^{N-1} w_i x(n-i)=w'x(n)=x'(n)w \qquad (9)$$

The mean square error cost function can be expressed in terms of the cross-correlation vector between the desired and input signals, $p(n) = E[x(n)\ d(n)]$, and the autocorrelation matrix of the input signal, $R(n)=E[x(n)x^T(n)]$

Subsequently, the error signal can be written as,

$\xi(n)=E[e^2(n)]$
$= E[(d(n)-y(n))^2]$
$= E[d^2(n) - 2d(n)w^T(n)x(n) + w^T(n)x(n)x^T(n)w(n)]$ $=E[d^2(n)]-2E[w^T(n)x(n)]+E[w^T(n)x(n)x^T(n)w(n)]$
$=E[d^2(n)]-2w^T p+w^T Rw$ (10)

When applied to FIR filtering the above cost function is an N-dimensional quadratic function [6]-[9]. The minimum value of $\xi(n)$ can be found by calculating its gradient vector related to the filter tap weights and equating it to 0 shown in equation.11.

$\frac{\partial}{\partial w_i} = 0$ for $i = 0, 1, 2, \ldots, N-1$

$$\nabla=\left[\frac{\partial}{\partial w_0}\ \frac{\partial}{\partial w_1} \ldots \ldots \frac{\partial}{\partial w_{N-1}}\right]^T$$

$$\nabla\xi = 0 \qquad (11)$$

By finding the gradient of equation.11 equating it to zero and rearranging gives us the optimal wiener solution for the filter tap weights w_0 shown in equation.12.

$$\nabla\xi = 0$$
$$2Rw_0\text{-}2p=0$$
$$w_0=R^{-1}p \qquad (12)$$

The optimal wiener solution is the set of filter tap weights, which reduce the cost function to zero. This vector can be found as the product of the inverse of the input vector autocorrelation matrix and the cross correlation vector between the desired signal and the input vector. The Least Mean Square algorithm of adaptive filtering attempts to find the optimal wiener solution using estimations based on instantaneous values. Where, w_0 indicates the optimum tap-weight vector. This equation is known as the Wiener-Hopf equation and can be solved to obtain the tap-weight vector which corresponds to the minimum point of the cost function shown in equation.6.

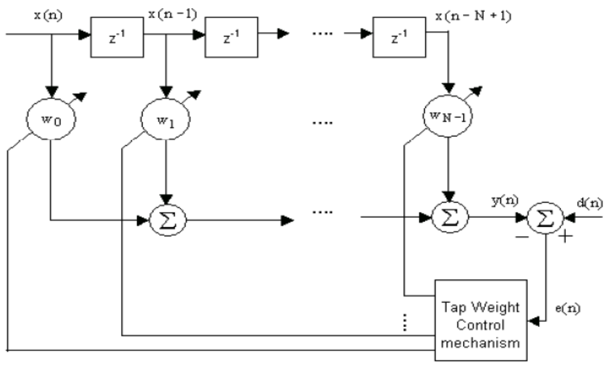

Figure.4: Structure of an Adaptive Transversal Filter [3], [9].

C. Least Mean Square (LMS) Algorithm

1). Derivation of LMS algorithm [8]: The conventional adaptive LMS algorithm is a stochastic implementation of the Method of Steepest Descent algorithm. It has derived by replacing the cost function [1], [2], [3].

$$\xi=E[e(n)^2]$$

The optimum weight vector is given in equation.12

$W_0=H^*=R^{-1}p$

The gradient vector is,

$$\nabla= 2RH - 2p \qquad (13)$$

Multiply equation.13 by $\frac{1}{2}R^{-1}$, we get equation.1

Since, $H^* = R^{-1}p$ from equation.12 and equation.13 we get the useful result of:

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$$H^{*} = H - \frac{1}{2}R^{-1}\nabla \quad (14)$$

Equation.14 Changes this result into an adaptive algorithm as:

$$H_{k+1}=H_k - \frac{1}{2}R^{-1}\nabla_k \quad (15)$$

Equation.15 modified to equation.16. The following algorithm expresses the method of steepest descent

$$H_{k+1} = H_k + \mu(-\nabla_k) \quad (16)$$

µ is a constant that regulates the speed and stability of adaptation. for detailed information about selection of µ, This work selects µ by trial.

$$\hat{\nabla}_k = \frac{\partial e_k^2}{\partial H} = 2e_k \frac{\partial e_k}{\partial H} = -2e_k X_k \quad (17)$$

From equation.16, equation.17 we can define a steepest descent type of adaptive algorithm as shown in equation.18. [5]-[9]

$$H_{k+1} = H_k + 2\mu e_k X_k \quad (18)$$

Equation.18 represents LMS algorithm [2]. This algorithm does not require the prior knowledge of the signal statistics; instead, it uses instantaneous samples.

$$X_k = \begin{bmatrix} x_{k-0} \\ x_{k-1} \\ . \\ . \\ x_{k-(N-1)} \end{bmatrix}; H = \begin{bmatrix} h(0) \\ h(1) \\ . \\ . \\ h(N-1) \end{bmatrix}$$

Therefore,

$$H_{k+1} = \begin{bmatrix} h_{k+1}(0) \\ h_{k+1}(1) \\ . \\ . \\ h_{k+1}(N-1) \end{bmatrix}; H_k = \begin{bmatrix} h_k(0) \\ h_k(1) \\ . \\ . \\ h_k(N-1) \end{bmatrix}$$

So, from above equation (3.16) we get:

$$\begin{bmatrix} h_{k+1}(0) \\ h_{k+1}(1) \\ . \\ . \\ h_{k+1}(N-1) \end{bmatrix} = \begin{bmatrix} h_k(0) \\ h_k(1) \\ . \\ . \\ h_k(N-1) \end{bmatrix} + 2\mu e_k \begin{bmatrix} x_{k-0} \\ x_{k-1} \\ . \\ . \\ x_{k-(N-1)} \end{bmatrix}$$

Let n stand for the time instant, k stand for the k^{th}element of input vector X and weight vector H or W. we get the following equation to update the k^{th} coefficient at time n+1. Finally, the coefficient updating algorithm and say W is H and we can write as. [2], [4].

$$W_{k+1} = W_k + 2\mu e_k X_k \quad (19)$$

$$W[n+1,k] = W[n,k] + 2\mu e[n] * X[n-k], \text{ k=0,1,..,N-1} \quad (20)$$

Equation.20 is the algorithm used in proposed work. From, equation.20 we can see, at each time n, there are N coefficients to be updated. LMS adaptive algorithm popularly used in adaptive signal processing. Since, adaptive filter is one of the most important elements in all-adaptive applications. The steps involved in design of an adaptive are calculation of filter output, error estimation and tap-weight adaption which are shown in equation.21-23[2]

The proposed work implements the LMS algorithm to design an adaptive filter [2], [5]-[9].

1. Filter output: y (n) =w' x (n) (21)
2. Error Estimation: e (n) =d (n)-y (n) (22)
3. Tap-weight adaption: w (n+1) =w (n) +µ e (n) x (n) (23)

And also tap-weight adaptions for different lms algorithms are given in equation.24-27 [2], [3], [8].

$$Signed\ error: w(n+1)=w(n)+ \mu * sign(e(n) * x(n) \quad (24)$$

$$Signed\ data: w(n+1)=w(n)+ \mu * e(n) * sign(x(n) \quad (25)$$

$$Dual\ signed: w(n+1)=w(n)+ \mu * sign(e(n) * sign(x(n)) \quad (26)$$

$$NLMS: w(n+1)=w(n) + \mu_1 *e(n)*x(n) \quad (27)$$

Where,

$$\mu_1 = \left(\left(\frac{beta}{0.01 + abs(x(n) * x(n))}\right)\right)$$

2). Step Size Parameter µ: Apparently, the convergence rate and asymptotic performance of the LMS algorithm are directly dependent on the step size parameter µ used in the tap weight adaptation formula shown in equation.20. When the step-size parameter increases, the LMS algorithm converges faster with worse asymptotic performance. Similarly, when the step-size parameter decreases, the LMS algorithm converges slower with better asymptotic performance [6]-[9]. The behaviour of varying the step-size is illustrated in Figure3. In addition, to ensure the stability (or convergent) of the LMS algorithm [7]; the step-size parameter is bounded shown in equation.28.

$$0 < \mu < \frac{2}{tap - input\ \ power} \quad (28)$$

Where, tap-input power is the sum of the mean-squared values of all the tap inputs in the transversal filter and is given in equation.29.

$$\sum_{k=0}^{N-1} E[\ |x(n-k)|^2\ ] \quad (29)$$

Note that the upper bound is dependent on the statistics of filter input signals [4], [7]. Intuitively, we may interpret from this equation that when the power of the input signals varies greatly, a smaller step-size is required to avoid instability or gradient noise amplification [7].

III. SYSTEM FLOW CHART

The figure.5 shows flowchart of the proposed work using LMS algorithm based adaptive filter design and flow charts of various LMS based adaptive filters can be represent by using appropriate mathematical functions shown in equation.23-27 for signed error LMS algorithm, Signed data LMS algorithm, dual signed LMS algorithm and Normalized LMS algorithms respectively. In the proposed work logical flow of estimation of unknown system characteristics will be

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as follows. Get the sample of unknown system i.e. desired system d(n) shown in equation.1. Calculation of output sample of adaptive filter y(n) using equation.2. Compute error using equation.22, equation.1 and equation.2. Compute the factor 2μe(n) and update the coefficient using equation.20 where, H=W in the proposed system from equation16-19. Calculate the error of desired signal and estimated signal continues the process until adaptive filter characteristics matches with the characteristics of unknown system.

IV. RESULTS

The experimental results show a system identification technique where desired signal has given as reference for adaptive system and input signal is given to the adaptive filter. The main aim is to identifying fixed system by using adaptive filter and the adaptive algorithms used are LMS, NLMS algorithms and various Quantized error algorithms. The adaptive filter keeps tracking the behaviour of an unknown system's input and output, as shown in figure.1. The output of adaptive filter $y(n)$ is going to be as close as the unknown system's output $d(n)$. Since both the unknown system and the adaptive filter use the same input shown in figure.2, the transfer function of the adaptive filter will approximate that of the unknown system reference and is given to the DSP kit, where the actual adaptation takes place using LMS algorithm.

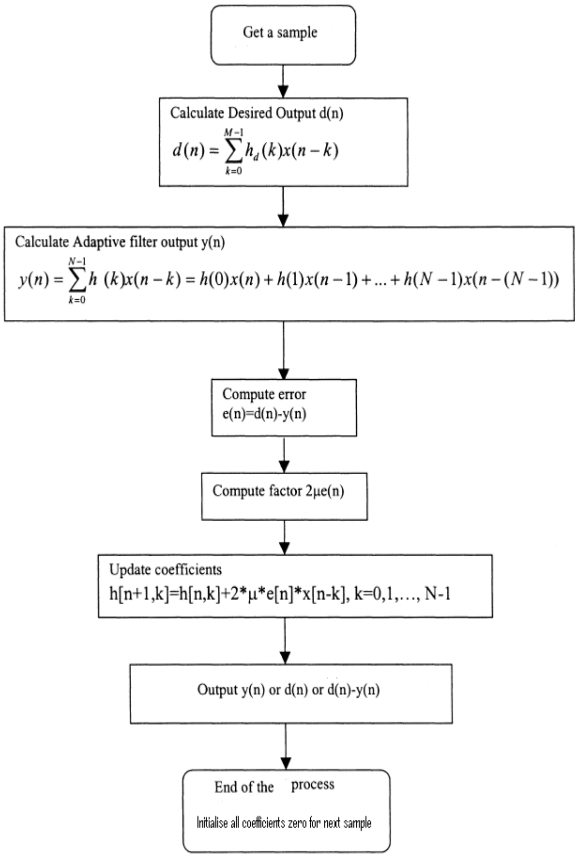
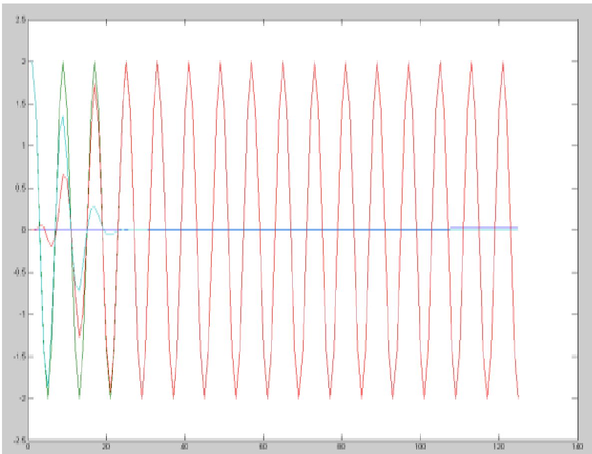


Figure.5 flow chart of weight adaption of adaptive filter coefficients using LMS algorithm

The proposed work focused on enhancing the performance of an LMS-based FIR adaptive filter for identifying the unknown system. The key reasons for selecting LMS as the adaptive algorithm is, Simplicity i.e. low computational cost and ease of implementation, Robust and Reliable. Moreover, the LMS algorithm can be easily modified to the quantized error algorithms like sign–data, signed-error, and dual sign algorithms and NLMS algorithm.

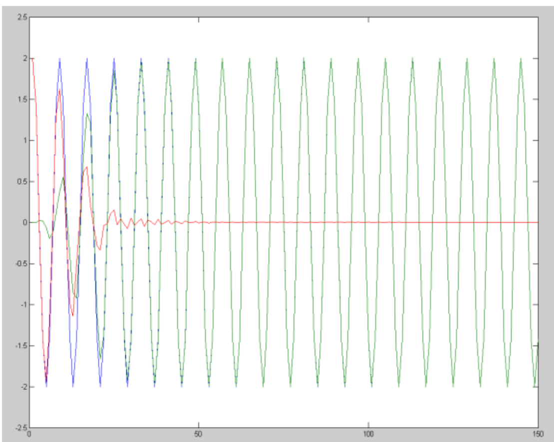
A good performance of the system identification is based on its step size. For lower step size it will give a good result but take more time to reach convergent condition. If the step size is higher than the optimum one the convergent condition will be faster, but the system does not give a good result. Here, x- axis indicates samples and y- axis indicates magnitude.

A. LMS Algorithm plots:



x- axis: samples; y- axis: magnitude
Figure.6:Fs=8000,d(n)=2*sin(2*pi*T*1000/Fs);μ=0.06; i/p=NOISE =cos(2*pi*T*1000/Fs); Ns=samples=125
Figure.6 shows improved result for desired, estimated and error signals and for these specifications for the step size 0.06.
System given improved performance with compared to other step size parameters.

B. Quantized LMS algorithm plots:
Figure.7 shows some improved results of signed data LMS algorithm and for μ=0.022906 it giving good results. Figure8-9 **shows** some improved results of dual sign LMS algorithm.



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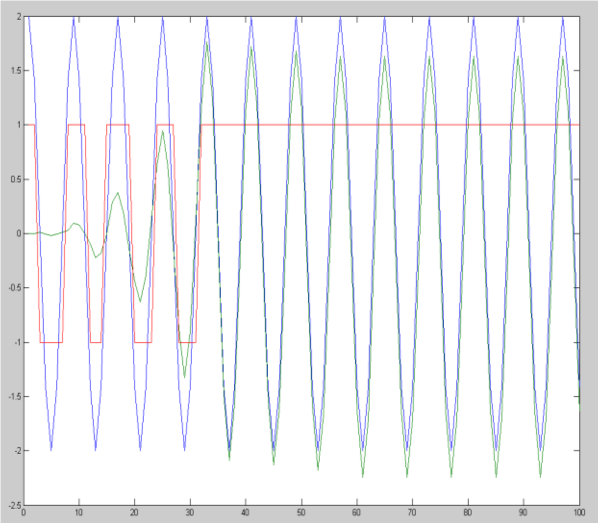
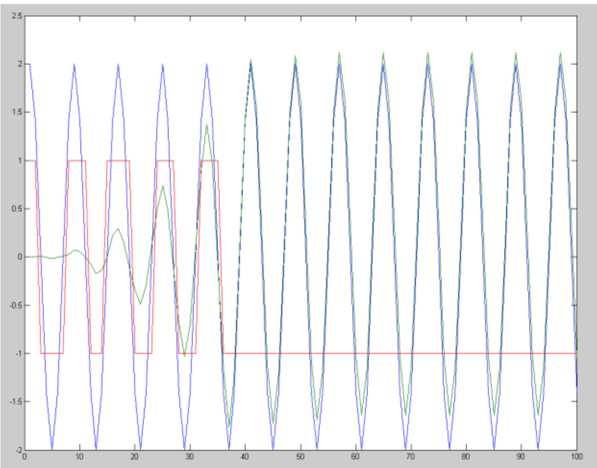
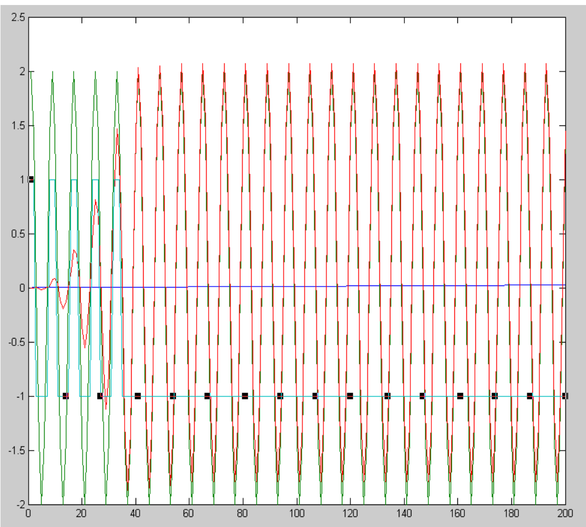
x- axis: samples; y- axis: magnitude
Figure.7 μ=0.022906; samples=Ns=150; Fs=8000



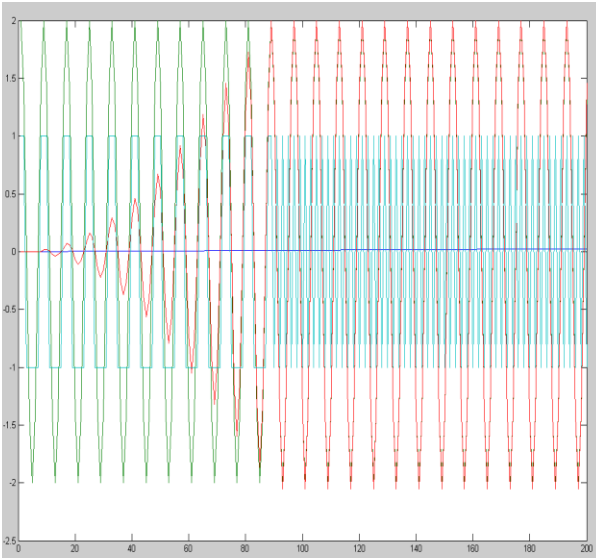
x- axis: samples; y- axis: magnitude
Figure.8: μ= 0.009 and order =55 ; samples =100 and Fs=8000 i/p cos(x) and o/p 2*sin(x)



x- axis: samples; y- axis: magnitude
Figure.9: μ =0.007 and order 55 samples 100 and Fs=8000 I/p cos(x) and o/p 2*sin(x)



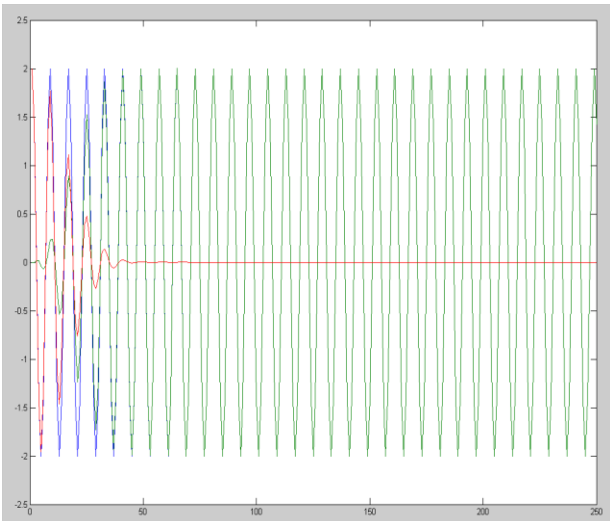
x- axis: samples; y- axis: magnitude
Figure.10 Fs=8000 ; μ=0.01; samples=Ns=200



x- axis: samples; y- axis: magnitude
Fig 11 Fs=8000; μ=0.002; samples=Ns=200;

Figure.10-11shows good performance of signed error lms algorithm and the adaptive system tracks desired signal and for step size value 0.01 system is fast but tracking performance is not good but for μ=0.002 it is taking more time to get steady state in the same time error fluctuated and giving good tracking performance. Figure.12-15 shows good performance of normalized LMS algorithm and the adaptive system tracks desired signal. Step size values 0.000605 gives improved tracking performance compared to other values of step size parameter. Figure.16 indicates comparison of error performance for different adaptive algorithms for NLMS algorithm μ = 0.0006 and NLMS gives improved results with compared to other adaptive LMS algorithms for same step size parameter and filter size.

C. Normalized LMS algorithm plots



x- axis: samples; y- axis: magnitude
Figure.12 beta μ= 0.0002 and μ 0.01; samples=200

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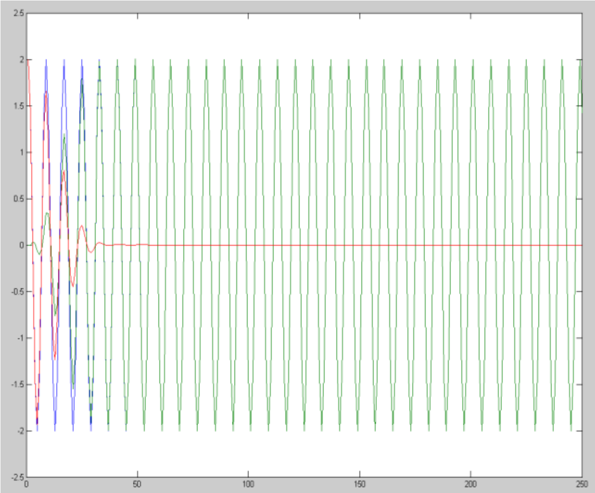
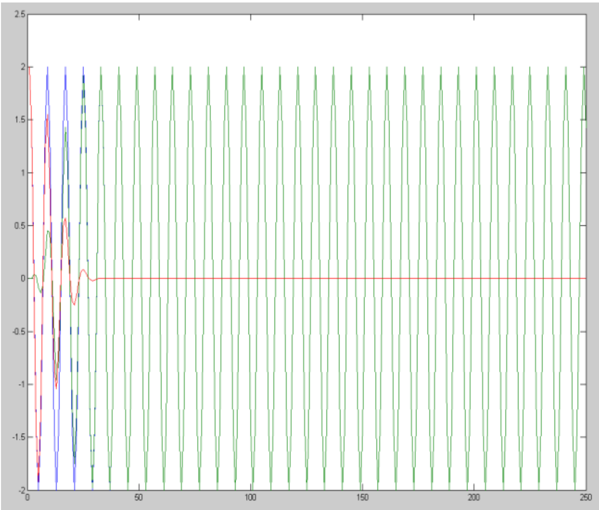
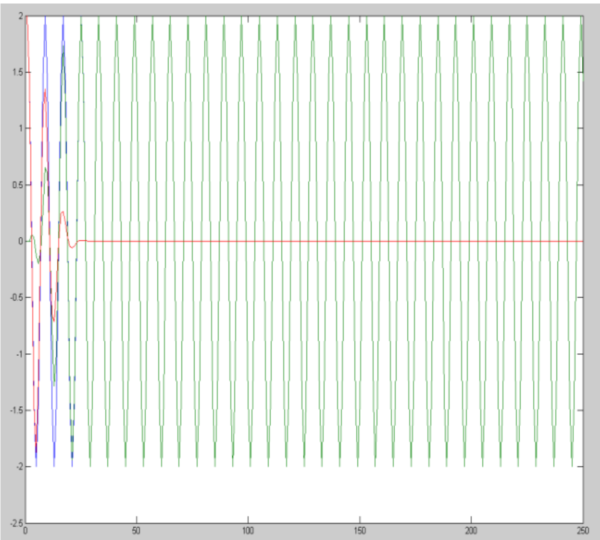


x- axis: samples; y- axis: magnitude
Figure.13 beta 0.0003 and μ as 0.01; samples=200

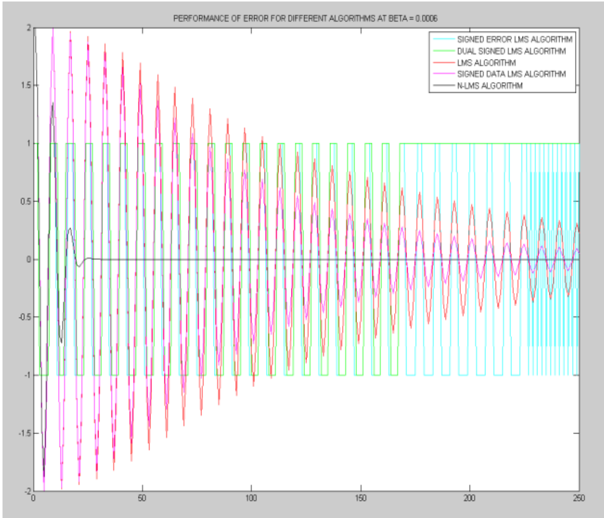
Figure.17: Fixed system having impulse response coefficients of Band Pass filter output of unknown system i.e. desired signal proposed system shown in figure.2.



x- axis: no of samples; y- axis: magnitude
Figure.14 beta 0.0004 and μ 0.01 samples = 200

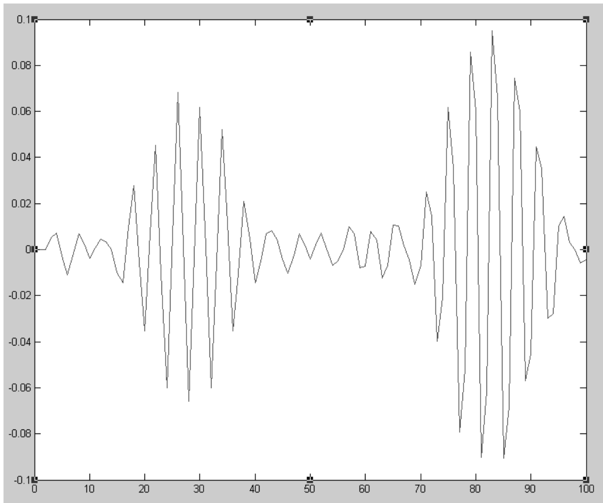


x- axis: no of samples; y- axis: magnitude
Figure 15 beta 0.000605 and μ = 0.01; samples=200



x- axis: no of samples; y- axis: magnitude
Figure.16: comparison of error signal for various LMS algorithms at same step size parameter value μ=0.01.

E. Desired signal of adaptive system:



x- axis: no of samples; y- axis: magnitude

F. Estimated signal by lms adaptive filter:

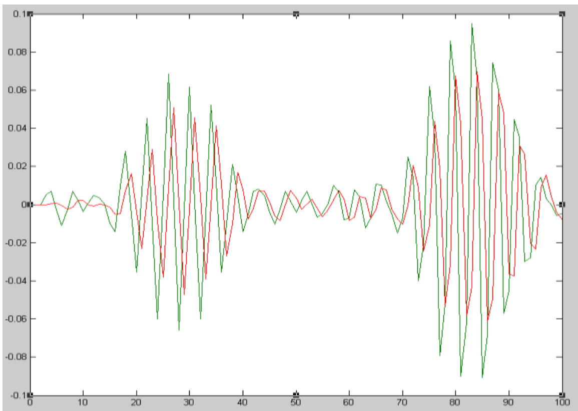


Fig.17 Beta=0.06; N=21; NS=samples=100; Fs=8000.

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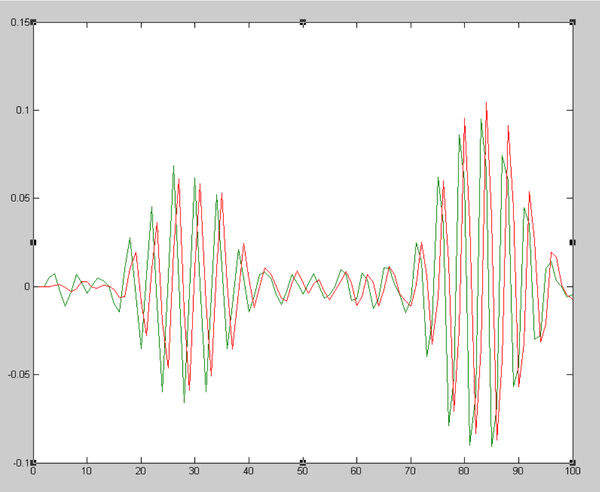

x- no of axis: samples; y- axis: magnitude
Fig.18 Beta=0.08; N=21; NS=samples=100; Fs=8000.

Figure.18-19 shows the response of system identification having unknown system as 55 coefficient band pass fir filter and we got good tracking performance at step size parameter 0.08 than 0.06 with the filter order N=21

V. CONCLUSION OF THE SYSTEM

The proposed system was successfully implemented using LMS, NLMS and various quantized LMS algorithms. The same system was implemented for both the systems proposed shown in figure.1 and figure.2. Figure.6-15 gives the results of proposed system shown in figure.1. NLMS algorithm given improved results with compared to other algorithms. Figure.15. gives the comparative study of various adaptive algorithms at same step size parameter. Figure.16-18 gives the results of proposed system shown in figure.2. The proposed system demonstrated with considering band pass filter as unknown system and the output of band pass filter will be desired signal and the adaptive filter matches its output with the desired signal hence the characteristics of unknown system has been estimated using proposed system. Same system was implemented on real time using TMS320C6713 processor using LMS algorithm at step size value at $\mu = 0.6$.

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