Improvements in the channel Equalizer Performance Using Modified LMS and BP Algorithms

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Abstract

This paper introduces a comparative study in the communication channel equalization problem. Different types of linear and nonlinear channel models including linear and nonlinear phase are considered in this study. Adaptive linear filter and neural networks are used to imitate different equalizer models. The equalizer models are tested using different transmitted signals with different characteristics. A modification in the learning algorithm driving each model is proposed to obtain the minimum mean-squared error in the recovery process of transmitted signals. The modified algorithms have demonstrated their effectiveness compared to other conventional techniques especially in the noisy environment.

Keywords: *Adaptive fiters, Neural Networks, Channel Equalization.*

1. Introduction

The equalization problem is a very important task in the electrical communication field; it has been studied since the early communication eras [1]-[10]. In this paper, we are considering the channel equalization problem and how we can improve the quality of the received signal by applying different techniques.

Many communication channels may have a nonlinear magnitude and/or phase frequency response, leading to a corrupted version of the transmitted signal when it reaches the receiving end. In addition to the distortions caused by the channel nonlinearity, noise due to random sources may also be added to the signal during the transmission process. It is the goal of channel equalizer to remove as much of the noise and distortion as possible to provide a clean signal at the receiving end. Therefore, using nonlinear equalizer is very useful in the case of using a nonlinear channel model.

The structure of the equalizer may be linear or nonlinear. A linear equalizer structures include FIR, IIR and a lattice filter. The linear structures are simple and may suffice for wide range of applications in which the communication channel can be modeled as a linear model. However, Channel non-linearity, distortion and additive noise are factors which can't be neglected and they affect the performance of linear equalizer. Due to these factors, linear equalizers suffer more weakness in its performance. One of the powerful alternative nonlinear structures is the neural networks; it gives better performance than that of linear models due to its ability to represent nonlinear functions. This advantage of neural network is on the expense of the large network size and the number of calculations.

The least-mean square (LMS) algorithm updates the linear filter coefficients such that the mean square error (MSE) cost function to be minimized [7],[8]. In the other hand, the back-propagation (BP) algorithm drives the neural network and updates its weights. BP algorithm is mainly based on the LMS algorithm in addition to the special manipulation of the nonlinear activation functions embedded in the neuron models and the error calculations in the hidden layers of the neural network. BP algorithm is suitable for the nonlinear neural filters, neural equalizers, and many other nonlinear signal processing applications.

Since the appearance of the LMS algorithm and the BP algorithm, they are of great power and interest and they are used in many different signal processing applications. However, they have been investigated till now to get better performances (See [2] for details).

Determination of the learning rate parameter value in both LMS and BP algorithms is a difficult problem and there is no unique method to determine its value. In this paper, we propose a modification for both LMS and BP algorithms with the aim of improving their performances by trying a method of estimating this value.

This modification is done by making the step size or the learning rate parameter of the algorithms to take a large value at the beginning instant of the process and then decays gradually until it reaches a fixed value (steady state value) in the rest of the learning process. This is supposed to give a great improvement in the algorithm performance compared with the algorithm in its conventional case, in which it has fixed value for its learning rate. This modification is done whenever it is needed through learning process. It is supposed to be of great importance to get rid of the local minimum in the error surface (if exists).

In this paper, we call the modified least-mean square algorithm "MLMS" and the modified back-propagation algorithm "MBP".

2. Equalizers and Algorithms

2.1. Linear Equalizer

A finite-impulse-response filter structure is used to represent a linear type equalizer, which has demonstrated a suitable performance since a long time in many applications. Here, we call it finite-impulse-response equalizer (FIRE).

Least mean square (LMS) algorithm is used to drive the FIRE model. The role of the LMS algorithm is to update the FIRE coefficients to reach their optimum values that give the minimum mean square error (MMSE) which means better performance. The updating process is based upon the Delta-rule as shown below:

$$\hat{w}_k(n+1) = w_k(n) + \mu e(n) x_k(n) \tag{1}$$

Where $\hat{w}_k(n+1)$ is the estimated value of the connection weight from k^{th} input sensor at time instant $n+1$, and $w_k(n)$ is the value of that weight at previous time instant n. $x_k(n)$ is the input value, $e(n)$ is the error value and μ is a positive constant called *learning-rate parameter*. (For LMS full derivation, see [11], [12])

2.2. Neural Network Equalizer

Conventional approaches that can handle nonlinear problems have typically been designed using a priori information about the problem at hand. Unfortunately, this type of information is not always available. Neural networks can learn to implement nonlinear functions without any prior knowledge about the problem domain. Another key property of neural networks in these applications is their ability to adapt continuously to incoming distinct data, allowing them to track changes in the system over time.

Conventional techniques like adaptive linear filters can adapt to new data, but they generally lack the power of neural network solutions (See [12]-[14]).

Here, a neural network equalizer (NNE) is used. It is driven by the back propagation algorithm, (BP).
In the BP algorithm, after the NNE produces its output, the error is propagated backward through the network layers, with each perceptron having its own error value based upon the subsequent layer errors. The BP algorithm relies upon the assumption that the perceptron activation function is differentiable. For the BP derivation, see [12].

From BP algorithm computations, we recall the equation of updating the connection weight parameters as indicated in the 4th line of Eq. (2):

$$\begin{aligned} v(n) &= \sum_{j=1}^{m} w_j(n) x_j(n) \\ y(n) &= F(v(n)), \\ e(n) &= d(n) - y(n) \\ \hat{w}_k(n+1) &= w_k(n) + \mu e(n) x_k(n) \end{aligned} \tag{2}$$

Where $F(.)$ is a sigmoid activation function, and $y(n)$ is the output of one neuron in the output layer computed at time instant n, $x_j(n)$ is the jth input to the specific neuron, $w_j(n)$ is the connection weight from the j^{th} input to that neuron, and m is the total number of inputs to that neuron.
$e(n)$ is the error value between the desired output $d(n)$ and the actual output $y(n)$ of the output neuron.
$\hat{w}_k(n+1)$ is the estimated value of the connection weight from k^{th} input at time instant n+1, and $w_k(n)$ is the value of that weight at previous time instant n and μ is a positive constant called *learning-rate parameter*.

3. The Proposed Modification

The learning rate parameter value in both the LMS and BP algorithms is a difficult problem and there is no unique method to determine it. In this paper, we propose a modification for both LMS and BP algorithms with the aim of improving their performances by adjusting the learning rate parameter according to the proposed modification.

The main point of the proposed modification is to make the step size or the learning rate parameter of the algorithms to take a large value at the beginning of the learning process and its value decays gradually until it reaches a steady state value μ_o in the rest of the learning process unless it is needed to repeat the modification process once more. The modification process is repeated whenever needed at any point in the learning process.

This is supposed to give a great improvement in the algorithm performance compared with the algorithm in its conventional case, in which it has fixed value for its learning rate parameter. Also, the proposed modification in the BP algorithm is of great importance to get rid of the local minimum in the error surface.

The proposed modification is done according to the following formula:

$\mu = \mu_o + r^N$, Where:

μ_o: Selected learning rate (Steady state value)
$0 < \mu_o < 1$

r: A small arbitrary value and its value is:
$0 < \mathbf{r} < 1$

N: Number of iterations in the learning process

Here, the modified least-mean square algorithm is called "MLMS" and the modified back propagation algorithm is called "MBP".

The MLMS and MBP algorithms have been tested, by applying it to a communication channel equalization problem. Different kinds of equalizer models are used to represent the inverse modeling of the communication channel under different channel conditions and different values of signal-to-noise ratio (SNR). Simulation results obtained by using MLMS and MBP are compared to those results obtained using the conventional LMS and BP algorithms. Also, the results are compared to those results obtained by neural network equalizer that uses BP with adjustable learning rate in the MATLAB software package named as "traingdx".

4. Types of Channel Model

As it were used in [3] and [15], we are using the same benchmark models to test these models using the proposed algorithms modifications:
Four models of channels are used as the following:

1- Linear and minimum phase.
2- Linear and non-minimum phase.
3- Nonlinear and minimum phase.
4- Nonlinear and Non-minimum phase.

The z-domain description of linear minimum phase and linear non-minimum phase models are shown in Eqns. (3) and (4) respectively.

$$H_{\min}(z) = 0.6963 + 0.6964\, Z^{-1} + 0.1741\, Z^{-2} \tag{3}$$

$$H_{non-\min}(z) = 0.3482 + 0.8704\, Z^{-1} + 0.3482\, Z^{-2} \tag{4}$$

A nonlinearity added to the pervious linear channel models, is similar that used in [1]:

$$v(k) = 0.3482\, s(k) + 0.8704\, s(k-1) + 0.3482\, s(k-2),$$
$$y(k) = v(k)[1 + 0.2v(k)] \tag{5}$$

5. Simulation Using modified algorithms.

In this section, the proposed MLMS and MBP algorithms have been tested by using different kinds of equalizer models under different signal-to-noise ratio (SNR). Simulation results obtained by using MLMS and MBP are compared to that of the equalizers using the conventional LMS and the BP algorithms. Furthermore, the results are compared to that obtained from neural equalizer model which uses BP with adjustable learning rate in the MATLAB software package named as "traingdx". Also, comparison has been done to the best performances obtained in [15].

In all simulations, we have selected the best results (minimum MSE) for each channel model among numerous simulations regardless the size of the model or the value of learning rate parameters.
The value of μ_o is not fixed in all programs for the same model, its value was adjusted by iteration to give minimum MSE.

A speech signal (used as benchmark in many research papers [3] and [15]), is sampled with sampling rate 11025 bit/second, total number of points is 110260 points, these points are divided into two sets, first set is taken from point 1 to point 22500, and this set is used to train the equalizer and to update its parameters to reach their optimum values. The updated equalizer parameters will be fixed and taken to represent the final model parameters. This phase of operation is called a training phase. The other phase of operation is called a testing phase, that phase in which the equalizer is operated with its fixed parameters and using a new set of signal points which have not been seen by the equalizer before. And the second set is taken from 22501 to 42000. This set is used to test the equalizer performance and is called a testing set. The rest of 110260 points are zeros

5.1. Results for Noise-free Speech Signal.

Table1: MSE values for noise-free signal

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CHANNEL Type / Type of Equalizer	Non-linear Min. Phase	Non-linear Non-min Phase	Linear Min. Phase	Linear Non-min. Phase
FIRE(LMS)	**3.721×10^{-4}**	**4.656×10^{-4}**	**2.521×10^{-7}**	**1.696×10^{-4}**
FIRE (MLMS) "Proposed"	**3.721×10^{-4}**	**4.656×10^{-4}**	**2.519×10^{-7}**	**1.696×10^{-4}**
NNE(BP)	**3.326×10^{-5}**	**1.915×10^{-4}**	**1.734×10^{-6}**	**1.668×10^{-4}**
NNE with Adjustable µ"traingdx"	**2.906×10^{-4}**	**12×10^{-4}**	**8.934×10^{-5}**	**2.058×10^{-4}**
NNE(MBP) "Proposed"	**2.361×10^{-5}**	**1.534×10^{-4}**	**7.361×10^{-7}**	**1.613×10^{-4}**

Table 1 shows the MSE value of each equalizer model derived with both conventional and modified algorithms. It is obvious from these results that the proposed or the modified back propagation (MBP) algorithm is of higher performance than any other equalizer models except for the case of "linear and minimum phase" channel condition, the modified least mean square (MLMS) is the best for that case, that agrees with the literature for the linear channel system modeling [11].

5.2. Results for Noisy Speech Signal.

The four plots, from Fig.1 to Fig.4 demonstrate the graph of the MSE vs. the SNR values in the simulation experiments for different equalizer models and using different channel conditions.

In all these graphs, we note that the neural network equalizer trained with the MBP has superiority over all other equalizers trained by any other algorithm.
For example, at SNR=20dB and for non-linear non-minimum phase channel type, neural network equalizer trained with the proposed MBP algorithm gives 41.2% better performance more than the conventional linear equalizer trained with conventional LMS algorithm. And 15% better performance more than the neural network equalizer trained with conventional BP algorithm.
This goodness in performance decreases gradually by increasing in the noise power (low SNR). But the overall result is that the proposed algorithms have valuable improvements in the corresponding driven equalizer especially in the noisy and nonlinear channel conditions.

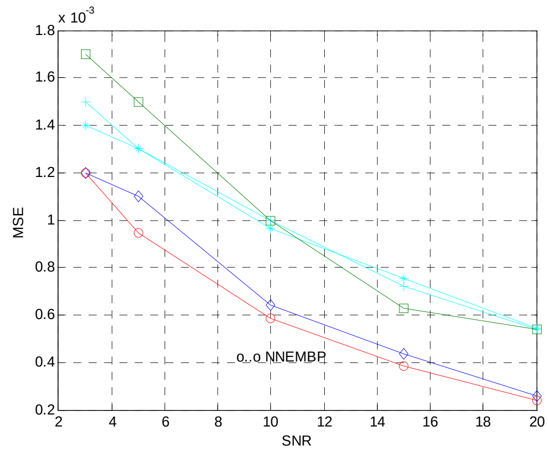

Fig.1 Results for nonlinear and minimum phase channel

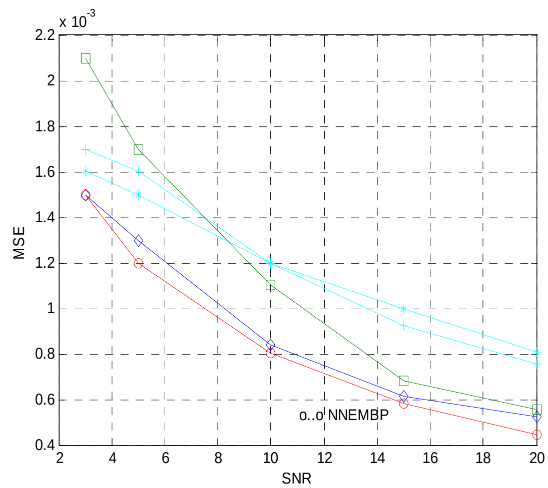

Fig.2 Results for nonlinear and non minimum phase channel

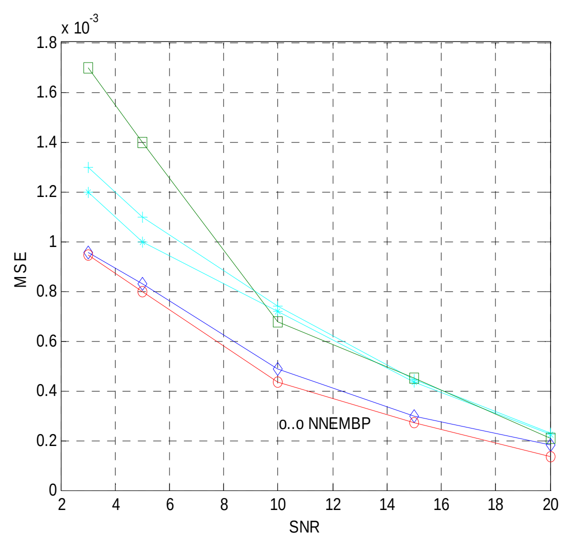

Fig.3 Results for linear and minimum phase channel

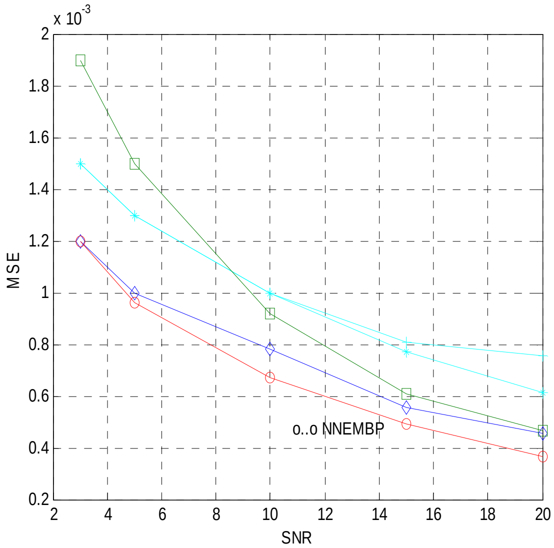

Fig.4 Results for linear and non minimum phase channel

6. Conclusion

From simulation results, we can conclude the following notes:

1- Compared with the conventional LMS algorithm, the MLMS algorithm shows a week effect when it works in noise-free conditions, however, it has a valuable effect when it works in a real world noisy conditions.

2- The MBP algorithm demonstrates a very good performance compared with the conventional BP algorithm in both noise-free and noisy environments.

3- In the noisy environment, neural network equalizer trained with the MBP has superiority over all types of equalizers trained by any other algorithm listed in this paper.

4- MLMS algorithm is very sensitive to the change in the value of its step size (i.e. learning rate should be selected carefully to reach the minimum MSE)

5- Neural network equalizer trained with the modified BP algorithm gives better performance than that of the same equalizer trained with the adjustable learning rate BP algorithm "traingdx" used in MATLAB for all cases of channel type and conditions.

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