

**A HIGHLY EFFICIENT ADAPTIVE CHANNEL EQUALISER
USING SINGLE LAYER ARCHITECTURE**

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ABSTRACT

This paper proposes a highly elegant adaptive digital equaliser structure using single neuron which possesses significantly low computational complexity compared to recently reported multilayered Artificial Neural Network based equaliser [2]. In terms of performance the proposed structure offers minimum residual mean square error in comparison to either the LMS or multilayered based structure. The learning rate of the proposed equaliser is also faster than that of the multilayered case[2].

**KEY WORDS : Digital Adaptive Equaliser, Artificial Neural
Network**

INTRODUCTION

Channel equalisation is an important subsystem in a communication receiver. Its objective is to remove the intersymbol interference and to recover the transmitted message in an undistorted form. A channel may be modelled as a digital filter. The transfer function of an equaliser is inverse to that of the channel filter as shown in Fig.1. Since the channel behaves randomly, a fixed inverse filter can not provide satisfactory performance. For this reason fixed impulse response equaliser have been replaced by adaptive equalisers based on algorithms such as Least Mean Square (LMS), Orthogonal Least Mean Square (OLMS), Block Least Mean Square (BLMS), Recursive Least Square (RLS) etc. But these adaptive filter structures fail to introduce the desired non-linearity as demanded by practical channels and as such do not perform satisfactorily. These equalisers recursively update the filter weights during the training mode until a desired performance is achieved. Their performance even degrades further in channels having high Eigen Value Ratios (EVRs) and under high noise conditions.

In recent past Artificial Neural Network (ANN) has played a very important role in all fields of research. Since ANN has a massively interconnected structure and has the inherent capability of introducing the non-linearity, it is

expected that the performance of ANN based equaliser will be superior to conventional equaliser structures. Keeping this in view an ANN based equaliser has recently been proposed [2]. It has been reported that the above equaliser provides much better performance relative to LMS based equaliser in terms of residual Mean Square Error (MSE). However, results available in the literature indicate that the convergence time is much slow compared to LMS based equaliser. Further, the structure being multilayered one, involves more computations per iteration during training period. This structure being complex, its hardware implementation using a microprocessor is difficult and cumbersome.

In this paper we propose a highly elegant equaliser structure based on a single neuron perceptron. Its performance is superior both in terms of convergence time and residual mean square error compared to multi-layered equaliser structure [2]. This structure involves much less computation and can easily be hardware implementable.

PROPOSED STRUCTURE

The structure of the equaliser has been presented in Fig.2. The input message sequence in the receiver undergoes a linear convolution with the neural weights as in case of transversal filter. The convolution output is added with a

threshold and the sum is then passed through a sigmoid type non-linear activation function. The output of the activation function is known as the recovered message (estimated output), which is then compared with the delayed version of the transmitted message (desired signal). The resulting error and the input vector are then used in the back propagation algorithm [1] to update the neural weights along with the threshold. This procedure is continued till the residual MSE is minimum. Under such a condition the neural net attains a generalisation which is capable of recovering the transmitted sequence without distortion.

DEVELOPMENT OF THE PROPOSED ALGORITHM [3]

The basic structure of a perceptron is presented in Fig.3. The operation in a perceptron involves the computation of the weighted sum of inputs and adds a threshold to it. The threshold is derived by multiplying an unity signal with an adaptable weight. This resultant signal is then passed through a non-linear sigmoid function. The output of the network is thus represented as

$$y = f \left(\sum_{i=1}^{i=M} w_i x_i + \theta \right) \quad \dots (1)$$

where,

θ = Threshold applied = $1 * w_{th}$

M = no. of inputs to the neuron.

w_i = Weight associated with i^{th} input.

x_i = i^{th} input.

$f(.)$ = A nonlinear sigmoid function given by

$$f(z) = \frac{1 - e^{-\phi z}}{1 + e^{-\phi z}} \quad \dots \quad (2)$$

where,

z = input to the sigmoid function.

$f(z)$ = output of sigmoid function.

ϕ = slope of the sigmoid.

The weights associated with each of the inputs are updated iteratively. The weight update equation using well known Back Propagation algorithm [1] is given by

$$\Delta w_i(n+1) = \eta \delta(n) x_i(n) + \alpha \Delta w_i(n) \quad \dots \quad (3)$$

Here,

$\Delta w_i(n+1)$ = increment in i^{th} weight at $(n+1)^{th}$ input time sample.

α = momentum parameter

η = gain factor

The magnitude of both α and η lies between 0 to 1.

$x_i(n)$ = i^{th} input signal at n^{th} time sample.

The error term $\delta(n)$ at n^{th} time sample given by following equation.

$$\delta(n) = \left[d(n) - y(n) \right] \left[1 - y(n)^2 \right] / 2 \quad \dots \quad (4)$$

where,

$d(n)$ = desired output at n^{th} time sample.

$y(n)$ = estimated output at n^{th} time sample.

Similarly the threshold is updated by

$$\Delta\theta (n+1) = \beta\delta(n) \quad \dots \quad (5)$$

where,

β = gain factor for threshold which has a value in between 0 to 1, and

$\Delta\theta(n+1)$ = increment in the threshold at n^{th} time sample.

In the proposed weight update equation the momentum term is replaced by an error derivative term. Thus the new update equation becomes

$$\Delta w_i (n+1) = \eta \delta(n) x_i (n) + \zeta x_i (n) \Delta\delta \quad \dots \quad (6)$$

where,

ζ = a constant which is less than unity

$\Delta\delta = \delta(n) - \delta(n-1)$ which is the difference in errors generated during two successive time samples.

The conventional and threshold weights are updated by eqns. 5 and 6 respectively and the output of the network is computed using eqn.1. The residual MSE defined in eqn.7 is computed for each time sample over a set of experiments.

$$\text{MSE}(n) = 10 \log_{10} \left[\frac{1}{K} \sum_{m=1}^K e_m^2(n) \right] \quad \dots \quad (7)$$

where,

$$e_m(n) = d_m(n) - y_m(n) \quad \dots (8)$$

K = number of experiments performed.

Here,

'm' and 'n' denote the experiment number and the iteration number respectively.

and the remaining terms have their usual meanings.

SIMULATION :

To validate the proposed structure its performance is compared with the other existing methods. Simulation study was carried out on channel equalisation problems where three types of channels (British Telecom channel no. 1, 2, and 3) were considered. The characteristics of the channels are given in Table 1.

TABLE # 1
CHANNEL CHARACTERISTICS

Sl.No.	Impulse Response	Eigen Value Ratio
1	$1.0 + 0.0 z^{-1} + 0.0 z^{-2}$	1
2	$0.2602 + 0.9298z^{-1} + 0.2602z^{-2}$	11.8
3	$0.3482 + 0.8704z^{-1} + 0.3482z^{-2}$	68.8

The performance of a channel is usually characterised by its EVR. The digital message applied to the channel was considered as a random binary sequence. The output of the

channel was contaminated with zero mean white Gaussian noise of -20dB strength relative to the signal power. The equaliser structure used for simulation is depicted in Fig.2. It has four tapped delay inputs in the feed-forward path formed by incoming message and another input formed by delaying the output by one sample, thus making the order of equaliser as 5 (N). The desired signal is generated by delaying the input message by (N+1)/2 time samples which is 3 in this case. The equaliser output is determined using eqns.1 and 2. The weights are updated employing eqns.4, 5 and 6. The simulation study was carried out by taking an ensemble of 50 experiments with each experiment having a set of different starting random weights with values between -0.5 to +0.5. In each experiment the MSE was computed over 2000 iterations and the residual MSE was calculated by eqn.7. To compare the performance of the proposed equaliser structure with existing methods, a multi-layered (3 layers) ANN equaliser dealt in [1] comprising of 9, 3, 1 neurons and an LMS equaliser of order 5 were considered. The following parameter values were chosen in the present simulation.

$$\eta = 0.6 \quad \beta = 0.6 \quad \zeta = 0.7 \quad \phi = 1$$

The results of the simulation have been presented in Fig. 4, 5 and 6 for channels 1, 2 and 3 respectively.

RESULTS AND DISCUSSION

From Fig.4, 5 and 6, it is observed that the rate of convergence is very fast in case of a single neuron based equaliser. Further it is found that for an additive noise of -20dB the MSE of the LMS based equaliser settles at -23dB, -19.5dB and -17dB in around 300 iterations for channel 1, 2 and 3 respectively. Similarly for the same noise condition and different channels the MSE of a multi-layer ANN based equaliser settles at -30dB, -29dB and -26dB respectively in around 1000 iteration. For a single neuron ANN based equaliser (proposed technique) the corresponding values are -39dB, -35dB, -32dB which are achieved at around 500 iterations. The following important conclusions have been arrived at from these results.

- i) With the proposed structure the rate of convergence during training is in between those of the LMS and multi-layer ANN based equaliser structures.
- ii) The proposed structure offers minimum residual MSE compared to the other two structures and therefore is the best among the three.
- iii) The proposed equaliser structure is less complex than multilayered ANN based equaliser [2] but almost identical to that of LMS based equaliser. As an illustration the number of weights updated per iteration in the simulation structures

are 5, 88 and 6 for the LMS, multy-layer ANN and single neuron based equalisers. Hence compared to the multy-layered structure, the proposed structure requires significant less computation per iteration and hence offers low computational complexity.

It is thus concluded that the proposed ANN structure out performs the multilayer ANN equaliser structure both in terms of speed of convergence and the residual MSE. Further, the structure being less complex may be easily hardware implementable using a dedicated microprocessor which is remote for the multy-layered ANN structure.

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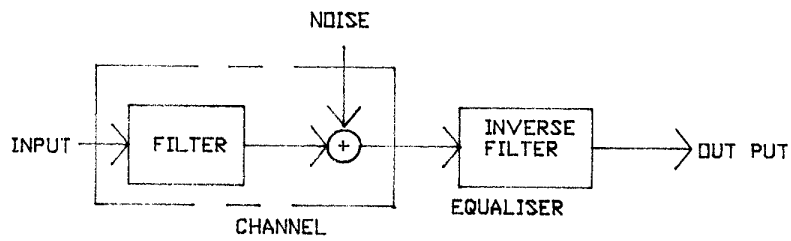
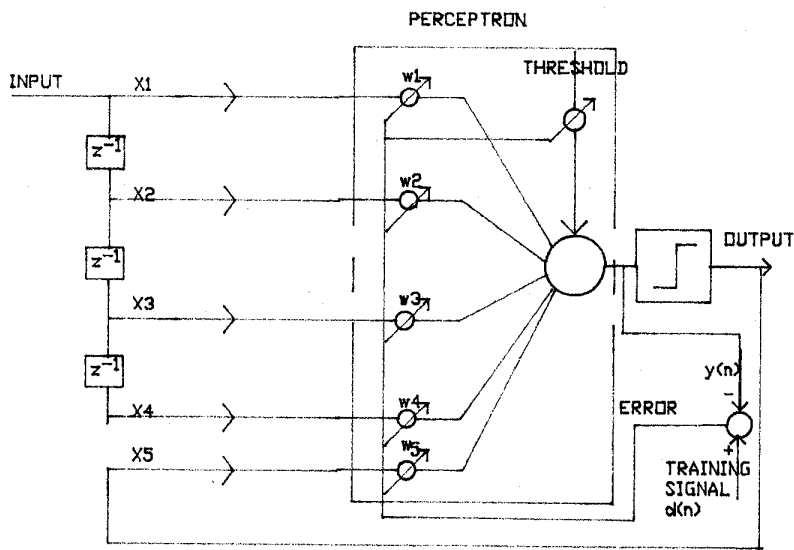
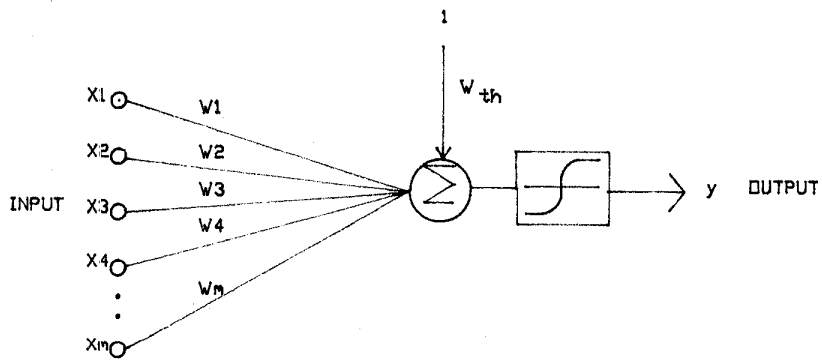


FIG.1



A SINGLE NEURON BASED ADAPTIVE EQUALISER

FIG.2



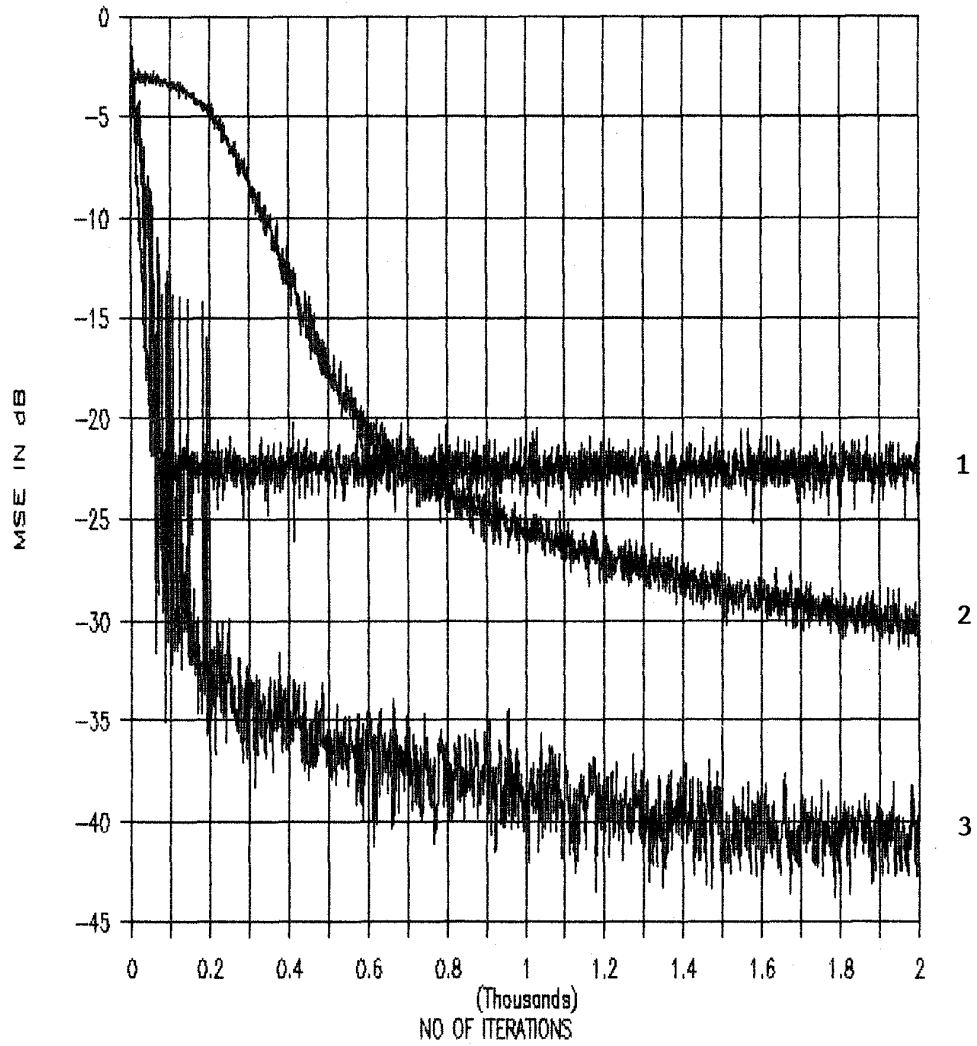
STRUCTURE OF A PERCEPTRON

FIG.3

PERFORMANCE OF DIFFERENT ADAPTIVE EQUALISERS

NOISE POWER = -20dB

CHANNEL - 1



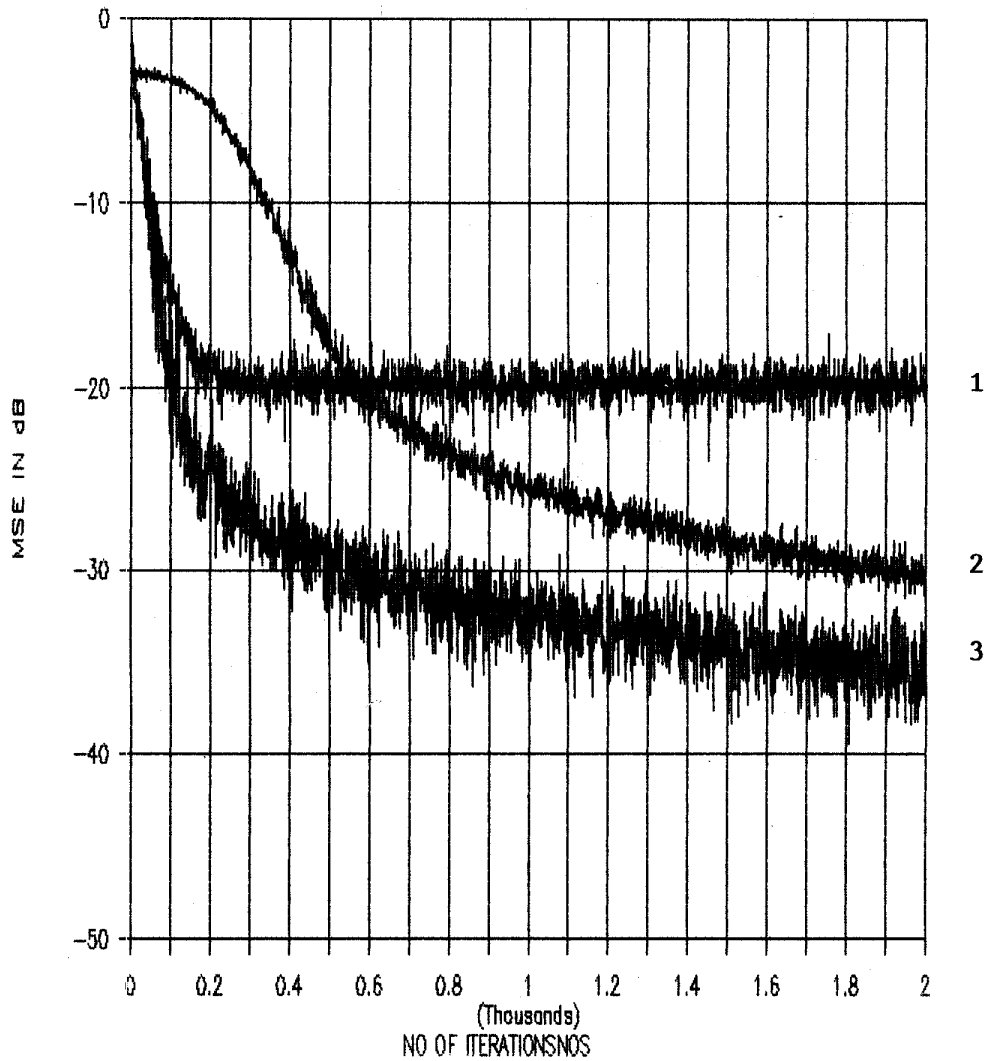
1 - LMS 2 - MULTI-LAYER ANN 3 - SINGLE NEURON (PROPOSED)

FIG.4

PERFORMANCE OF DIFFERENT ADAPTIVE EQUALISERS

NOISE POWER = -20dB

CHANNEL - 2



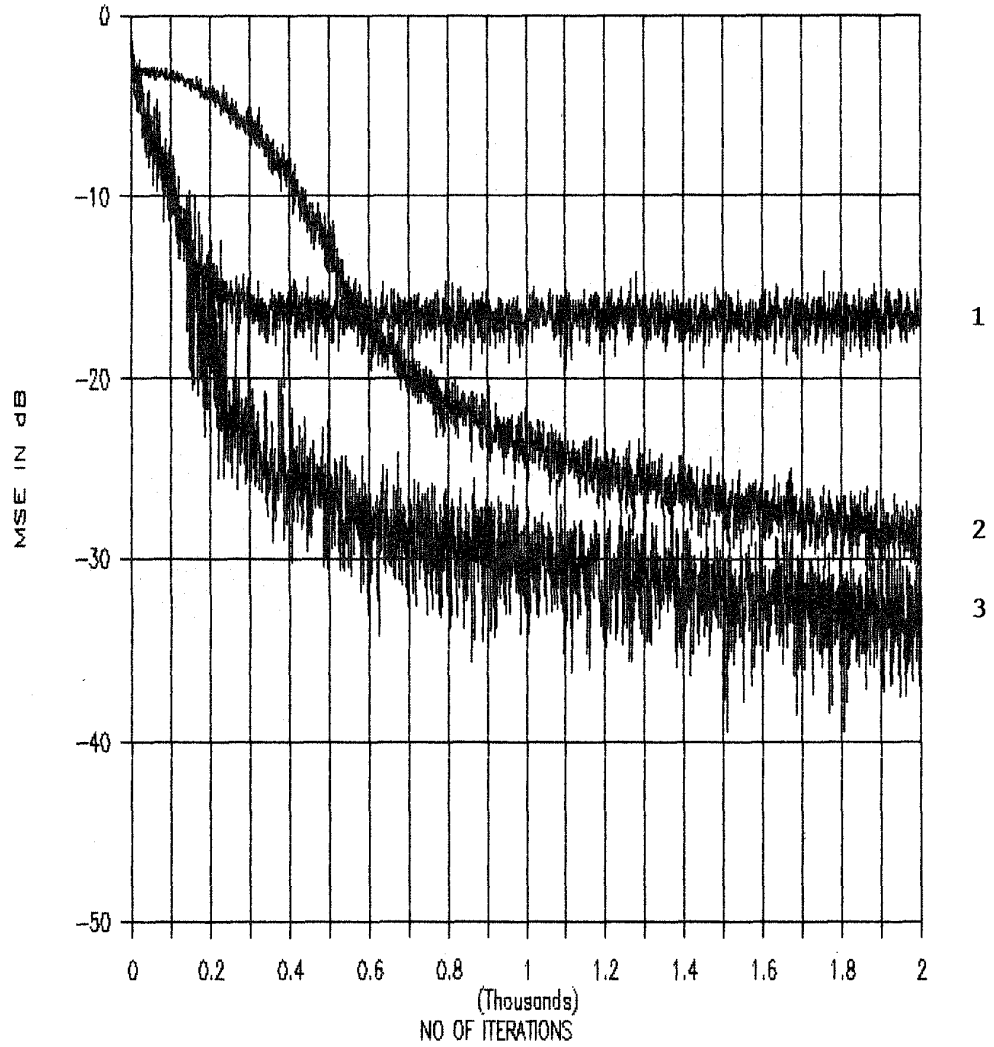
1 - LMS 2 - MULTI-LAYER ANN 3 - SINGLE NEURON (PROPOSED)

FIG.5

PERFORMANCE OF DIFFERENT ADAPTIVE EQUALISERS

NOISE POWER = -20dB

CHANNEL - 3



1 - LMS 2 - MULTI-LAYER ANN 3 - SINGLE NEURON (PROPOSED)

FIG. 6