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Blind Channel Equalization Using Elman Network

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Abstract: Advanced communication techniques sometimes also cause limitations due to destructive influence on digital communication system. Occurrence of noise due to co-channel interference, multipath delays causing channel fading, etc. are the factors that cause the receiver to get corrupted bits. Several equalization techniques have been proposed to remove this effect of Inter-Symbol Interference (ISI) and Multi-User Interference (MUI), but they suffer from some limitations, and their performance is somehow suboptimal.

This paper introduces equalization methods and compares their performance and proposes a better solution, which is efficient in removing ISI, moreover saves the bandwidth by eradicating the training sequences. We employ Elman Network, which is a classical recurrent neural network to work as an equalizer. We have showed through simulation that our designed recurrent neural network to work as an equalizer performs better, given that the network is trained properly.

Keywords: Communication Systems, Blind Channel Equalization, Intersymbol Interference, ELMAN Network

I. INTRODUCTION

The rapid growth of communication services in last decades has altered the human life style. Though attempts are taken to improve quality of services yet the destructive influence of Inter symbol Interference (ISI) on a digital communication system performance has to be counteracted by special receiver and/or transmitter design. A fundamental part of the receiver is the channel equalizer. An equalizer is a device that removes (ISI) on the channel using digital data transmission system. In a digital communications signal, ISI is a condition in which a given symbol overlaps with one or more other symbols (either immediately preceding it or immediately following it), upsetting the ability of the receiver to decipher signals in certain time intervals. The adaptive equalizer is able to adaptively compensate the distorting channel characteristics and simultaneously track the changes of channel characteristics in time.

The development in the findings about human brain, new models for Artificial Neural Network (ANN) are being invented. Researchers are interested in creating the capability of solving the problem using the ANN. ANN is basically an interconnection of processing elements and the way they are interconnected represents its structure. On the basis of its structure, they can be broadly classified as Feed-Forward or Recurrent Network. One example of Recurrent Neural Network is Hopefield network, which is simple Recurrent Network (SRN) having one hidden layer with feedback connections within nodes as shown in **(Fig. 1).** All the nodes are interconnected.

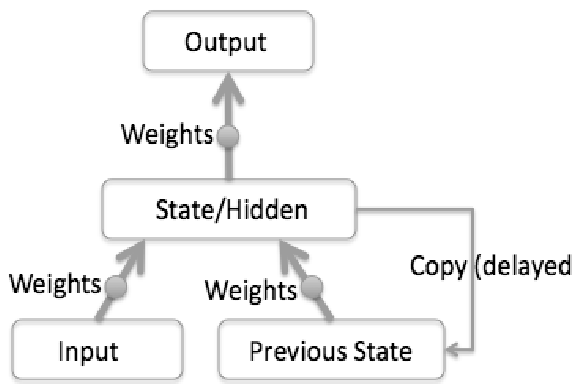

Fig. 1 Recurrent Network

In Recurrent Network the input is propagated along with its weights (i.e. synaptic weights tell the contribution of input towards possible outcome) through activation function (or transfer function) and combines with the previous activation function due to feedback connections. The activation function plays great importance in attempting to solve specific class of problem and can be linear or non-linear in nature. The various types of activation functions defined in (Haykin, 1994) are Sigmoid, Threshold, and Piecewise-Linear function. The recurrent has delay taps and thus they maintain a short-term memory.

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The main advantage of Elman network, a type of recurrent network is that it allows feedback connections. This paper proposes the use of Elman Network for the blind channel equalization. The results are compared with other algorithms (i.e. Least Mean Square, Blind Zero Forcing MMSE, Adaptive Constant Modulus Algorithm, and Adaptive CMA method in Fractional Space) used for the same purpose to evaluate the performance of the proposed method. The simulated results report the proposed ELMAN Network better performed as compared with other algorithms considered in this paper.

Roadmap of this paper is as Section 0 describes related work, Section 3 discusses proposed approach, whereas the experimental results and application of the proposed framework are reported in Section 4 and Section 5 respectively; and finally conclusions are driven in Section 6.

2. RELATED WORK

The wireless communication medium is severely affected by noise, co-channel interference and multipath delays that is the signal bounces off the objects and creates a fading, causing the receiver to get corrupted bits. To solve this problem, some sorts of detection algorithms are employed that require the knowledge of CIR (Channel Impulse Response). To acquire CIR, some sort of channel estimation technique is required.

Since the mid-1980s, adaptive equalizer research has focused less on development of new algorithms and more on either characterizing popular algorithms or tweaking them for performance improvement or complexity reduction. Not much of development has happened on the structure of linear and decision-feedback equalizers recently. Efforts have been taken in developing adaptive algorithms for equalizers in accordance with (CIR) by (Duttweiler, Mazo, and Messerschmitt, 1974), (Smee and Beaulieu, 1998), and (Altekar and Beaulieu, 1993) has contributed their research and reported the phenomenon of error propagation in the Decision Feedback Equalizers. Later on, solutions were proposed by (Tomlinson, 1971), (Harashima and Miyakawa, 1972), (Russell, 1995), and (Chiani, 1997) for decreasing the impact of error propagation.

A number of research groups are emerging in the field of Neural Networks (NN) in different independent funded institutes and universities. These efforts are leading to maturity in the field of NN development.

The feature of being highly adaptive and easily generalize or organize any data with certain limits has motivated to address the most demanding issue in telecommunication which is to differentiate the noise from useful data. Different models have been introduced as (Rosenblatt, 1962) presented a model trying to replicate biological neuron called Perceptron model and then (Widrow, 1960) came up with model named as 'Adaline' (Adaptive Linear Element) model, which was trained with a method called 'Least Mean Squares (LMS)'.

Later, couple of researchers (Malsburg, 1973) and (Fukushima, 1975) have taken part in developing the groundwork over the field of competitive learning and self-organization. Adaptive Resonance Theory (ART) model was introduced by (Grossberg, 1972), (Grossberg, 1976), and (Carpenter & Grossberg, 1987), their model was introduced with capability of doing stable clustering based on competitive learning using any arbitrary sequence of data as an input in the real time. The modern era of Neural Network starts with publications of (Hopfield, 1982), (Hopfield, 1984), and (Hopfield & Tank, 1986), with great success of the model introduced on system level approach rather than at neuron level. The reason behind its success was its recurrent architecture, i.e. it had feedbacks to previous layer. Where as in the area of adaptive equalizers, firstly introduced in (Sato, 1975), and (Benveniste & Goursat, 1984), replaced the training signal. In the Least Mean Square (LMS) algorithm (Xu and Wu, 2004), (Goel, 2005), (Faid, Luo, and Ding, 2005) with the output of a decision device at the receiver. However, it is dependent on the ability to make good decisions at initialization, which is not always the case. A more sophisticated blind equalizer, the Constant Modulus Algorithm (CMA), introduced in the early 80s (Godard, 1980), (Treichler and Agee, 1983), (Foschini, 1985), (Johnson, 1998), which assumes the transmitted data has a constant modulus, and the equalizer attempts to restore this property. The goal of blind estimation is to determine the channel or the signals based on the prior temporal or spatial knowledge.

This paper investigates the potential of Artificial Neural Network as channel equalizer. In particular, the paper presents the use of Elman Network for designing blind channel equalization. The proposed design is simulated in MATLAB and the results are compared with other algorithms (i.e. Least Mean Square, Blind Zero Forcing MMSE, Adaptive Constant Modulus Algorithm, and Adaptive CMA method in Fractional Space) used for the same purpose.

3. METHODOLOGY

A typical scenario of wireless communication and the factors affecting the successful transmission of signals from transmitter to the receiver is represented in **(Fig. 2)**

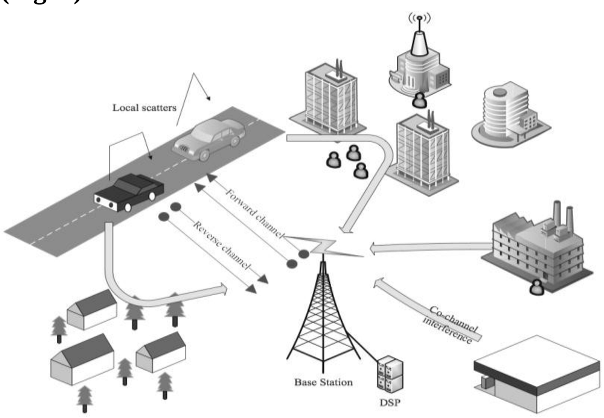

Fig. 2 Wireless Communication Scenario

There are basically two standard approaches to solve co-channel interference and multi-path delays.

- **Estimation of Channel Quality** - the goal is to estimate the channel transfer function of the upcoming transmit slot, so that proper transmission parameters are selected for the next transmission. These parameters can be modulation rate, coding mode etc. This change of information is delivered to the receiver, so that it can properly adjust its demodulation parameters for successful reception. Some examples of channel estimation techniques are: Training sequence, Higher Order Statistics (HOS), and Second Order Statistics (SOS).
- **Equalization of Channel** - the technique in which received signal with ISI & AWGN is recovered by multiplying with the inverse of the estimated channel. This is eventually the exact copy of the transmitted signal: Least Mean Square Method, and Zero Forcing MMSE Method etc. The drawback with these techniques is that, due to time varying channel responses, and as the channel estimation and equalization are not being performed simultaneously.

This leads to poor performance in coping the ISI. Here the estimator is used to detect the transmitted sequence, which can be done using either zero-forcing, or Viterbi algorithm. Conventional Neural Networks like MLP (Multi-Layer Perceptron) and RBF (Radial Basis Function), which don’t have feedback connections, are not optimal choice for applications that have time varying response. Elman Network, which is a type of recurrent network and allows feedback connections introduced in (Elman, 1990) uses Error Back-Propagation (EBP) Algorithm as MLP and RBF Networks to train the network and at every step, it calculates local gradient, multiply with the input and some learning parameter plus new weight; because every time error is being used. Which simply means error is propagating back as its name implies.

A. Design of Wireless Communication Model

Emergence of wireless communication has brought great impact in the field of telecommunication. And one of most important challenging task in the field of wireless communication are to reduce the BER (Bit Error Rate is the bit-by-bit comparison (XOR logical operation) of the received data stream with the input transmitted stream. Simply, the ratio of error bits to the total number of bits transmitted) increase the throughput and utilize the bandwidth efficiently.

Simulating a real world scenario for wireless communication system is a difficult task. To accomplish this task, MATLAB tool is used to design the model and is made flexible in a way that, one can define several different system characteristics that are adjustable to test the performance of designed Elman network to work as an equalizer.

The block diagram of simulated wireless communication system model using Elman Equalization is shown in **(**

Fig. 3**).**

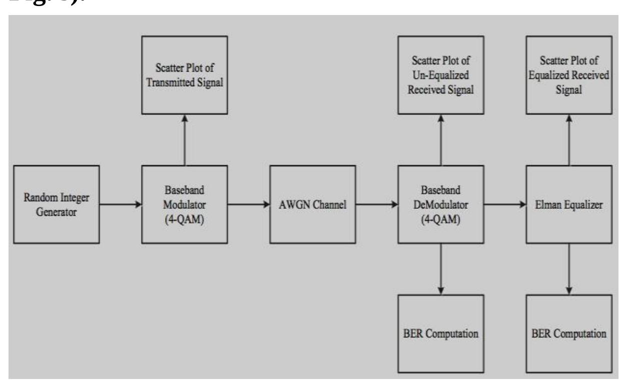

Fig. 3 Block diagram of channel equalization using Elman Network

B. Simulation Parameters

The designed wireless communication model parameters are initialized with several different characteristics such as number of data points to process, the signal constellation size, signal to noise ratio, energy per bit to noise power spectral density etc. After initializing the parameters, a random signal source (data stream) is generated containing 1000 data points, which is uniformly distributed matrix (column vector) of size $1000-$by -1. The bit stream is then mapped to symbols using binary to decimal conversion function. The mapped symbols are then baseband modulated using 4− QAM scheme.

The block diagram of simulated transmission system is shown in (

Fig. 4**).**

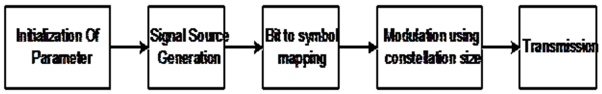

Fig. 4 Block diagram of wireless transmission system

The modulated signal (QAM) is then passed through Additive White Gaussian noise (AWGN) channel with specific energy efficiency metric. Energy per bit to noise power spectral density (E_b/N_o) is used to set the specific value of signal to noise ratio (SNR). The model for receiver is designed and the received signal is demodulated and is mapped back to bits and the bit error rate is calculated whose block diagram is shown in (

Fig. 5**).**

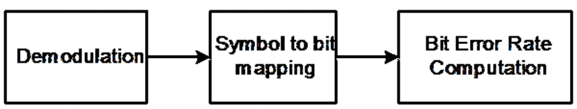

Fig. 5 Block diagram of wireless reception system

The aim is to reduce the bit error rate using the designed Elman network equalizer and compare its performance with previously reported channel equalization methods. The results of simulation of un-Equalized received signal are Errors = 81.0000 and BER = 0.0810. **(Fig. 6)** shows the behavior of transmitted (black dots) and un-equalized received signal (graydots).

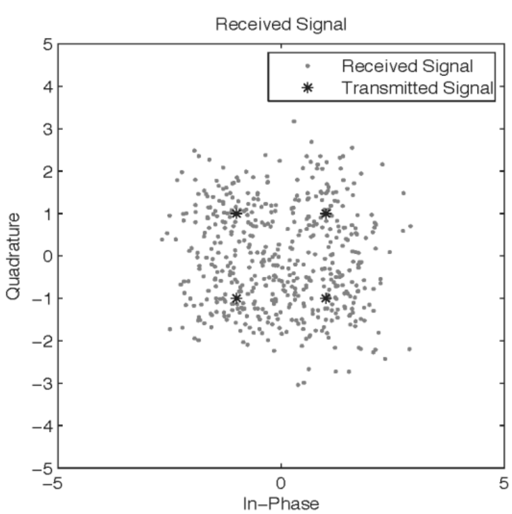

Fig. 6 Scatter plot of transmitted and received signal

The scattered dots represent the effect of noise over the transmitted signal causing the receiver to falsely detect the bits or receive corrupted data stream.

C. Design of Elman Network

The Elman network is designed to receive the data either in chunk's or bits and has the ability to differentiate the received information as either being data or noise. This ability is achieved by training the Elman network up to satisfactory level. The training function employed to update and optimize weight and bias states, which is the fastest BP algorithm and recommended choice for supervised algorithm. The learning function used along the training function is gradient descent with momentum weights and bias. The design characteristics of Elman Network are summarized in **(Table 1).**

Table 1 Elman network design characteristics

PARAMETERS	VALUE
NUMBER OF HIDDEN LAYER NEURONS	20
NUMBER OF HIDDEN LAYERS	1
NUMBER OF INPUTS	1000
NUMBER OF OUTPUTS	1000
HIDDEN LAYER TRANSFER FUNCTION	TANGENT SIGMOID
OUTPUT LAYER TRANSFER FUNCTION	LINEAR
BACKPROPAGATION NETWORK TRAINING FUNCTION	LEVENBERG MARQUARDT
BACKPROPAGATION WEIGHT OR BIAS LEARNING FUNCTION	GRADIENT DESCENT WITH MOMENTUM
PERFORMANCE FUNCTION	MEAN SQUARED ERROR
DATA DIVISION FUNCTION	DIVIDERAND

D.Training of Elman Network

The Elman network is then created using the design characteristics mentioned in Table 1 to work as an Equalizer. The assigned input and output vector to the Elman network is the received signal and the transmitted signal, which are row vector with dimension 1−by −1000. The Elman network is then trained properly with no false data. The definition of training parameters is illustrated in **(Table 2).**

Table 2 Elman network training parameters

PARAMETERS	VALUE
MAXIMUM NUMBER OF EPOCHS TO TRAIN	300
EPOCHS BETWEEN DISPLAYS	25
LEARNING RATE	0.01
RATIO TO INCREASE LEARNING RATE	1.05
RATIO TO DECREASE LEARNING RATE	0.7
MAXIMUM PERFORMANCE INCREASE	1.04
MOMENTUM CONSTANT	0.9
PERFORMANCE GOAL	$1E^{-5}$
MINIMUM PERFORMANCE GRADIENT	$1E^{-10}$

For training, the input and output vectors to Elman Network are then converted from concurrent form to sequential form. The trained Elman network is then simulated for its performance and the sequential vectors are again converted back to concurrent form. The simulated output, which is a row vector is the equalized data stream. Bit error rate (BER) is then computed for the Elman equalized signal, whose results are Errors = 0.0000 and BER = 0.0000.

4. EXPERIMENTAL RESULTS

(Fig. 7) shows the behavior of corrupted received signal and the Elman equalized signal. The scattered gray dots represent the noise effected received signal, the asterisk's dark black in color represent the Elman equalized output. Comparing **(Fig. 7)** with **(Fig. 6)**, results clearly show that transmitted signal is correctly received despite going through severe noisy channel. Please note the label's represented in **(Fig. 7)** and **(Fig. 6)**; the scattered gray dots in **(Fig. 7)** represent the noisy received signal data points which are equalized (dark black dots) now, to be exact copy of transmitted signal as shown in **(Fig. 6)**.

(

Fig. 8**)** is another way of representing the results shown in **(Fig. 7)**. **(**

Fig. 8**)** shows the summarized behavior of transmitted, received and Elman equalized output. The results clearly show that Elman network, which is the type of recurrent Neural Network, can be employed at the receiver end to equalize the signal and has better efficiency as compared to the traditional already reported equalization methods. The initial training process is slow, once the network is trained; retrieving the output for any random data stream is very fast and accurate. Several tests were conducted against random bit stream to check the validation of Elman network to work as an equalizer. All those tests prove to be successful.

In our model, only single hidden layer and mere 20 number of neurons were sufficient to successfully reproduce the exact copy of transmitted signal.

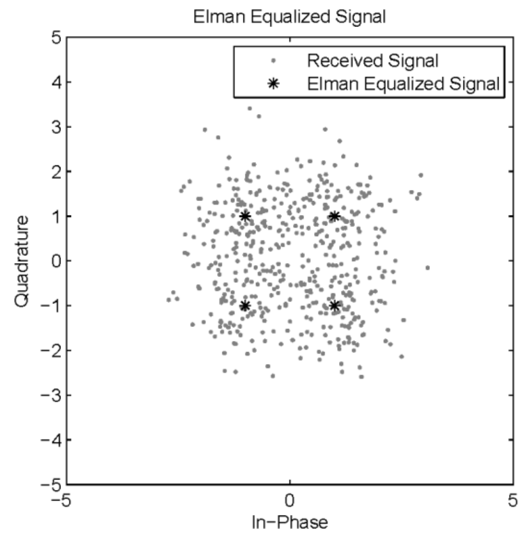

Fig. 7 Scatter plot of received signal and Elman equalized output

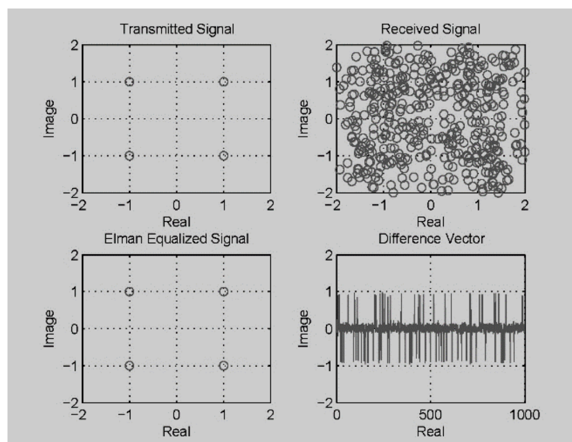

Fig. 8 Summarized transmitted, received and Elman equalized output

The designed Elman network was tested with different training and learning algorithms, the results of those tests were found to be somewhat similar. Good training set and proper selection of neuron is critical task, as they might cause the problem of over/under fitting.

5. PERFORMANCE EVALUATION

Performance tests were carried out to compare the efficiency of reported blind channel equalization methods in mitigating ISI based on Least Mean Square, Blind Zero Forcing MMSE, Adaptive Constant Modulus

Algorithm, and Adaptive CMA method in Fractional Space. These algorithms have been simulated using MATLAB under similar conditions (Number of data points T=1000, AWGN Channel with 25dB SNR, 4−QAM Modulation Technique, Channel Length Lh = 5).

The working procedure of Least Mean Square Method is summarized in following steps;

- Computation of transversal filter output
- Generation of estimation error
- Estimation Error is used to adapt the tap weights of the filter

This is an iterative procedure that does the adjustments of tap weights using gradient (Method of Steepest Descent) algorithm (Haykin, 1985). Filtering is performed by Transversal Filter block and an adjustment of tap weights of the transversal filter is done by adaptive control process block. The wireless communication model that utilizes the LMS algorithm based equalizer was designed using MATLAB tool and was simulated with several system characteristics such as, T = 3000 data points, M = 2000 number of symbols, SNR = 25db, QPSK Modulation, Lh = 5 channel length and N = 20 Smoothing length.

The results show that LMS algorithm based equalizer was found have slow convergence time due to the spread in the Eigen value. The main factor affecting the convergence behavior and control stability of the LMS algorithm is the step-size parameter μ. **(Fig. 9)** shows the eye diagram of the transmitted, received and equalized signal with e(n) = 0.6032.

In Minimum Mean Square Error (MMSE) equalization technique, the equalizers task is to decrease the error that is the average Mean Square Error (MSE) between the channel estimate and the transmitted symbols. The purpose of Zero Forcing (ZF) equalizer is to maximize the signal strength at frequencies which are attenuated by noise. However, Zero Forcing (ZF) equalizers tend to perform poorly when the channel noise is significant. Both the MMSE equalizer and the ZF equalizer are of a general Infinite Impulse Response (IIR) form. Since linear equalizers are usually implemented as Finite Impulse Response (FIR) filters, FIR approximations are necessary for both IIR equalizers in practice, often based on a well-defined criterion such as the MMSE between the two impulse responses. The Blind Zero Forcing MMSE algorithm based equalizer was designed using MATLAB tool and was simulated with same system characteristics such as, T = 1000 data points, M = 500 number of symbols, SNR = 25db, QPSK Modulation, Lh = 5 channel length and N = 20 Smoothing length. The results show that Blind Zero Forcing MMSE method based equalizer has faster convergence time than LMS algorithm but performance of algorithm is same what similar. **(Fig. 10)** shows the eye diagram of the transmitted, received and equalized signal with e(n) = 0.9876.

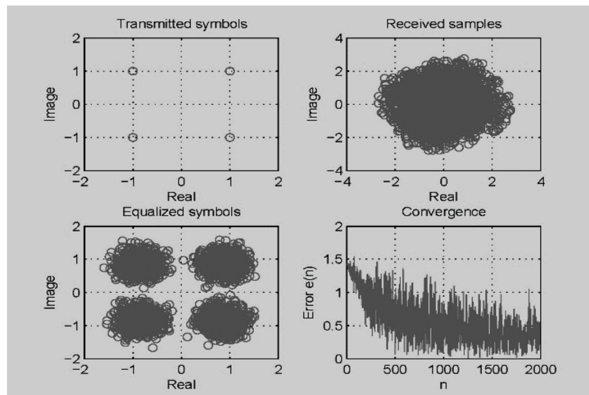

Fig. 9 Performance of LMS algorithm as an equalizer

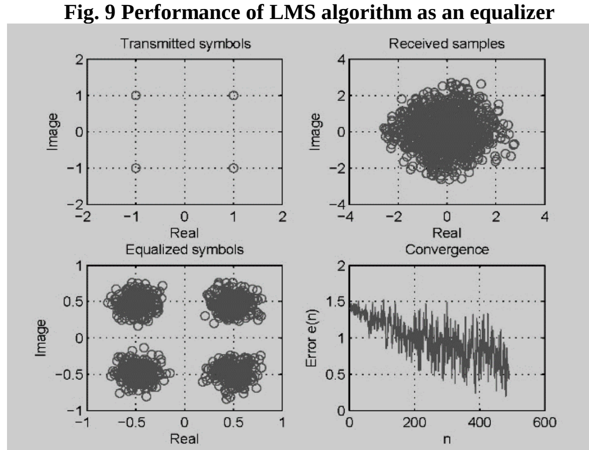

Fig. 10 Performance of ZF-MMSE Algorithm as an Equalizer

Adaptive constant modulus algorithm minimizes the distance between the predefined constant values and the modulus of equalizer output, while not utilizing the reference signal. The constellation symbol represents the constant values. The constellation symbols are the same that are utilized while in the process of modulation (Diniz, 2008). The main assumption made by the constant modulus algorithm is that the signal is modulated with constant amplitude. The variation in amplitude of the received signal is considered to be distortion introduced by the channel.

The adaptive Constant Modulus Algorithm (CMA) based equalizer was designed using MATLAB tool and was simulated with same system characteristics such as, T = 3000 data points, M = 2000 number of symbols, SNR = 25db, SER = 3.3557×10−4db, QPSK/4−QAM Modulation, Lh = 5 channel length and N = 20 Smoothing length.

The results show that CMA based equalizer has slow convergence time, but it offers the benefit of separating the ISI equalization and carrier phase recovery problems. **(Fig. 11)** shows the eye diagram of the transmitted, received and equalized signal with e(n) = 0.6761.

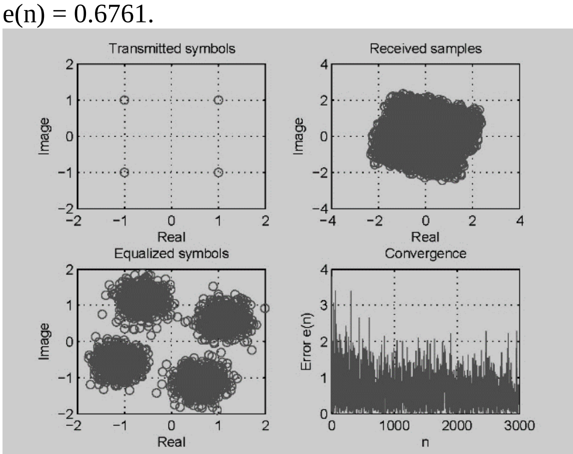

Fig. 11 Performance of CMA algorithm as an equalizer

Adaptive Constant Modulus Algorithm (CMA) in fractional spaced equalizer structure was originally proposed for the over-sampled, or in other words, fractionally spaced sampled communication systems. They are not only known for their advantages of low insensitivity to timing phase error, they are also capable of global convergence under a simple and mild length-and-zero condition. Moreover, they can be applied to spatial as well as spectral channel diversities. Researchers have caught much attention because of its robustness to channel noise, channel disparity, and the equalizer length has been presented in (Fijalkow, Touzni, and Treichler, 1997), and (Endres, Anderson, and Johnson Jr, 1999).

The wireless communication model that utilizes the adaptive constant modulus algorithm in fractional space based equalizer was designed using MATLAB tool and was simulated with same system characteristics such as, T = 1000 data points, M = 500 number of symbols, SNR = 25db, 4−QAM Modulation, Lh = 5 channel length and N =5 Smoothing length. The results show that CMA in fractional space based equalizer has better performance in eradicating the noise and has good convergence rate as compared to the previously reported blind algorithms. **(Fig. 12)** shows the eye diagram of the transmitted, received and equalized signal with e(n) = 0.3320.

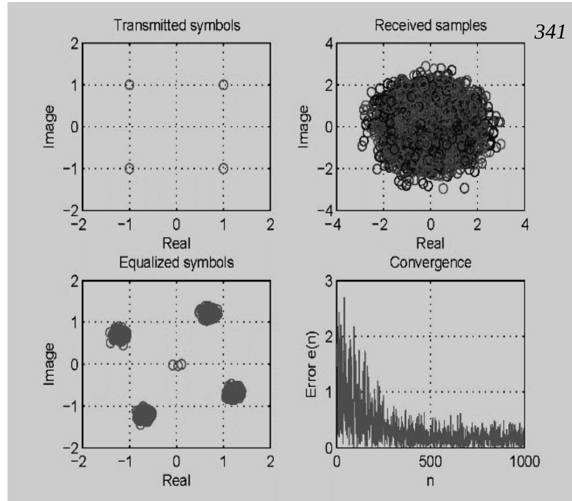

Fig. 12 Performance of adaptive CMA in fractional space based equalizer

The simulation results demonstrated that the behavior of Adaptive CMA in Fractional Space was most efficient, but its performance is sub-optimal in presence of noise. As artificial neural networks have the ability to cope the errors caused by noisy channel. Elman Network was developed and its MATLAB simulation results demonstrated a significant performance improvement and a better efficiency of coping with ISI as compared to previously reported Equalization methods.

The performance is shown to exceed that of traditional equalization algorithms and Feed-Forward Neural Network schemes, especially in the presence of spectral nulls and/or severe non- linearity. The results of our designed Elman Networks output (see details in Section 4,

Fig. 8) show better results in coping with noise as compared to the results produced by these algorithms (Fig. 9, Fig. 10, Fig. 11, Fig. 12). Not only the results produced by our designed Elman Network were better but had faster convergence than reported algorithms. One of the main advantages of Elman equalizer is its flexibility to be retrained in case of results produced is not optimal. Secondly, it is fault tolerant, meaning in worst case, there is graceful performance degradation.

Furthermore, due to the small number of neurons involved, the computational cost of their training may in practice be much smaller than that of the MLP-based equalizers of similar performance.

6. CONCLUSION

In this paper, MATLAB based simulation was initially carried out for four different algorithms, but some limitations were observed, particularly in presence of low SNR channels. Therefore, simulation of Elman Network based Equalizer was examined. An improvement was observed by increasing the neurons in hidden layer and the use of 20 hidden layer neurons were able to remove any errors caused by noisy channel under similar condition to which other equalization algorithms weren't successful in coping it.

It was observed that simple Recurrent Neural Network structures can equalize linear and nonlinear channels better than the traditional constant modulus algorithm. Lastly, there are several articles showing efficient VLSI (Very Large Scale Integration) hardware implementation of Neural Network. Hardware implementation and testing of designed Elman Networks performance in real world scenario is left as part of future work. This work assumes that the transmitted symbols are corrupted with white Gaussian noise. It will be interesting to investigate the use of Elman Network in presence of other types of noise. Elman network is a recurrent neural network, which has a good potential to be used as an equalizer. However, a number of other neural network architectures are also available which may be explored as a possible alternative to the Elman network.

The work presented is based on 4-QAM modulation technique. The future researchers may explore the use of Elman Network for other digital modulation schemes such as 8-PSK, 16-PSK, 16-QAM etc. However work has not calculated the bandwidth of a system with the use of an equalizer. The future researchers may focus on this issue and determine qualitatively how much bandwidth can be saved.

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