FUNCTIONAL LINK EQUALISER WITH DECISION SELECTION FOR COMBATTING COCHANNEL INTERFERENCE

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ABSTRACT

A Neural Network based Functional Link equalizer structure, incorporating Decision Selection, for overcoming cochannel interference is proposed. The Bit Error Rate performance of this new structure is evaluated by direct comparison with the Decision Feedback Functional Link Equaliser (DFFLE). The new structure offers the proven capability of the decision feedback functional link equalizer with a significant reduction in computations per symbol.

1. INTRODUCTION

Equalisation is an essential element of an efficient Digital Communication System and equalisers that can cope with and suppress co-channel interference are desirable. Recent research has highlighted several adaptive equaliser structures designed to suppress co-channel interference [1,2,3]. In [4] the author justifies the continued demand for equaliser structures that offer different balances of computational complexity and performance.

The Decision Feedback Equaliser (DFE) [5] is capable of producing a hyperplane decision boundary and uses previously detected symbols to adjust the location of this decision boundary, but not its orientation. In [6] the authors propose an alternative to the DFE, the Adaptive Decision Selection Equaliser (ADSE) that uses decision feedback to select sets of equaliser coefficients. The benefit of this approach is that the hyperplane decision boundary conditioned on feedback has different location and orientation. In [3] it has been shown that decision feedback simplifies the cochannel interference problem and allows a significant reduction in computational complexity.

In [1] the authors propose a novel Artificial Neural Network (ANN) structure using Functional Link (FL) expansion and nonlinearly combined decision feedback and showed this structures ability to out perform many alternative equalisers. This paper investigates the adaptive selection form of decision feedback applied to the Decision Feedback Functional Link Equaliser (DFFLE) neural network based equaliser of Hussain et al [1]. Simulation results using the proposed Decision Selection Functional Link Equaliser (DSFLE) show it to perform as well as the DFFLE of the same order whilst reducing the computations per symbol by almost a factor of two.

2. PROBLEM MODEL

The communication system model considered in this investigation is depicted in Figure 1. The inputs to the model are the signal of interest s_0 and the p co-channel interference signals s_i , $1 \le i \le p$. The own and co-channel interference linear dispersive channels are modeled as finite impulse response filters H_0 and H_i $1 \le i \le p$ respectively,

$$H_i = \sum_{j=0}^{n_i - 1} a_{i,j} z^{-j}, 0 \le i \le p \tag{1}$$

where n_i and $a_{i,j}$ are the Channel Impulse Response (CIR) length and tap weights of the *i*th channel respectively. The received signal $r(k)$ forms the input to the equaliser and can be represented as,

$$r(k) = \hat{r}(k) + u(k) + n(k) \tag{2}$$

where, $\hat{r}(k)$ represents the Inter Symbol Interference (ISI) corrupted signal of interest, $u(k)$ represents the summation of the ISI corrupted co-channel interferers and $n(k)$ is a zero mean additive gaussian noise term with variance σ_n^2. For this investigation the user symbols were assumed to be binary Independent Identically Distributed (IID) symbols with values +1 and -1.

The task of a decision feedback equaliser is to return

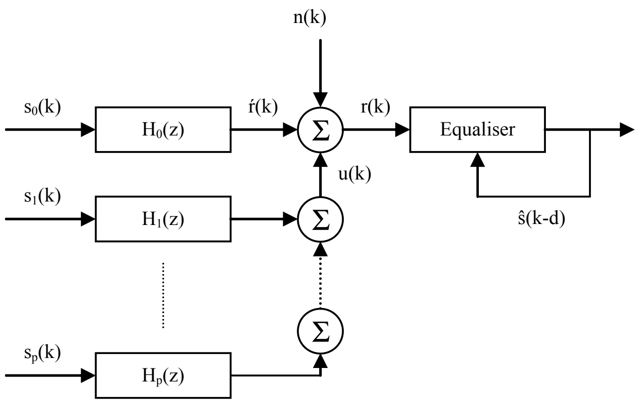

Fig 1. Communication System Model.

$\hat{s}(k-d)$, an estimate of the transmitted symbol $s(k-d)$, with decision delay d using the information present in the observation vector $\mathbf{r}(k)$, given by,

$$\mathbf{r}(k) = \left[r(k) \cdots r(k-m+1)\right]^T \tag{3}$$

and the past detected symbol vector,

$$\hat{\mathbf{s}}_b(k) = \left[\hat{s}(k-d-1) \cdots \hat{s}(k-d-n)\right]^T \tag{4}$$

where, m and n are the equaliser feedforward and feedback orders respectively.

If the effect of noise is removed from the mixing model it can be seen that there is a finite number of states which $\mathbf{r}(k)$ can assume [7]. When the set of states that $\mathbf{r}(k)$ can take is partitioned on the transmitted symbol $s(k-d)$ we end up with two sets of noise free states which each represent one of the two possible transmitted symbols. The decision feedback vector $\hat{\mathbf{s}}_b(k)$ is also limited to 2^n possible states due to the bipolar binary output from the equaliser. Each of the possible feedback vector states further subdivides the sets of states of $\mathbf{r}(k)$ [3]. Decision feedback therefore simplifies the classification problem by reducing the overall number of states that must be classified at any time. The standard decision feedback approach taken in the DFE and DFFLE is to incorporate the feedback directly into the nonlinear equaliser. This allows the DFFLE to modify its decision boundary dependent on the feedback but does not take full advantage of the inherently simpler classification problem. By utilizing the concept of decision selection we can allow the equaliser to directly work on the simpler subset classification problems and therefore we can safely reduce the modeling capability of the equaliser, and hence its computational cost, whilst retaining performance.

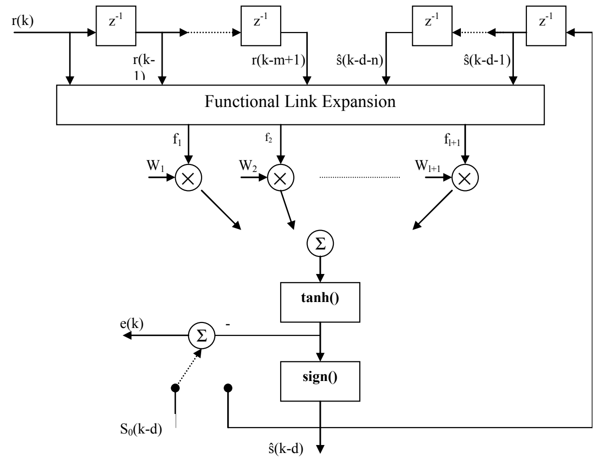

Fig 2. The DFFLE Structure.

3. THE DFFLE

The DFFLE(m,n,l) [1,8] structure is depicted in Figure 2. The DFFLE consists of a Funtional Link (FL) expander and a single output neuron with a sigmoidal transfer function. The FL input layer nonlinearly expands the m input and n decision feedback terms to l combinations and a bias term giving $l+1$ inputs to the linear combiner. The functional link model for a DFFLE (2,2,42), denoted as $\mathbf{v}$ is given by,

$$\mathbf{v} = \begin{bmatrix} 1, e, f, g, h, ef, gh, eg, fg, fh, eh, efh, \\ efg, egh, fgh, efgh, \sin(n.\pi.e), \\ \sin(n.\pi.f), \cos(n.\pi.e), \cos(n.\pi.f), \\ e.\sin(\pi.f), e.\cos(\pi.f), f.\sin(\pi.e), \\ f.\cos(\pi.e), g.\sin(\pi.e), g.\sin(\pi.f), \\ g.\cos(\pi.e), g.\cos(\pi.f), h.\sin(\pi.e), \\ h.\sin(\pi.f), h.\cos(\pi.e), h.\cos(\pi.f), \\ sign(e), sign(f) \end{bmatrix} \text{for } n = 1,2,3 \tag{5}$$

where, e and f represent $r(k)$ and $r(k-l)$ of the observation vector $\mathbf{r}(k)$ and g and h represent $\hat{s}(k-d-1)$ and $\hat{s}(k-d-2)$ of the decision feedback vector $\hat{\mathbf{s}}_b(k)$.

The adaptive weights $\mathbf{W} = \left[w_0, w_1, ...w_l\right]$ are updated using the error signal $e(k) = s(k-d) - \hat{s}(k-d)$ during training. Decision directed training can be used thereafter to track slowly changing channels using the error signal

$e(k) = \hat{s}(k-d) - y(k)$. A delta rule update equation is used to take into account the sigmoidal nonlinearity of the output neuron.

$$\mathbf{W}(k+1) = \mathbf{W}(k) + \mu . e(k).(1 - y^2(k)).\mathbf{f}(k) \qquad (6)$$

where, μ is the adaptation step size and $\mathbf{f}(k)$ is the output of the functional expander. The final symbol decisions are made by a hard threshold device that returns +1 for all inputs greater than or equal to 0 and –1 for all other inputs.

4. THE DSFLE

The proposed DSFLE(m,n,l) structure is depicted in Figure 3. The FL expander vector $\mathbf{v}$ for a DSFLE with $m = n = 2$ is as follows

$$\mathbf{v} = \begin{bmatrix} 1, e, f, ef, \sin(n.\pi.e), \\ \sin(n.\pi.f), \cos(n.\pi.e), \\ \cos(n.\pi.f), e.\sin(\pi.f), \\ e.\cos(\pi.f), f.\sin(\pi.e), \\ f.\cos(\pi.e), sign(e), \\ sign(f) \end{bmatrix} \text{ for } n = 1,2,3 \qquad (7)$$

This modification to the FL vector of (5) for the DSFLE removes direct incorporation of the decision feedback from the structure and in this example reduces the number of terms by a factor of two. By comparing the number of terms that make up the FL vector we can see the difference in complexity of the two algorithms. The DFFLE(m,n,l) structure requires M_{DFFLE} terms where,

$$M_{DFFLE} = 1 + 2n^2 + 5n + 2nm + \sum_{i=1}^{n+m} P_i^{n+m} \qquad (8)$$

$$P_i^{n+m} = (n+m)!/(n+m-i)!i! \qquad (9)$$

The DSFLE(m,n,l) structure requires,

$$M_{DSFLE} = 1 + 2n^2 + 5n + \sum_{i=1}^{n} n!/(n-i)!i! \qquad (10)$$

terms. Equations (8) and (10) show that the DSFLE(m,n,l) structure uses $2nm + 2^n\left(2^m - 1\right)$ fewer terms in its FL vector.

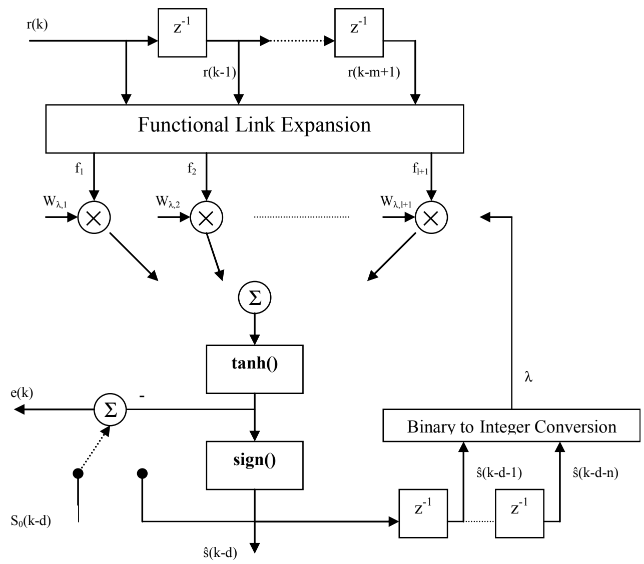

Fig 3. The DSFLE Structure.

n	m	Number of Terms in FL Vector	
		DSFLE(m,n,l)	DFFLE(m,n,l)
2	2	22	42
4	2	68	132
4	4	68	340
6	4	166	1174

Table 1. Comparison of the number of terms in the Functional Link vector for the DSFLE(m,n,l) and DFFLE(m,n,l) structures.

Table 1 shows a comparison of the number of terms required for several configurations.

What was a weight vector in the DFFLE structure is now expanded to a matrix with 2^n rows as shown in (11). Each of the 2^n possible decision feedback vectors is now given a one-to-one mapping to a row λ in the adaptive weight matrix using a simple mapping such as that given in Table 2 for $n = 2$. The weight update equation is also altered to reflect these changes (12).

$$\mathbf{W} = \begin{bmatrix} w_{1,1} & w_{2,1} & \cdots & w_{1,l+1} \\ w_{2,1} & \ddots & & \\ \vdots & & & \\ w_{2^m,1} & & & w_{2^m,l+1} \end{bmatrix} \qquad (11)$$

$$\mathbf{W}_{\lambda,i}(k+1) = \mathbf{W}_{\lambda,i}(k) + \mu . e(k).(1 - y^2(k)).\mathbf{f}_i(k) \quad \text{for} \quad 1 \le i \le l+1 \qquad (12)$$

$\hat{s}_b(1)$	$\hat{s}_b(2)$	λ
-1	-1	1
-1	1	2
1	-1	3
1	1	4

Table 2. Decision feedback mapping to lambda.

In this way each row of **W** is trained on a subset of the possible input vectors. Decision directed training can again be used to track slowly changing channels. A benefit of this equaliser structure is that training on an incorrect decision will affect only one of the equaliser's boundaries and not the whole equaliser as is the case for the DFFLE.

5. RESULTS

A comparative study of the DSFLE(2,2,21) and DFFLE(2,2,41) has been conducted. For this study a single cochannel interferer model is used. The mixing model channels chosen for the study are,

$$A_0 = (0.34 + 0.88z^{-1} + 0.34z^{-2}) \tag{13}$$

and,

$$A_1 = \alpha(0.8 + 0.6z^{-1}) \tag{14}$$

where α is a gain applied to the cochannel filter to allow control over the Signal to Interference Ratio (SIR). Two sets of simulations have been conducted and these are described below.

5.1. Simulation Set 1

Simulations were carried out using the above channels for both the DFFLE(2,2,41) and DSFLE(2,2,21) without decision directed training. The simulations were carried out for SIRs of 5, 10 and 15 dB with SNRs ranging from 2 to 28 dB. In all cases the learning rate μ was set to 0.3 and the equalisers were trained for 1000 symbols to ensure convergence. The BER rate performance of the equalisers over 750000 symbols was measured and averaged over 10 runs to produce the results shown in Figure 4.

The results of the first set of simulations show that the DSFLE structure is capable of near identical performance to the DFFLE at low SIR/ low SNR points.

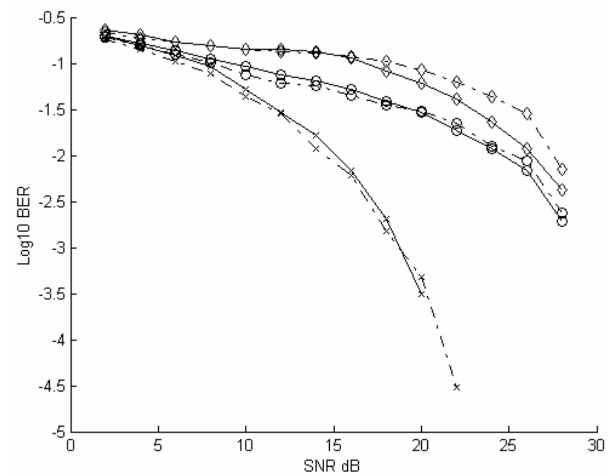

Fig 4. BER performance comparison of DFFLE and DSFLE for SIR = 5 (◊), 10 (o) and 15dB (x). DFFLE(2,2,41) dashed line and DSFLE(2,2,21) solid.

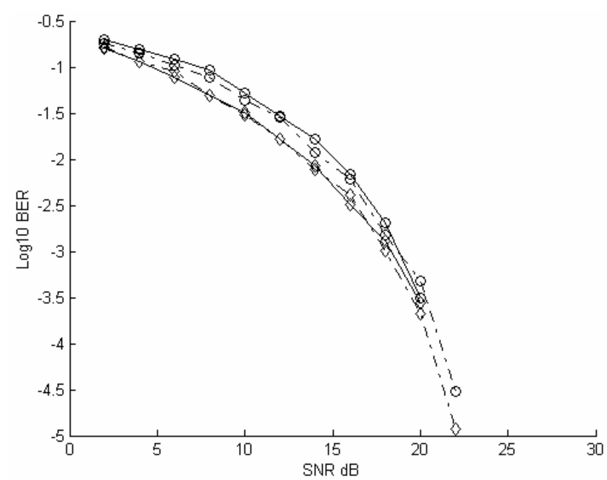

Fig 5. BER performance comparison of DFFLE and DSFLE for SIR of 15dB and correct feedback bits (◊) and equaliser decision feedback (o). DFFLE(2,2,41) dashed line and DSFLE(2,2,21) solid.

As the level of noise reduces the DSFLE starts to outperform the DFFLE. This is most noticeable for SIR=5dB where the DSFLE starts to significantly outperform the DFFLE for SNR > 18.

5.2. Simulation Set 2

The error propagation of the two equaliser structures was compared by conducting simulations set up in the same way as set 1 for SIR of 15dB but using the correct feedback bits, $s(k-d-1)$ and $s(k-d-2)$, instead of the equalisers decisions $\hat{s}(k-d-1)$ and $\hat{s}(k-d-2)$. The results from this set of simulations are shown in Figure 5.

The second set of results show the DSFLE to effectively match the error propagation performance of the DFFLE.

6. CONCLUSIONS

The Decision Selection Functional Link Equaliser has been presented. The concept of decision selection has been applied to the FL equaliser and the benefit of this discussed. Comparative BER performance and error propagation results between the DFFLE(2,2,41) and the DSFLE(2,2,21) have been given. It has been shown that the new structure, the DSFLE(2,2,21), offers comparable performance to the DFFLE(2,2,41) with approximately half the computations per symbol. The comparison of FL vector complexity given in Table 2 shows that greater computational savings can be made as the equalizer order is increased.

7. REFERENCES

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