MINIMAL RESOURCE ALLOCATION NETWORK (MRAN) FOR MAGNETIC RECORDING CHANNEL EQUALIZATION

Deng Jianping*, N Sundararajan** and P Saratchandran**
**School of Electrical & Electronic Engineering, Nanyang Technological University
Singapore 639798, Email: ensundara@ntu.edu.sg
*Centre for Signal Processing, Nanyang Technological University, Singapore 639798

ABSTRACT

This paper presents the performance results of a recently developed minimal radial basis function neural network referred to as Minimal Resource Allocation Network (MRAN) for equalization of a highly nonlinear magnetic recording data storage channel. Using a realistic magnetic channel model, MRAN equalizer's performance has been studied in the presence of channel impairments like partial erasure, additive white gaussian noise and jitter and width variance. Compared with the earlier neural equalizers, MRAN equalizer has better performance in terms of higher Signal to Distortion Ratios (SDR).

1. INTRODUCTION

Channel equalization problems are of great concern in recent years for obtaining high-speed data transfer in communication system and also for getting high-density data storage in magnetic recording system. The adverse effects of the dispersive channel causing inter-symbol interference (ISI), the non-linearities introduced by the modulation/demodulation process or non-ideal channel nature and the noise generated in the system are to be suitably compensated. While communicators are concerned with maximizing the rate (in bits per second) whereby digital information can be transmitted and reliably received, storage researchers are largely concerned with maximizing the density for storing and reliably retrieving information. Since there is general similarity of the disk read and write processes to data-detection and transmission in communication, sophisticated equalization techniques that have been widely employed in communication applications are now being adapted [1,2].

Neural network-based equalizers for magnetic recording channels have recently been addressed in [3,4]. Nair and Moon [3] have proposed a nonlinear equalizer using a theoretically derived neural network and have shown that it performs better than linear methods in terms of Signal to Distortion Ratios (SDR) for highly nonlinear channels when the channel model is known accurately. They have also shown in [3] that their theoretical method produces an equalizer performance close to that of a trained backpropagation (BP) neural network equalizer but without the need for training as the weights are obtained based on their theory. Further in their method, the number of hidden layers and the number of hidden neurons are worked out as part of the theoretical calculation unlike a BP network where these have to be selected using a trial and error process. So whenever the channel model is known accurately Nair and Moon have shown that their theoretically designed neural equalizer is to be preferred to linear or other neural network based equalizers.

Recently a minimal Radial basis Function network referred to as a minimal resource allocation network (MRAN) has been developed [5] and successfully used for communication channel equalization [6]. MRAN has the same structure as a RBF but has the ability to add and prune hidden neurons based on the training data so as to produce a compact structure. In this paper we have compared the performance of MRAN with that of Nair and Moon equalizer for the same problem used in [3]. Simulation results show that MRAN is able to produce better SDR for all cases of the problem considered in [3]; namely severe partial erasure, jitter, width variation and additive white Gaussian noise. Further MRAN does not require an accurate model of the channel, as is the case with the Nair and Moon equalizer.

This paper is organized as follows. In section 2, the nonlinear magnetic recording channel model along with the equalizer is described. A brief description of the MRAN network and its form as an equalizer is given in section 3. In section 4, the application of MRAN for realistic nonlinear magnetic channel equalization is presented and its performance is compared with that of Nair's theoretical MSDR method [3]. Section 5 summarizes the conclusion from this study.

2. NONLINEAR MAGNETIC STORAGE CHANNEL EQUALIZATION

In this paper, we compare the performance of the MRAN equalizer with those of Nair's nonlinear equalizer for the same problem given in [3]. This problem uses a realistic channel model that has the popular Lorenzian transition response in the presence of AWGN, transition noise and partial erasure. The channel model along with the equalizer is shown in figure 1. The binary data sequence to be stored in the recording disk is denoted by b_k, which takes values of -1 and + 1. The data is stored in tiny magnetized regions called bit cells arranged along the track. At read-back, the signal gets differentiated and corrupted by noise and nonlinear distortions. A magnetic flux transition occurs when the polarity of the bit cells changes. Let the transitions' sequence be defined as a'_k, which is equal to b_k-b_{k-1}. Note that a'_k takes values from the set {-2, 0, +2} with alternating polarities for the nonzero transitions. At high recording densities, the size of bit regions decreases. The net result is that written bit regions are partially erased. According to [3], this nonlinear distortion phenomenon can be modeled as pair wise erasure of the amplitude of the adjacent magnetic transition,

$$a_k = (1 - \chi)\, a'_k.$$

where χ denotes the partial erasure parameter. Since partial erasure can only occur for minimum-width bit regions, a transition with no neighboring transitions a bit cell away is always intact. Therefore, a magnetic transition undergoes partial erasure in all cases except when it is the last one in a cluster of an odd number of consecutive transitions. Out of these, the amplitudes of erased transitions a_k can have values from the set {-2, -2(1-χ), 0, 2(1-χ), and 2}. Besides these errors, there is noise arising from the receiving amplifier and filter, which is usually modeled as additive white Gaussian (AWGN).

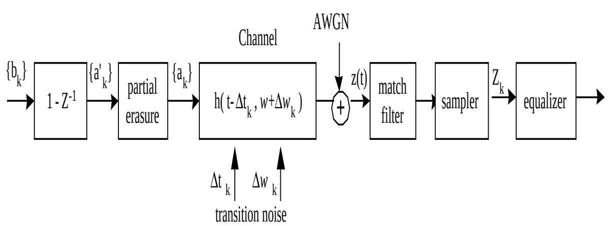

Fig. 1 Nonlinear Magnetic channel model with equalizer

An isolated magnetic flux transition induces a voltage pulse in the read head, which is often modeled by a Lorenzian pulse shape, h (t, *w*) as

$$h(t, w) = \frac{1}{w} \frac{1}{1 + (\frac{t}{w})^2}$$

Where t is the time and *w* is the width parameter. Due to noise originating from the recording medium around the magnetic transitions, the width, the amplitude, and the position of the transition response pulses vary randomly. If h (t, *w*) denotes the read-back response to a noise free transition at t=0, the noisy read-back response can be written as

$$z(t) = \sum a_k\, h(t - kT - \Delta t_k,\, w + \Delta w_k) + n(t)$$

Δt_k and Δw_k are random parameters representing deviations in the position and width, respectively, from the nominal values. The former represents magnetic transition "jitter" and the latter "width variation" and they are data-dependent noises. In this study, the quantities of Δt_k and Δw_k are modeled as independent and identically distributed Gaussian random variables. The last term, n (t) is the additive white Gaussian noise (AWGN).

Assuming a front-end filter matched to h (t, *w*) and a symbol-rate sampler, the read-back sequences can be expressed using the following equation, [3] where h_k is the sampled auto-correlation function of h(t, *w*); h^t_k and h^w_k are sampled derivatives of h(t, *w*) with respect to t and *w* respectively.

$$Z_k = \sum_{i=-L}^{L} (h_i a_{k-i} + (h_i^t \Delta t_{k-i} + h_i^w \Delta w_{k-i}) a_{k-i}) + n_k$$

Thus, the aim of the equalizer is to classify the read and corrupted data sequence into the three classes of {-2, 0, +2} based on the magnetic transition sequence of a'_k.

Nair and Moon's MSDR equalizer method [3] assumes that the noisy observation vectors form clusters in the Euclidean space whose centers mark the average of the received vectors in the clusters. The structure of the MSDR equalizer is as follows: considering a neural network where its first layer is elements of the observation vector, the second layer is made up of an array of linear classifiers. Each one of these can determine which cluster the received vector ***Z*** is closer to, in a given pair of clusters. By performing an "AND" operation on the classification results of the second layer, the third layer defines convex regions around the cluster centers. In other words, convex regions are approximated by an intersection of several half-spaces of piece-wise linear hyper-planes. The "OR" operations are done at the fourth layer combining one or more convex regions to form the class membership sets. After the structure is decided, from the knowledge of the channel characteristics and various noise power, the connection weights can be optimally designed by maximizing the signal to distortion ratio (SDR) at the piecewise linear classification boundaries.

In this paper, the signal to distortion ratio is defined as follows: first find the mean signal at the equalizer output for transitions of 0, – and + polarities. Let mean of the equalized signal corresponding to $a'_k = \pm 2$ be r_a and $-r_b$ respectively. Therefore, the signal to distortion ratio (SDR) is expressed as:

$$SDR1 = r^2_a / 4e^2$$
$$SDR2 = r^2_b / 4e^2$$
$$SDR = \min(SDR1, SDR2)$$
$$e^2 = E\{e^2_k\} = E\{(y_k - d_k)^2\}$$

where the error sequence e_k is defined as the difference between d_k , the desired undistorted channel output, and y_k , the actual equalizer output. The higher the SDR, the lower the probability of error for practical distortion distributions.

Before presenting the performance comparison of the MSDR and MRAN equalizers, a brief description of MRAN is given in the next section.

3. MINIMAL RESOURCE ALLOCATION NETWORK (MRAN)

MRAN is a sequential learning algorithm for minimum RBF neural network, recently developed by Yingwei et al [5], which combines the growth criteria of an RAN with a pruning strategy to realize a minimal RAN. The centers, widths and weights of the hidden neurons are adjusted using an extended Kalman filter (EKF). Here, only a brief description of the network is given. For details please refer to [5][6].

The output of an MRAN equalizer has the following form:

$$f(x_n) = \alpha_0 + \sum_{k=1}^{h} \alpha_k \phi_k(x_n)$$

Where ϕ_k ($\mathbf{x}_n$) is the response of the k^{th}-hidden neuron to the input $\mathbf{x}_n$, and α_k is the weight connecting the k^{th}-hidden unit to the output unit. α_0 is the bias term and *h* represents the number of hidden neurons in the network. $\phi_k(\mathbf{x}_n)$ is a Gaussian function given by,

$$\phi_k(x_n) = \exp\left(-\frac{1}{(\sigma_k)^2}\|x_n - \mu_k\|^2\right)$$

Where $\boldsymbol{\mu}_k$ is the center and σ_k is the width of the Gaussian function. $\| \, \|$ denotes the Euclidean norm. In the MRAN algorithm, the network begins with no hidden units. As each input-output training data ($\mathbf{x}_n$, y_n) is received, the network is built up based on certain growth criteria. The algorithm adds hidden units, as well as adjusts the existing network parameters.

A brief outline of the various steps is given below:

1. Obtain an input $\mathbf{x}_k$ and calculate the network output y_k and the corresponding errors

$$e_n = y_n - f(x_n) \qquad e_{rmsn} = \sqrt{\sum_{i=n-(M-1)}^{n} \frac{e_i^2}{M}}$$

2. Create a new RBF center if the following conditions are met:

(a) the error $\|e_n\|^2$ exceeds a minimum threshold value (e_{min}),

(b) the root mean squared error (e_{rmsn}) of the network averaged over a window size 'M' has been above a certain threshold value (e_{min1}) for a series of past data, and

(c) the new input is sufficiently far from the existing centers ($\|\mathbf{x}_k - \boldsymbol{\mu}_n\| > \varepsilon_n$).

3. Perform pruning if a center's normalized contribution to the output for a certain number 'Sw' of consecutive inputs is found to be below a threshold value.
4. Adjust the weights and widths of the existing RBF centres by using the Extended Kalman Filter (EKF) Algorithm.
5. Increment k and go to step 1.

The performance of MRAN equalizer has been evaluated on a number of examples from communication area in [6]. It is adapted to magnetic channel equalization next.

4. PERFORMANCE OF MRAN EQUALIZER

In this section, the realistic recording channel model discussed in Section 2 is used to evaluate the error performance of MRAN equalizer and compare it with that of Nair and Moon's MSDR equalizer [3]. The impulse response matrices for this channel considered are given by [3]

$$h = [\ 0.1480 \quad 0.7132 \quad 0.2574\ ]' = [\ h_{-1} \ \ h_0 \ \ h_1]\ '$$
$$h^t = [\ 0.2476/T \ \ 0.1356/T \ \ -0.3512/T\ ]\ ' = [\ h^t_{-1} \ \ h^t_0 \ \ h^t_1\ ]\ '$$
$$h^w = [\ 0.2593/T \ \ -1.6230/T \ \ -0.0996/T\ ]' = [\ h^w_{-1} \ \ h^w_0 \ \ h^w_1]\ '$$

and the read-back signals are given by the following equation:

$$Z_k = [a_{k+1} \quad a_k \quad a_{k-1}]\begin{bmatrix} h_{-1} \\ h_0 \\ h_1 \end{bmatrix} + [a_{k+1}\Delta t_{k+1} \quad a_k\Delta t_k \quad a_{k-1}\Delta t_{k-1}]\begin{bmatrix} h^t_{-1} \\ h^t_0 \\ h^t_1 \end{bmatrix} +$$
$$[a_{k+1}\Delta w_{k+1} \quad a_k\Delta w_k \quad a_{k-1}\Delta w_{k-1}]\begin{bmatrix} h^w_{-1} \\ h^w_0 \\ h^w_1 \end{bmatrix} + n_k$$

The observation vector ***z*** has a length of four [3]. Four channel error conditions have been studied and they are partial erasure in the channel, additive white Gaussian noise (AWGN) in the channel, jittery channel conditions, and width variation in the channel. They represent different types of nonlinearities and distortions in the stored signal.

Case 1: Partial Erasure

The effect of partial erasure variation on the detection performance is first investigated. MRAN was used to train 2000 data bits with noise corrupted at σ^2_n=0.004, σ^2_t=0.01T^2, σ^2_w=0.000625T^2, χ =0.4. The values of the parameters used in MRAN were: e_{min}=0.4, e_{min1}=0.6, ε_{max}=0.4, γ =1, the size of the two sliding windows M and Sw is 60, 50 respectively, pruning threshold δ=0.001. The resulting MRAN network had 13 hidden units. Under the same noise condition, the parameters for MSDR network with a structure 0f 4-72-15-3 is also obtained. 10^5 data bits with partial erasure parameter χ varying from 0-0.7 were then used to test the performance of resulting MRAN and MSDR network. Figure 2 shows the detection SDR result. It is seen that when the partial erasure cannot be estimated correctly, the performance of MSDR detector degrades a lot. In the presence of severe partial erasure (χ= 0.7), MRAN equalizer has an advantage of about 6dB over the neural network based on MSDR criterion.

Case 2: Additive White Gaussian Noise

For a channel corrupted entirely by additive white Gaussian noise (AWGN), the partial erasure is set to zero. The MRAN algorithm was used to train the neural network with 2000 data samples at 15dB SNR using the parameters as e_{min}=0.5, e_{min1}=0.5, the size of the sliding window M is 80, pruning threshold δ=0.001. 18 centers have been built up. The resulting network was tested with 10^5 test data for each SNR to obtain the SDR curve in figure 3. It is observed that at low SNR the MRAN network has a performance measure very close to that of MSDR networks, while at high SNR the MRAN scheme has more performance superiority. It is clear that the performance of MRAN equalizer is indeed better than that of MSDR.

Case 3: Jitter Variance

Let training be done under the condition –2*log(RMS jitter/T) =1.4. The values of the parameters used in MRAN were: e_{min}=0.5, e_{min1}=0.8, ε_{max}=0.4, γ =1, the size of the two sliding windows M and Sw is 80, pruning threshold δ=0.001. After 2000 samples training, MRAN ends up with 24 hidden neurons. The neural network based on MSDR method is obtained under the exactly same noise condition. Noisy data with varying jitter noise variance are then used for testing the two resulting neural networks. The detection SDR is plotted against channel jitter noise intensity in figure 4. When channel signals are severely distorted by the jitter distortion, MRAN equalizer and MSDR neural network have similar performance. In other cases, MRAN equalizer has clear performance advantage. We see, the SDR curve of MSDR method is limited on the upper side by the residual ISI, while the nonlinear scheme using MRAN has performance improvements of more than 4 dB over the MSDR network at those points.

Case 4: Width Variance

For a channel corrupted entirely by width variation noise, samples data with width variation noise σ^2_w=0.005 (which corresponds to $-\log \sigma^2_w / T^2 = 2.3$) are used for training. The parameters of MRAN are set as: e_{min}=0.6, e_{min1}=0.7, ε_{max}=1, ε_{max}=0.4, the size of the two sliding windows M and Sw is 80, pruning threshold δ=0.01. In order to compare the performance of the resulting MRAN equalizer after about 2000 iterations with that of the MSDR equalizer, a plot of the SDR for 10^5 test data of varying width noise power is shown in figure 5. It is clear that the performance of MRAN equalizer with 24 centers gain far more SDR advantage over the Nair's MSDR neural network.

5. CONCLUSION

An evaluation of MRAN equalizer for a severe nonlinear ISI and signal-dependent distortion in the digital magnetic recording system has been carried out. Using a realistic magnetic channel model and in the presence of data dependent noise like jitter and width variations and also partial erasure channels, MRAN's performance in terms of Signal to Distortion Ratio (SDR) has been compared to that of MSDR equalizer designed by Nair and Moon [3]. The results show a higher signal to distortion ratio (SDR) for MRAN compared to that of Nair and Moon's equalizer. Further, MRAN does not need an accurate knowledge of the channel model and has the ability to build it up from the input and output data, providing a good way to do the equalization.

References:

1. J. Moon, "The Role of SP in Data-Storage Systems," IEEE Signal Processing Magazine, Vol.15, No.4, pp.54-72, July, 1998.
2. J. Proakis, " Equalization Techniques for high density magnetic recording ", IEEE Signal Processing Magazine, Vol.15, No.4, pp.73-82, July, 1998.
3. S.K.Nair and J.Moon, "A Theoretical Study of Linear and Nonlinear Equalization in the Nonlinear Magnetic Storage Channels ", IEEE Trans. on Neural Networks, Vol. 8, No. 5, pp. 1106-1118, September 1997.
4. S. K. Nair and J. Moon, "Data Storage Channel Equalization Using Neural Networks, " IEEE Trans. on Neural Networks, Vol. 8, No. 5, pp. 1037-1048, Sep. 1997
5. Yingwei Lu, N. Sundararajan and P. Saratchandran, "Performance Evaluation of a Sequential Minimal Radial Basis Function (RBF) Neural Network Learning Algorithm", IEEE Transactions on Neural Networks, Vol. 9, No. 2, pp 308 – 318, March 1998.
6. Chandra Kumar, P, Saratchandranand N. Sundararajan, "Nonlinear Channel Equalisation Using Minimal Radial Basis Function Neural Networks" Proc. Intl. Conference on Acoustics Speech and Signal Processing (ICASSP), Seattle, Washington, USA, 1998.

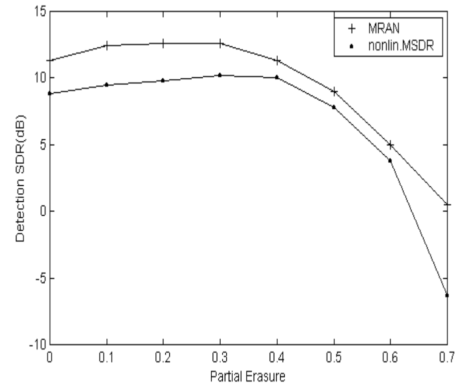

Fig.2. Channel with Partial erasure

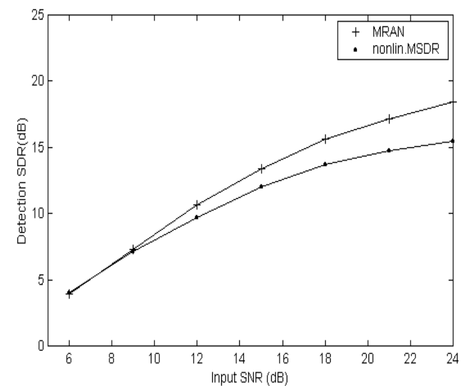

Fig. 3. Channel with AWGN

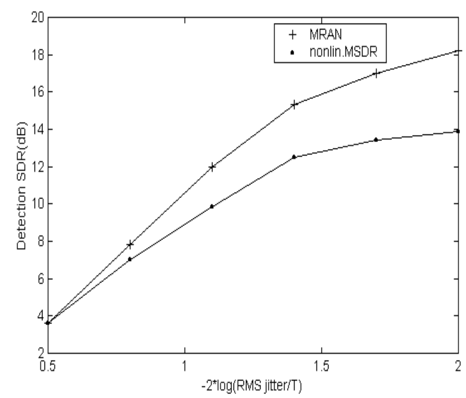

Fig.4 Jitter dominant channel

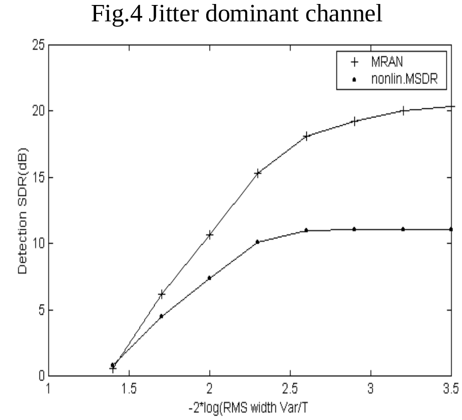

Fig.5. Width variation noise dominant channel