Multiuser Detection for DS-CDMA transmission Systems using Neural Network Techniques

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Abstract

we present in this paper a new multiuser receiver using a neural network-based decision scheme for interference suppression in Direct Sequence Code Division Multiple Access (DS-CDMA) wireless networks. This receiver is mainly made of a decision feedback functional link equalizer (DFFLE) combined with an eigenvector network. This structure well approximates a Bayesian receiver and exhibits several advantages when compared to the classical Minimum Mean Square Error (MMSE) receivers as it is demonstrated in the results part.

I Introduction

Recently, Code Division Multiple Access (CDMA) has emerged as one of the most promising systems for multiuser wireless communication. The purpose of this paper is to present a new kind of multiuser detector based on neural techniques which is able to outperform some well known classical receiver structures like MMSE receivers [1], [2]. In fact, one promising approach to interference suppression in a DS-CDMA system is based on using neural networks. This is due to the contribution of Aazhang [3] who have demonstrated that the performance of a multilayer perceptron in this context is comparable to that of the optimum receiver [4]. Recently, [5], [6] Hussein and Kaushik [7] have proposed a Decision Feedback Functional Link Equalizer (DFFLE) for mitigating Intersymbol Interference (ISI) and Multiple Access Interference (MAI) in dispersive communication channels.

In the presented paper, the adaptive DFFLE receiver applied to a DS-CDMA system is investigated for single-user detection, i.e demodulation of one desired user in the presence of interfering users. We assume that the signature sequences or spreading codes of the interfering users will be unknown to the receiver. The proposed DFFLE receiver consists of an eigenvector network, followed by a DFFLE and fed by previous decision symbols. This detector configuration is well suited for downlink communication between a base station and a mobile user in a digital wireless network like UMTS. The proposed receiver approximates a Bayesian receiver and computes the receiver coefficients with the help of a training sequence prior to data transmission. When the Mean Square Error (MSE) has been decreased to a given threshold, then information sequence is sent.

The paper is organized as follows : in section II, we describe the communication system model and we recall the definition of a Bayesian receiver. The DFFLE receiver is described in section III. Section IV contains the performance results. Section V contains the conclusions and some ideas for further investigations.

II Communication System Model

We consider here a coherent synchronous DS-CDMA system employing Binary Phase-Shift Keying (BPSK) modulation over a wireless channel. The baseband signal in a single symbol interval T can be represented as :

$$x(t) = \sum_{j=1}^{L}\sum_{i=1}^{N} A_j . b_j(t).c_j(i).p(t - i.T_c) + n(t) \quad \text{for } 0 \le t \le T \quad (1)$$

where x(t) is the received continuous signal. The generalization towards a QPSK DS-CDMA system like UMTS can be easily done. L is the number of active users, N is the length of the spreading code, A_j is the received amplitude of user j, $b_j(t) \in \{+-1\}$is the symbol transmitted by user j at time t and n(t) is the additive Gaussian noise. The spreading code or, equivalently, the pseudorandom (PN) sequence of user j is denoted by c_j and p(t) is the rectangular chip pulse (of duration Tc). Individual chips in c_j are denoted by the elements in $[c_j(1), c_j(2),\ldots,c_j(N)]$with each $c_j(t) \in \{\pm 1\}$. After chip matched-filtering and chip rate sampling, such a signal can be written in discrete time as:

$$x_k = \sum_{j=1}^{L} A_j . b_j^k . c_j + n_k \qquad (2)$$

where $x_k = [x(1), x(2),..., x(N)]_k$ is a vector of chip-rate samples during the k^{th} symbol interval. To be more realistic and to feet more efficiently with an actual wireless system, we add the two following impairments :

<u>a) Power Control Error</u> : $\{\chi_j A_j\}$ represents the effect of imperfect power control on the received amplitude for user j. $\{\chi_j\}$ is a random variable which represents the power fluctuations in the gain control loop and is log-normally distributed with a standard deviation between 1 and 2 dB [8].

<u>b) Multipath Fading</u> : A discrete model with M paths is considered. Hence, for a slowly time varying channel, the impulse response of the channel $h_j(t)$ can be written as :

$$h_j(t) = \sum_{k=1}^{M} \alpha_{j,k} . \delta(t - \tau_{j,k}) \qquad (3)$$

where M is the number of resolvable paths between the j^{th} transmitter and the desired receiver normally referred as number one. The quantities $\alpha_{j,k}$ and $\tau_{j,k}$ are respectively the path gain and time delay for the k^{th} path. The parameter $\alpha_{j,k}$ is a Rayleigh random variable and $\tau_{j,k}$ is a random variable uniformly distributed in [0,T].

III DFFLE receiver and learning algorithm

The proposed receiver, depicted in figure 1, is mainly made of an eigenvector network followed by a DFFLE neural network. The input to the eigenvector network is r_k, which is a vector of dimension (N×1). For user 1, r_k is given by :

$$r_k = \frac{1}{N} . [x(1).c_1(1), x(2).c_1(2),..., x(N).c_1(N)] \qquad (4)$$

That means, the sampled received sequence x_k is discretely correlated with the desired code sequence c_1.

<u>a) Eigenvector Network</u> : Similar to the MUSIC algorithm [9], the eigenvector network provides a means of identifying orthogonal vectors and reduces the dimension of the state-space from one determined by the length of the code to one which is proportional to the number of users. Hence, the noise components at the output of the eigenvector network are uncorrelated. The eigenvector network is defined by a transformation matrix Es of dimension (N×L) employed to reduce the dimension of the received vector of length N to L where L denotes the number of users. The obtained vector $s_k = E_S^T . r_k$ of length L is further processed by the DFFLE algorithm.

In practice, eigenvectors are identified by an eigenvalue decomposition of the sample correlation matrix

$$R_G = \frac{1}{G} . \sum_{k=1}^{G} r_k . r_k^{*T} = E.L.E^T = E_S.L_S.E_S^T + E_n.L_n.E_n^T \qquad (5)$$

Then, s_k is found as : $s_k = E_S^T . r_k$ (6)

<u>b) DFFLE filter and the learning algorithm:</u> The DFLLE (L,m,M) neural network is the main component of the receiver giving its improved potential capacity to the global receiver when compared with conventional MMSE receivers. It consists of two parts : the Functional-Link (FL) expander and a linear combiner with a sigmoïdal thresholder. The first part employs a (M+1)-term FL expansion model, denoted in vector notation as V with each element $f_p \in \{f_0, f_1, \ldots, f_M\}$. This part nonlinearly combines both the neural network's L-feedforward and m-decision feedback symbols (taken as the outputs from a binary threshold). The FL expander performs a non-linear transformation on the input data such that the dimension of the output is much larger than that of the input.

For example, when L = m = 2, the inputs to the DFFLE filter are $s_k(1)$, $s_k(2)$ as feedforward symbols and $\hat{s}_{k-1}, \hat{s}_{k-2}$ as decision feedback symbols. Note that both $\hat{s}_{k-1}$ and $\hat{s}_{k-2}$ are denoted as $\hat{s}_0(k-1)$ and $\hat{s}_o(k-2)$ in the block diagram of figure 1. For simplicity reasons, these parameters will be further denoted as :

$s_k(1) = e, s_k(2) = f, \hat{s}_{k-1} = g, \hat{s}_{k-2} = h$, so the input data is written as the tuple {e,f,g,h}.

The functional expansion model for the example of figure 1 is given by V.

The DFFLE weights W=$\{w_0(k), w_1(k),..., w_M(k)\}$ are updated using a delta rule (DR) which takes into account the sigmoïdal non-linearity.

We have :

$$V = \begin{pmatrix} e, f, g, h, ef, gh, eg, fg, fh, eh, efh, efg, egh, fgh, efgh, \\ \sin(n.\pi.e), \sin(n.\pi.f), \cos(n.\pi.e), \cos(n.\pi.f), (e)\sin(\pi.f), (e).\cos(\pi.f), \\ (f)\sin(\pi.e), (f)\cos(\pi.e), (g)\sin(\pi.e), (g)\sin(\pi.f), (g)\cos(\pi.e), \\ (g)\cos(\pi.f), (h)\sin(\pi.e), (h)\sin(\pi.f), \\ (h)\cos(\pi.e), (h)\cos(\pi.f), \mathrm{sgn}(e), \mathrm{sgn}(f) \quad \text{for} \quad n = 1,2,3 \end{pmatrix} \qquad (7)$$

$$w_p(k+1) = w_p(k) + \mu.\varepsilon(k).(1 - z^2(k)) f_p(k) \qquad (8)$$

where the error is $\varepsilon(k) = d(k) - z(k)$ with d(k) being the desired response available during training and z(k) is the soft decision at the output of the non-linearity written as :

$$z(k) = \tanh\left(\sum_{p=0}^{M} f_p(k).w_p(k)\right) = \tanh(y_k) \qquad (9)$$

f_0 is the bias input and μ is the DR step size. When the error has been lowered to a tolerable given threshold the actual data is sent. During data transmission the filter operates in a decision-directed mode by using its own output as the desired reference for continuous training with the error signal being $\varepsilon(k) = \hat{d}(k) - z(k)$. $\hat{d}(k)$ is the result of a hard decision which gives the estimated bit value :

$$\hat{d}(k) = \mathrm{sgn}(z(k)) \qquad (10)$$

IV Performance results

The performance evaluation of the DFFLE receiver for CDMA is carried out by means of computer simulations. The eigenvectors are computed, the algorithm is trained and the BER is evaluated. The value of G in (6) is taken as 10.N data symbols. The performance measure is the BER. Two degrees of freedom are considered, the signal-to-noise ratio (SNR) with respect to the desired user and the near-far ratio (NFR) of user j. These quantities are defined as follows :

$$SNR = \frac{\text{signal power}}{\text{noise power}} = \frac{A_1^2}{2.\sigma^2} \qquad (11)$$

$$NFR_j = \frac{j^{th} \text{ user power}}{\text{first user power}} = \frac{A_j^2}{A_1^2} \qquad (12)$$

where σ^2 is the variance of the noise and A_j is the amplitude of user j's signal. As we mentioned before the user one is assumed to be the desired user. SNR denotes the per-symbol or per-bit SNR since BPSK modulation is considered.

Gold sequences of length 31 are employed as spreading sequences. A four user (L = 4, m = 2) system is considered. The adaptation gain μ for the DFFLE receiver is chosen experimentally equal to 0.001 and the algorithm is trained for 2000 iterations.

We simulate the behaviour of the DFFLE in a static and in a dynamic environment with a severe near-far situation and multipath fading respectively. The wireless channel goes through a Rayleigh fading of 30-bit duration for a 300-bit data frame. Each user's signal experiences two paths with average path powers of 90% and 10%, respectively.

The performance of the conventional Matched Filter (MF) receiver is also calculated (indicated by the word conventional in the figures) in each BER plot for reference purposes. We also compare the BER results of the DFFLE receiver with the BER results of one specific nonneural receiver structure, commonly known as the MMSE interference suppression scheme. In this case we assume that the channel parameters are perfectly estimated. The chosen value of μ_{MMSE} for the MMSE receiver is 0.005 and the algorithm is trained for 2000 iterations. The dimensionality of the MMSE receiver is equal to the number of chips (31) per symbol.

The performance results are given on figures 2 and 3 over a Gaussian channel. The desired user's power in figure 2 is held at unity and the NFR of the other three interferers is set to 10 dB. with a standard deviation of the power control error equal to 2 dB. This deviation is the same for all further simulation runs As a function of SNR for the desired user, the DFFLE receiver is found to outperform the conventional MF receiver and to perform slightly worse than the MMSE detector. However, one has to remind that channel parameters are supposed to be perfectly estimated for the MMSE receiver.

Figure 3 shows the BER result as function of NFR for the four-user system with SNR = 10dB. It is found that the DFFLE receiver's performance improves as the communication scenario becomes more hostile for the desired

user. We observe that the performance degradation at low NFR’s (< 4.0 dB), is due to the somewhat imprecise on-line eigenvector computation at those values of NFR.
When correct eigenvector computation is carried out with a larger value of G (20 N) and the values are used for training, the performance is significantly improved at lower NFR’s and shown as diamonds (◊) in figure 3. Figure 4 shows the results obtained over the Rayleigh fading channel described before with NFR_j = 10 dB for $j \neq 1$.
The simulation results, including the comparison with the MMSE receiver, provide some important insights. It is found that performance of the DFFLE receiver is comparable to that of the MMSE receiver which is well known to approach the single-user bound. However, one important advantage of the DFFLE receiver is its inherent capability to recompute its coefficients in the decision-directed mode.

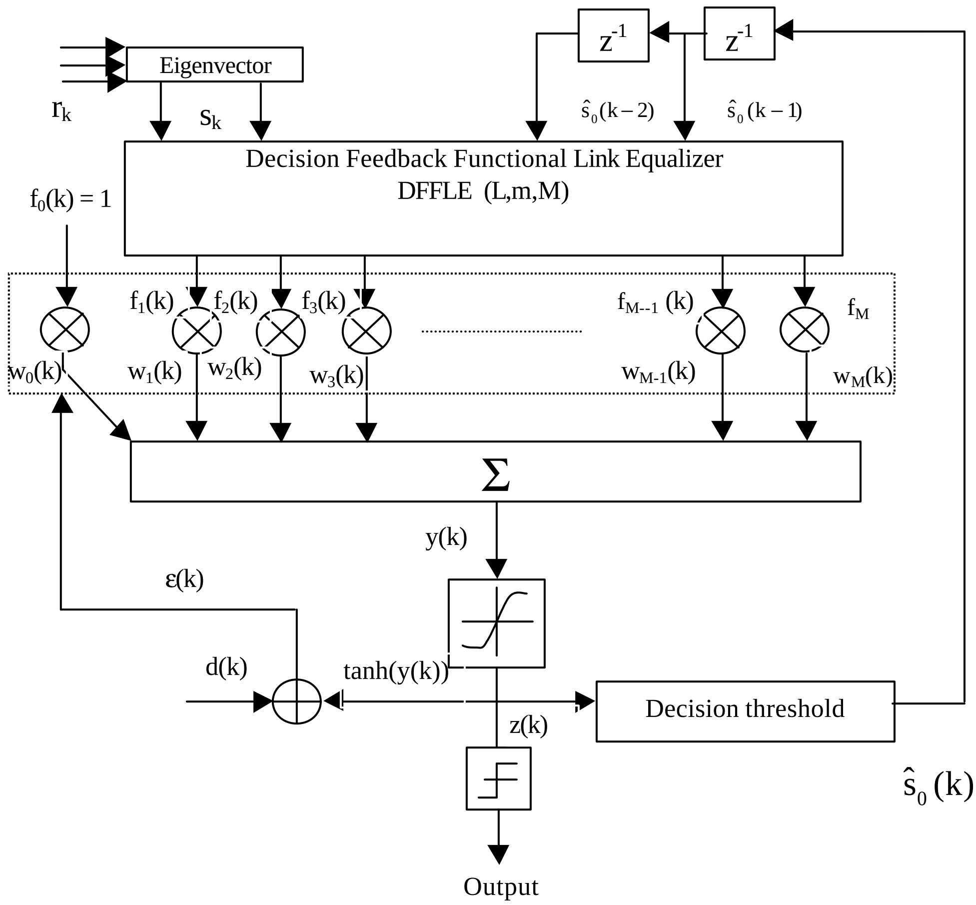

Figure 1 : DFFLE block diagram

This property doesn’t apply for the MMSE receiver due to the difficulty to compute the inverse crosscorelation matrix of signature sequences. The simulation results suggest that the DFFLE receiver for CDMA does not require retraining when the receiver weights move from their ideal values ; this property is fundamental for performing well in nonstationary environments. Our observation is that the DFFLE will perform well after initial training and continuous updating in the tracking mode.

V Conclusion

In this paper we have investigated the performances of a neural network based receiver for a single user demodulation scheme in a multiuser communications environment. The receiver is near-far resistant and also robust to increasing levels of interference. It is mainly made of a decision feedback functional link equalizer (DFFLE) combined with an eigenvector network. This structure exhibits several advantages when compared to the classical Minimum Mean Square Error (MMSE) receivers. In fact, one important advantage of the DFFLE receiver is its inherent capability to recompute its coefficients in the decision-directed mode enforcing the potential capacities of such receiver for downlink communication between a base station and a mobile user in a digital wireless network like UMTS.

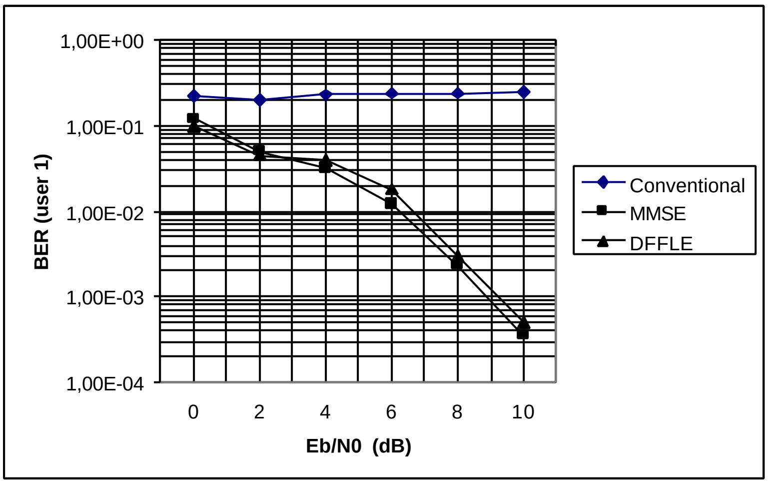

Figure 2 : BER performance for DFFLE receiver as a function of varying SNR in a four-user severe MAI environment over a Gaussian channel (N = 31)

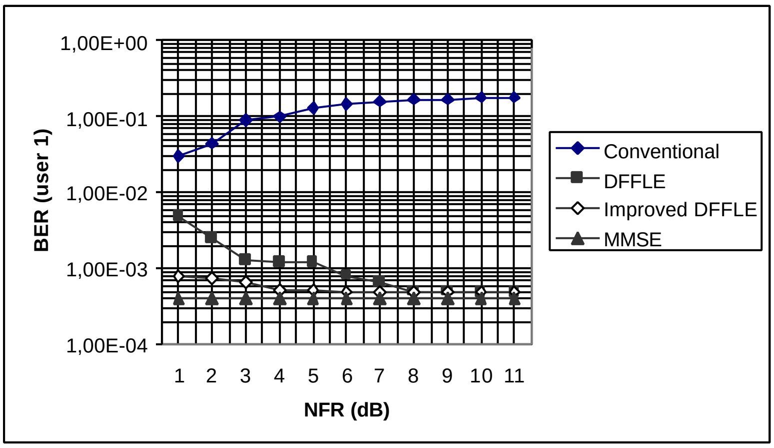

Figure 3 : Robustness of DFFLE receiver to increasing levels of interference

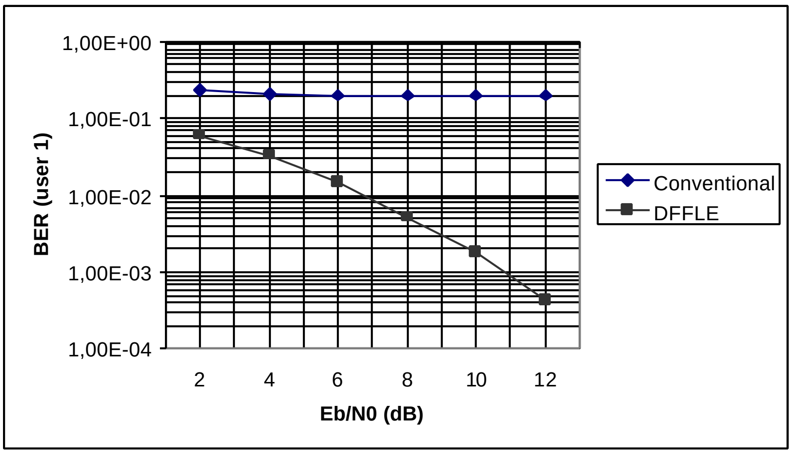

Figure 4 : DFFLE performance over Rayleigh fading channel (NFR_j = 10 dB)

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