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Channel Estimation Algorithm For Multi Input Multi Output System To Reduce The Mean Shift Error And Improve The Desired Signal Quality

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Abstract: **The appropriate choice of the convergence factor in the Least Mean Square (LMS) and recursive least-squares (RLS) algorithm with the forgetting factor in the are key to assuring good performance for the adaptive filter. These choices are environment dependent and optimal ked values for these factors are difficult to determine especially in non stationary environments (High Noise). In this paper, 3 adaptive filtering algorithms with variable convergence factor are analyzed. We compare Least Mean Square algorithm (LMS), Recursive Means Square algorithm (RMS) and our proposed algorithm. The relations of these algorithms with the conventional LMS algorithm are first addressed. Their performance in stationary and non stationary environments is studied and then compare with one exiting and one proposed algorithm. Our Proposed algorithm reduces the noise effect and MSE on signal and gives better desired output as compare to existing algorithms. The paper concludes with experimental results analysis presented.** ***Keywords:*** **Static hand gesture, Fourier Descriptors, Support Vector Machine, Classification Accuracy.**

Index Terms— **Adaptive Filtering, adaptive algorithm, Least Mean Square (LMS), Normalized Recursive Least Squares (RLS) *and noisereduction.***

I. INTRODUCTION

*T*here are many digital signal processing (DSP) algorithms for optimizing the input signal and gets desired signal. Such algorithms include channel equalization echo cancellation and noise cancellation like LMS, RLS and LMSN etc. In these algorithms, filters with adjustable coefficients called Adaptive filters. An adaptive filter is a filter that self adjusts its transfer function according to algorithm. It adapts the performance based on the input signal. Such filters incorporate algorithms that allow the filter coefficients to adapt to the signal statics. There are different approaches used in adaptive filtering, which are as follows

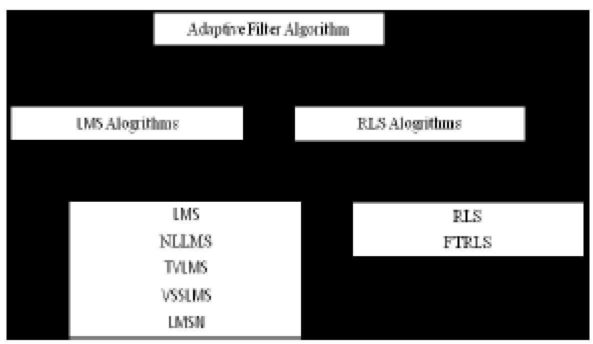


FIG. 1 TYPES OF ADAPTIVE FILTER ALGORITHMS

Adaptive techniques use algorithms, which enable the adaptive filter to adjust its parameters to produce an output that matches the output of an unknown system. This algorithm employs an individual convergence factor that is updated for each adaptive filter coefficient at each iteration. This algorithms reduce the mean square error and noise, provide desired signal, which are best to known.

Channel estimation is based on the training sequence of bits and which is unique for a certain transmitter and which is repeated in every transmitted burst. The modulated corrupted signal from the channel has to be undergoing the channel estimation using Least Mean Squares (LMS), Normalized LMS (NLMS), Variable Step Size LMS (VSS LMS), Recursive Least Squares (RLS), Least Mean-Squares Newton (LMSN) Algorithm etc before the demodulation takes place at the receiver side. The channel estimator is shown in figure 2.

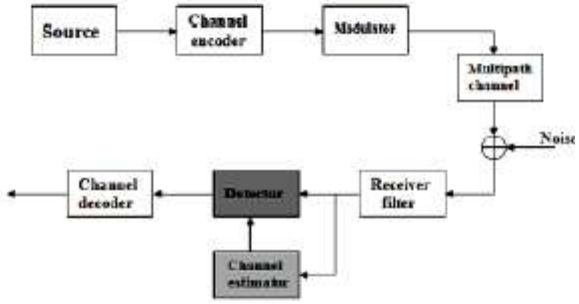


FIG. 2 THE BLOCK DIAGRAM OF THE CHANNEL ESTIMATOR

In communications especially in wireless communications, interference is anything which modifies, or disrupts a signal as it travels along channel between a source and a receiver. The term typically refers to the addition of unwanted signals to a useful signal.

II. CHANNEL ESTIMATION ALGORITHMS

Adaptive CE is one the most important current research interests in the wireless communications where the channel is rapidly time-varying. An adaptive algorithm is a process that changes its parameter as it gains more information of its possibly changing environment. This method tries to adjust the filter parameter in such a way that minimizes the Mean square error (MSE) between the output of the filter and the desired signal. Therefore, the adaptive filter parameters are entirely known, replicates the system in question whose parameters are unknown. In other words, the parameters of the adaptive filter give a good approximation of the parameters of the unknown scheme. The performance of this type CE algorithm is dependent on the convergence towards the true channel coefficients, computational complexity as well as minimum MSE performance [14].

A.Least Mean Squares (LMS) Algorithm

LMS algorithm has been the most popular as it is simple and effective. However, a limiting factor of LMS is that if the step-size of the algorithm is kept high then the algorithm converges quickly but the resultant error floor is high. Lowering the step-size is results in improvement in the error performance but the speed of the algorithm becomes slow [15]. Least Mean Square (LMS) algorithm used in the area of automatic control, radar, signal processing.
LMS algorithm is given by the following iteration equation

$y(n) = WT(n)\,X(n)$;
$e(n) = d(n) - y(n)$;
$W(n+1) = W(n) + 2\mu\, e(n)\, X(n)$…………………(1)

Where **y (n)** is the output of adaptive filter, **W (n)** is the weight coefficient vector of adaptive filter, **X (n)** is the input vector, **d (n)** is the desired output, **e (n)** is the error signal, and μ is the step-size. LMS algorithm can converge when $0 < \mu < 1/\lambda$, in which $\boldsymbol{\lambda}$ is the maximum Eigen value of input signals' autocorrelation matrix.
In all practical applications, the signals involved might be corrupted by noise. When the noise is present in the received sequence, interference will also in the coefficients adaption process through the error. As a result, where the distribution of the noise is highly impulsive, the LMS scheme might have low convergence and lower steady state MSE performance. The step size parameter, μ determines the convergence rate of the algorithm and higher value provides faster convergence. However, if μ exceeds certain bound then the algorithm will diverge. As the bound on μ is not known a priori and is dependent on the various statistics. In practice, a somewhat conservative scalar value of μ is used. Also a higher value of μ results in higher variations in the tap weight vector estimate after the initial convergence phase. Such variations result in increased distortion in the combined output which in turn results in an increased MSE [7], [15].

B. Normalized LMS (NLMS) Algorithm

The main problem of the LMS CE algorithm is that it is sensitive to the scaling of its input signals. This makes it very hard to choose μ that guarantees stability of the algorithm. The NLMS is a variant of the LMS algorithm that solves this problem by normalizing with the power of the input signal. The NLMS algorithm can be summarized as [11] [15].

$y(n) = WT(n)\,X(n)$;
$e(n) = d(n) - y(n)$;
$W(n+1) = W(n) + 2\mu\, e(n)\, X(n)$……………………(2)

When a constant scalar step size μ is employed in the LMS/NLMS algorithm, there is a trade off among the steady state error-convergence towards the true channel coefficients W(n), which avoids a fast convergence when the step size μ is preferred to be small for small output estimation error e(n). In order to guarantee the algorithm to be convergent, the range of step size μ is specified but the choice of optimal learning step size has not been appropriately addressed. In order to deal with these troubles, one key idea is to exploit varying step size during adaptation.

C.Variable Step Size LMS (VSS LMS) Algorithm

The VSS-LMS algorithm involves one additional step size update equation compared with the standard LMS algorithm. The VSS algorithm is [4], [5], [6]

y(n) = WT(n) X(n) ;
e(n) = d(n) – y(n);
μ(n) = β (1 – exp(-α|e(n)|2));
W(n + 1) = W(n) + 2μ e(n) X(n)…………………..(3)

When the channel is fast time-varying then algorithm cannot accurately measure the autocorrelation between estimation error e(n) to control step size μ update. So, this CE algorithm cannot provide the minimum MSE in the tracking problem, since it cannot acquire and track the optimum step size μ. It may even cause worse steady state results, when the algorithm parameters are not appropriately adjusted. In addition, control parameters α and β need to be adjusted for a better performance. As can be seen here, a general characteristic of these VSS CE methods is that predetermined control parameters are necessary to improve the performance. Though, in most of them, rules to choose control parameters are not specified. Those parameters are always selected from extensive simulations, or from experience. It is clear that the choice of parameters would significantly influence the performance of these schemes [12].

Various Variable step-sizes (VSS) based LMS have a high step-size initially for fast convergence but then reduce the step-size with time in order to achieve a low error performance. All VSS algorithms aim to improve performance at the cost of computational complexity. This trade-off is generally acceptable due to the improvement in performance. [10], [16], [20]

Several variable step-size algorithms designed to enhance the performance of the LMS algorithm have been given. However, the algorithms in are very sensitive to interference noise, while the method in needs the noise signal to be uncorrelated, and the method proposed in is only suitable for stationary and low-level noise conditions; thus, they are limited in many applications. To the best of our knowledge, no variable step-size LMS algorithm has been proposed for a wide range of applications where the noise signal is correlated, potentially high variance, such as speech signals. [1], [2]

D.Recursive Least Squares (RLS) Algorithm

To combat the channel dynamics, the RLS based CE algorithm is frequently used for rapid convergence and improved MSE performance [18]. The standard RLS algorithm is

y(n) = WT(n) X(n) ;
e(n) = d(n) – y(n);
W(n + 1) = W(n) + 2μ e(n) X(n)……………..(4)

Where l is the exponential forgetting factor with 0 < μ < 1. The smaller value of l leads to faster convergence rate as well as larger fluctuations in the weight signal after the initial convergence. On the other hand, too small l value makes this algorithm unstable. Subsequently, it requires best possible forgetting factor such that the estimator error is decreased. Although a lot of modified CE algorithm has been studied on employing adaptive forgetting factor and parallel forgetting factor, the CE performance is severely degraded in highly dynamic fading channel even when the forgetting factor is well optimized [15]. However, this scheme also has computational complexity-performance trade off problem that is the major obstacle for practical mobile terminal as well as base station (BS) implementation [9], [18]. Consequently, an efficient CE algorithm better than existing algorithms is required which gives both fast convergence and minimum steady state MSE. The Recursive Section is shown in figure 3.

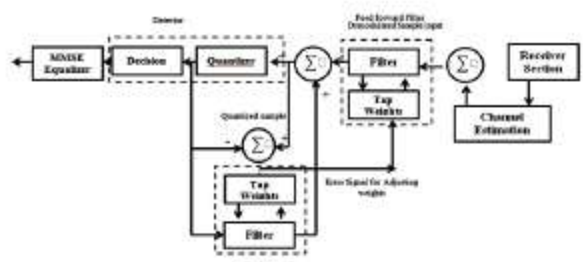


FIG.3 BLOCK DIAGRAM OF RECURSIVE SECTION

E.Least Mean-Squares Newton (LMSN) Algorithm:

LMSN is known to outperform the standard LMS algorithm when the data use as a large Eigen values spread or when the regressor matrix involved are in conditions such as is the case with the memory polynomial model. This algorithm exhibits many desirable characteristics such as stability, robustness and accuracy. LMSN algorithm used less parameter than the RLS algorithm, which utilized forgetting factors. This algorithm depended on a user selected constant is removed by dropping the parameter. [19]

For n = 1 : N
R-1(0) = δI

$W(0) = [\ 0 \ldots 0\ ]T$
for $n = 1 : N$
$e(n) = d(n) – y(n)$
$R_{-1}(n) = R_{-1}(n-1) – R_{-1}(n-1)\, xH(n)\, x(n)\, R-1(n-1)$
$1+ x(n)\, R_{-1}(n-1)\, xH(n)$
$W(n) = W(n-1) + \mu\, R-1(n)\, xH(n)\, e(n)$ ………………(5)

Where δ is a constant usually having large values (≥ 103 in this study).
μ is the step size, where $0 < \mu < 1$
R-1(n) is the modified input variable which is affect by x(n)
If we compare between all previous Channel Estimation Algorithms with Proposed Algorithm on the bases of output parameters like Computational complexity, Mean Square Error & Noise, Range and Response time than we found that our proposed algorithm is more successful to reduce noise (noise reduction) comparatively all previous Channel Estimation Algorithms. Our Proposed Algorithm is also better than Least Mean Square Newton Algorithm because it also reduces the Mean Square Error & Noise problem which is occur in LMSN algorithm.

S. No.	Algorithm	Output Parameters			
		Computational complexity	MSE & Noise	Range	Response Time
1	LMS	Low	High	Low	High
2	NLMS	High	High	Low	Low
3	VSS LMS	Medium	Medium	Medium	Medium
4	RLS	High	Low	High	Medium
5	LMSN	Low	Medium	High	High

TABLE 1: COMPARE WITHIN EXITING METHODS

III. PROPOSED ALGORITHM

In proposed algorithm, we reduce noise and MSE on the output desired signal. Firstly we buffering the input signal (signal + noise) and other end we remove the noise and get noise free desired signal. For noise reduction we use modified LMS based adaptive filter and add buffer on input end and filter on output end. For the help this algorithm, we receive almost noise free and low error signal at any environment. We tested this algorithm based filter different conditions and converge factors to get optimize solution and compare with existing algorithms LMS and RLS.

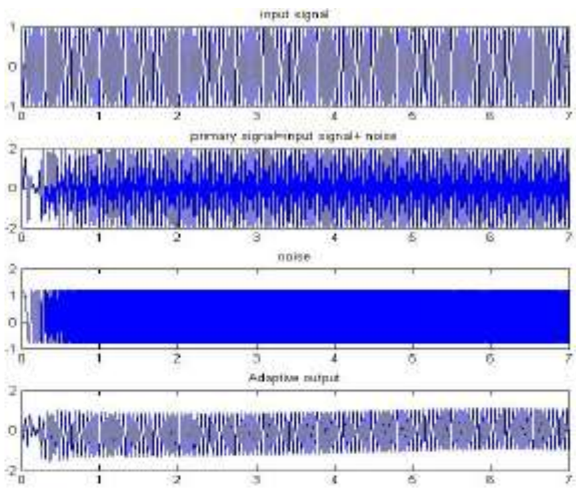
MATLAB CODING OF PROPOSED ALGORITHM

```
clc
close all
clear all
N=input('length of sequence N = ');
t=[0:N-1];
w0=0.005; phi=0.5;
d=sin(2*pi*[1:N]*w0+phi);
x=d+randn(1,N)*1.0;
w=zeros(1,N);
mu=input('mu = ');
for i=1:N
e(i) = d(i) - w(i)' * x(i);
w(i+1) = w(i) + mu * e(i) * x(i);
order=7;
size=7; %time duration of inputs
fs=8192; %digital sampling frequency
t=[0:1/fs:size];
N=fs*size; %size of inputs
f1=35/2; %frequency of signal
f2=99/2; %frequency of noise
voice=cos(2*pi*f1*t);
subplot(4,1,1)
plot(t,voice);
title('input signal')
noise=cos(2*pi*f2*t.^2); %increasy frequency noise
noise=.1*rand(1,length(voice)); %white noise
primary=voice+noise;
subplot(4,1,2)
plot(t,primary)
title('primary signal=input signal+ noise')
ref=noise+.25*rand; %noisy noise
subplot(4,1,3)
plot(t,ref)
title('noise');
w=zeros(order,1);
mu=.006;
for i=1:N-order
buffer = ref(i:i+order-1); %current 32 points of reference
desired(i) = primary(i)-buffer*w;
%dot product reference and coeffs
w=w+(buffer.*mu*desired(i)/norm(buffer))';
mu*desired(i)/norm(buffer))';
%update coeffs
end
subplot(4,1,4)
plot(t(order+1:N),desired)
title('Adaptive output') end
```

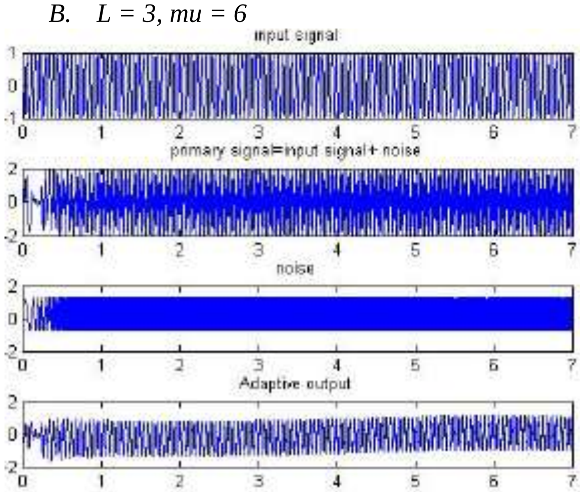
IV. RESULTS AND DISCUSSION

We tested some different input variables with noise on this algorithms and get results shown in below :

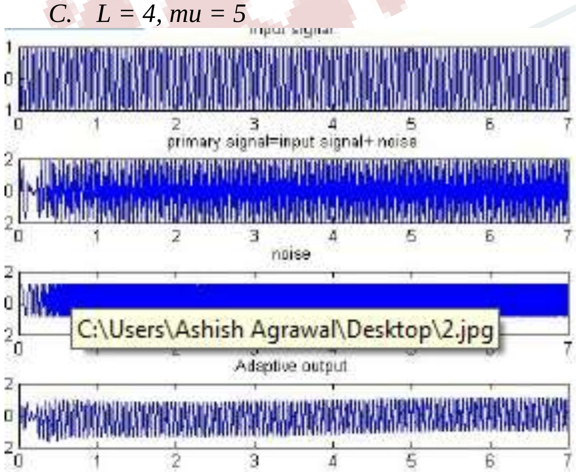
A. L = 3, mu = 5



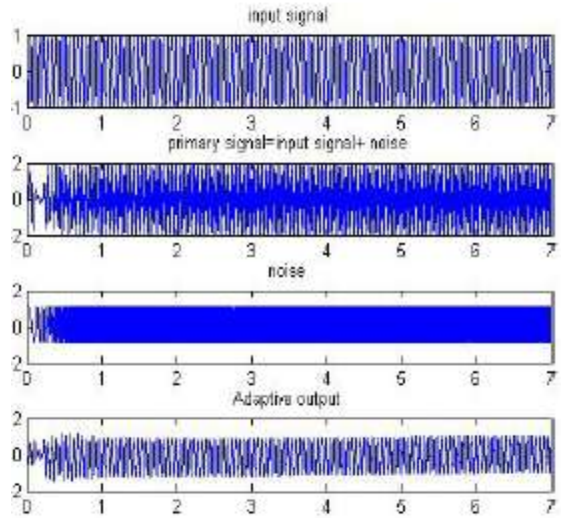
B. L = 3, mu = 6



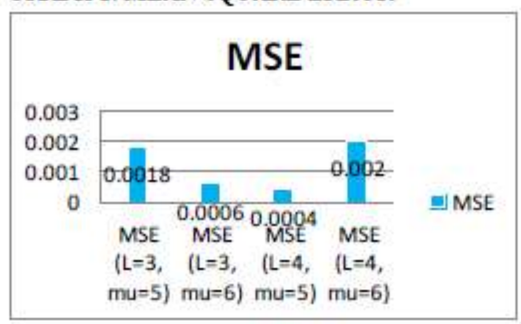
C. L = 4, mu = 5



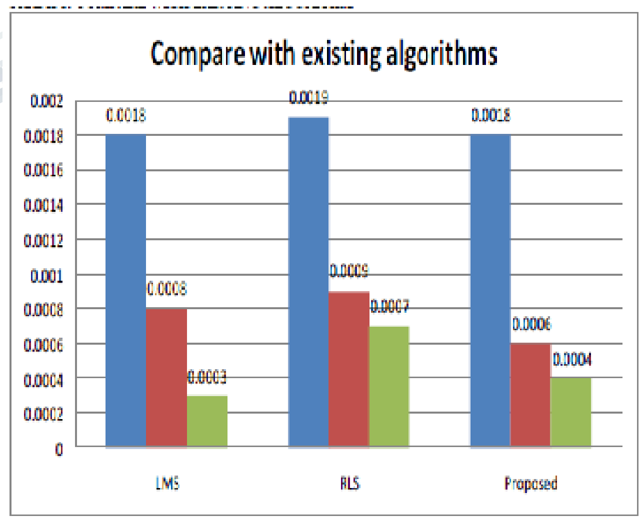
D. L = 4, mu = 6



GRAPH 1: MEAN SQUARE ERROR



GRAPH 2: COMPARE WITH EXISTING ALGORITHM



V. CONCLUSION

An accurate CE is one of the most important issues for reliable future wireless communication systems. In this paper a new channel estimation algorithm is designed by using modified LMS based adaptive filter and add buffer on input end and filter on output end. For the help of this algorithm, we receive almost noise free and low error signal at any environment. This proposed algorithm provides low computational complexity, low MSE & Noise, it is used for high range communication and its response time is also high. But here we tested this proposed algorithm for only mobile signals communication and it gives very good result, in future we can also tested this algorithm for other high range wireless communication signals, like wireless internet, DTS signal, Satellite communication.

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