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Comparative Performance Analysis of ANN Implemented LMS with ANN for Channel Estimation in AWGN Channel Scenario

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Abstract- In this paper we have done channel estimation using the concepts of LMS algorithm, after that we have implemented the logic of LMS algorithm using the concepts of Supervised Artificial Neural Network and then we have performed channel estimation directly applying the concepts of Supervised Artificial Neural Network. Finally we have compared the performances (BER v/s SNR and Throughput v/s SNR) of these three methods for channel estimation under AWGN channel scenario. Matlab (version 7.9) is used here as the simulation platform.

Keywords- Channel estimation, LMS, Artificial Neural Network, BER, Throughput

I. INTRODUCTION

The approach of the problem of predicting and analyzing the observable properties of transmission, it is must first define what we mean by a channel. In its most general sense, a channel can describe everything from the source to the sink of a radio signal. This includes the physical medium (free space, fiber, waveguides etc.) between the transmitter and the receiver through which the signal propagates. The word channel refers to this physical medium throughout this work. An essential feature of any physical medium is, that the transmitted signal is received at the receiver, corrupted in a variety of ways by frequency and phase-distortion, inter symbol interference and thermal noise.

A channel model on the other hand can be thought of as a mathematical representation of the transfer characteristics of this physical medium. This model could be based on some known underlying physical phenomenon or it could be formed by fitting the best mathematical / statistical model on the observed channel behavior.

Most channel models are formulated by observing the characteristics of the received signals for each specific environment. Different mathematical models that explain the received signal are then fit over the accumulated data. Usually the one that best explains the behavior of the received signal is used to model the given physical channel.

Channel estimation is simply defined as the process of characterizing the effect of the physical channel on the input sequence.

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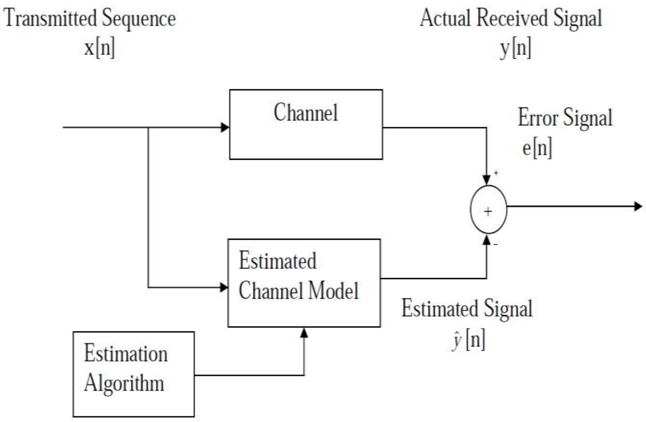

Figure 1.Simple block diagram for channel estimation

If the channel is assumed to be linear, the channel estimate is simply the estimate of the impulse response of the system. It must be stressed once more that channel estimation is only a mathematical representation of what is truly happening. A “good” channel estimate is one where some sort of error minimization criteria is satisfied.

In the figure.1 e*(n)* is the estimation error. The aim of most channel estimation algorithms is to minimize the mean squared error, *E* [*e*2 (*n*)] while utilizing as little computational resources as possible in the estimation process. Channel estimation algorithms allow the receiver to approximate the impulse response of the channel and explain the behavior of the channel. This knowledge of the channel's behavior is well-utilized in modern radio communications. Adaptive channel equalizers utilize channel estimates to overcome the effects of inter symbol interference.

Rest of the paper is organized as, In Section II different methods of channel estimation are described, In section III Result analysis for those three methods are given ,then in section IV conclusions are given and finally References are given.

II. METHODS USED FOR CHANNEL ESTIMATION

A. Least Mean Square (Lms) Algorithm

The Least Mean Square (LMS) algorithm, introduced by Widrow and Hoff in 1959 is an adaptive algorithm, which uses a gradient-based method of steepest decent .LMS algorithm uses the estimates of the gradient vector from the available data. LMS incorporates an iterative procedure that makes successive corrections to the weight vector in the direction of the negative of the gradient vector which eventually leads to the minimum mean square error.

Compared to other algorithms LMS algorithm is relatively simple; it does not require correlation function calculation nor does it require matrix inversions. A most robust equalizer is the LMS equalizer where the criterion used is the minimization of the mean square error (MSE) between the desired equalizer output and the actual equalizer output. In the LMS algorithm, the correction that is applied in updating the old estimate of the coefficient vector is based on the instantaneous sample value of the tap-input vector and the signal. The objective is to change (adapt) the coefficients of an FIR filter, *W*, to match as closely as possible the response of an unknown system, *H*. The unknown system and the adapting filter process the same input signal x[n] and have outputs d[n](also referred to as the desired signal) and y[n]. The input applied to the system is a random signal. The total number of transmitted symbols is denoted as *N*. The channel block introduces inter symbol interference (ISI) using a finite impulse response (FIR) type of channel model. The transfer function of the channel $H(z)$ can be expressed as

$$H(z)= h_0+ h_1 z^{-1}+ h_2 z^{-2}+\ldots+ h_{L-1} z^{-(L-1)}$$

(1)

where $h_l(l=0, \ldots, L-1)$ are the values of the sampled impulse responses and L is the number of channel filter coefficients. At the output of the channel, a noise sequence n is added. This noise is assumed to be additive white Gaussian noise (AWGN) The LMS algorithm update of the equalizer coefficient vector is given by

$$w(n+1) = w(n) + \mu x(n)[d(n) - x^h(n)w(n)]$$
$$= w(n) + \mu x(n)e(n)$$

(2) Where, w(n) is the weight vector, e(n) is the error signal and μ is the step size.

The LMS algorithm is initiated with an arbitrary value w(0) for the weight vector at n=0. The successive corrections of the weight vector eventually leads to the minimum value of the mean squared error.

This step size μ controls the adaptation speed of the adaptive filter. In the method of steepest descent the biggest problem is the computation involved in finding the values r and R matrices in real time. The LMS algorithm on the other hand simplifies this by using the instantaneous values of covariance matrices r and R instead of their actual values i.e.

$$R(n) = x(n) x^T(n)$$

(3)

$$r(n) = d(n)x(n)$$

(4)

In order to implement the adaptive equalizer, we need to generate a reference signal for the adaptive algorithm. For the initial adaptation of the filter coefficients we need at the receiver to be able to generate a replica of the transmitted data sequence. This known sequence is referred to as the training sequence. During the training period the desired signal is used as a reference signal and the error signal is defined as e(n) = d(n) – y(n). After the training period, the equalization can be performed in decision-directed manner. This mode can be utilized if the channel can be assumed to be time-variant. Therefore, it can be assumed that the decisions in the output are correct most of the time and the decisions can be used as reference signal. In the decision-directed mode, the error signal is defined as:

$$e(n) = d(n) - y(n)$$

(5)

The filter output is expressed as

$$y(n) = w^h x(n)$$

(6)

B. Ann Implemented LMS Algorithm

We have implemented the logic of LMS algorithm for channel estimation using the concept of Supervised Artificial Network, Function approximation task of ANN is applied here, to train the network we have taken channel output i.e, noisy signal as the input to the network and equalized output by LMS algorithm as desired or target to the network, after that we have simulated the network by unknown values of data which were not known to the network during training for noise cancelation.

Table I. Network parameters for ANN implemented LMS

Learning Algorithm	Back-Propagation
Number of hidden layers	4
Number of neurons in Input layer	1
Number of neurons in hidden layer	20 20 20 10
Number of neurons in output layer	4
Error goal	10^{-6}

C. Supervised Artificial Neural Network Method

This method is same as the preceding method ,but here to train the network we have taken original transmitted signal as the desired or target to the network and then simulated the network by unknown values of data for noise cancelation.

Table II. Network parameters for Supervised ANN

Learning Algorithm	Back-Propagation
Number of hidden layers	2
Number of neurons in Input layer	1
Number of neurons in hidden layer	20 20
Number of neurons in output layer	4
Error goal	10^{-6}

III. RESULTS

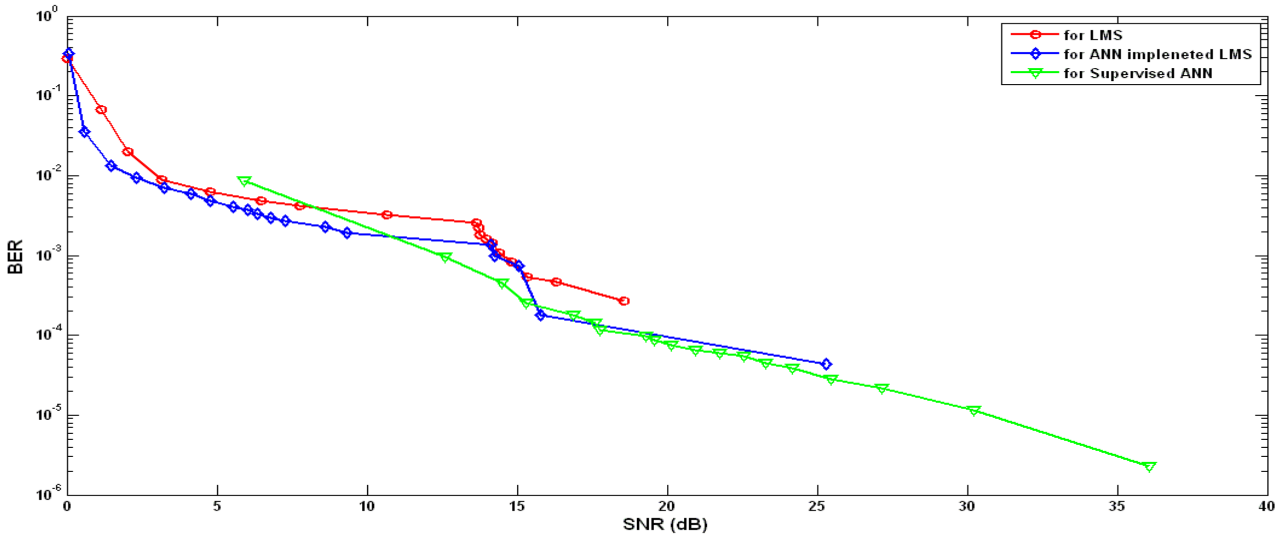

Figure 2. SNR v/s BER plot

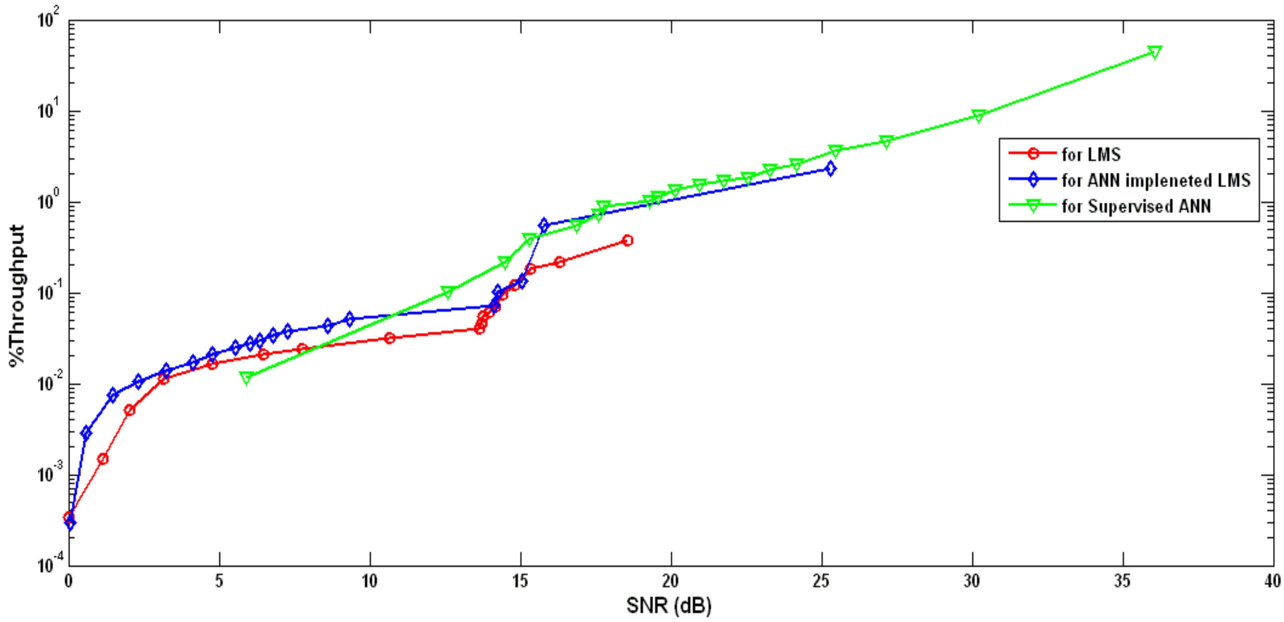

Figure 3. SNR v/s %Throughput plot

IV. CONCLUSION

From figures 3 and 4 Performance analysis of three methods that we have approached for channel estimation can be done. In figure 2 SNR v/s BER plot is shown where order of decreasing BER with respect to SNR is 'Supervised ANN<ANN implemented LMS<LMS' and in figure 3 SNR v/s % Throughput is shown where order of increasing %Throughput with respect to SNR is 'Supervised ANN>ANN implemented LMS>LMS'. Again Mean and Standard deviation of BER for three methods are given below

Table III. Mean and Standard Deviation

Method	Mean	Standard Deviation
LMS	0.0229	0.0760
ANN implemented LMS	0.0219	0.0667
Supervised ANN	0.00059	0.0019

From table III, it is clear that order of three methods for Mean and Standard Deviation of BER is 'Supervised ANN<ANN implemented LMS<LMS'. From the above discussions it can be concluded that Supervised ANN method is far better for channel estimation with respect to the other two methods considered .So in communication systems at the receiver side logic of Supervised ANN should be implemented to ensure noise free reception of signals at the receiver.

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