DECISION FEEDBACK TURBO EQUALIZATION FOR SPACE-TIME CODED SYSTEMS

Miguel González-López Joaquín Míguez Luis Castedo

Departamento de Electrónica y Sistemas, Universidad de A Coruña,
Facultad de Informática, Campus de Elviña, s/n, 15.071, A Coruña, SPAIN,
e-mail: miguelgl@mail2.udc, {jmiguez, luis}@udc.es

ABSTRACT

In this paper we present a novel Turbo Equalization structure for Space-Time Coded systems. It is based on performing channel equalization via a Decision Feedback Equalizer (DFE) designed using a novel Maximum Likelihood criterion. The resulting optimization problem is solved using the Space-Alternating Generalized EM (SAGE) algorithm. This results in expressions for the forward and backward filters of the DFE that take large benefit from the more and more refined estimations of the transmitted symbols iteratively obtained by the outer decoder.

1. INTRODUCTION

Space-Time Coding (STC) refers to those signal processing and/or coding techniques specifically designed for wireless communication systems that employ multielement antennas at both transmission and reception [1]. These systems have the ability to increase the capacity of multipath wireless channels at no extra bandwidth or power consumption.

Recently, Tarokh *et al.* [2] have investigated the design of space-time trellis (STT) codes that perform extremely well but at the cost of a relatively high complexity. Indeed, Maximum Likelihood (ML) decoding of this type of codes is typically accomplished by means of a Viterbi-like algorithm [2] whose complexity grows exponentially with the number of the states of the code. The problem of decoding complexity aggravates when transmitting over channels that introduce time dispersion since in this case the complexity of the Viterbi algorithm also grows exponentially with the Inter-Symbol Interference (ISI) spread rendering this type of decoders impractical even in moderately dispersive environments.

An appealing alternative is to perform Space-Time decoding according to the Turbo principle. In the recent years, the so-called Turbo codes [3] have produced an enormous impact on the design of digital transmission systems due to their astonishing high performance. Turbo codes are constituted by two component codes concatenated, serially or parallelly, via an interleaver. Decoding is carried out by a suboptimal but extremely powerful scheme in which the *Maximum A Posteriori* (MAP) probabilities of the original symbols are obtained for each component code and then exchanged in an iterative fashion.

Usually, equalization is carried out by means of the Bahl-Cocke-Jelinek-Raviv (BCJR) algorithm [4]. For STC systems, its complexity grows exponentially in both the number of transmitting antennas and the channel ISI. So it is interesting to consider suboptimal and reduced-complexity algorithms for equalization when channel ISI is large. A reasonable and simple approach is to use a Decision Feedback Equalizer (DFE) to compensate both co-channel and intersymbol interferences. The utilization of DFE in Turbo Equalization was first addressed in [5] for a single antenna system but considering a MMSE criterion.

This work has been supported by Ministerio de Ciencia y Tecnología of Spain and FEDER funds from the European Union under grant number TIC2001-0751-C04-01

In this paper we will consider a novel approach to Decision Feedback Turbo Equalization for STC systems. Our main contribution is to consider a DFE designed using an alternative criterion that comes from applying the Maximum Likelihood (ML) principle to obtain the coefficients of both the forward and backward filters. We show how this kind of DFE takes a large benefit of a Turbo Equalization structure, since in the computation of the filter coefficients one can make use of the more and more refined *a priori* log-probabilities about the transmitted symbols fed back from the ST channel decoder through the iterative decoding process.

The remainder of the paper is organized as follows. Section 2 presents the signal model. Section 3 describes the way we obtain the DFE parameters using the ML principle. Since we arrive at an optimization problem with no closed-form solution, we show in Section 4 how to apply an iterative method, the Space-Alternating Generalized EM (SAGE) algorithm, to compute the solution. Section 5 explains how to fit the proposed DFE into a Turbo Equalization structure. Computer simulations showing the performance of the proposed equalizer and comparing it with the optimum MAP detector are detailed in Section 6. Finally, Section 7 is devoted to the conclusions.

2. SIGNAL MODEL

Figure 1 shows the block diagram of the transmitter side of a STC system. The information bearing sequence $\mathbf{u} = [u(0), u(1), ..., u(K-1)]^T$, where K is the total number of transmitted bits, is encoded with a ST encoder to produce a sequence of vectors

$$\tilde{\mathbf{c}} = [\mathbf{c}^T(0)\ \mathbf{c}^T(1)\ \cdots\ \mathbf{c}^T(K-1)]^T$$

with $\mathbf{c}(k) = [c_1(k), c_2(k), ..., c_N(k)]^T$, being N the number of transmitting antennas. This encoded sequence is interleaved and constellation mapped to produce the sequence of symbols to be fed into the channel, $\tilde{\mathbf{s}} = [\mathbf{s}^T(0)\ \mathbf{s}^T(1)\ \cdots\ \mathbf{s}^T(K-1)]^T$, where $\mathbf{s}(k) = [s_1(k), s_2(k), ..., s_N(k)]^T$ is the vector of symbols transmitted at time k. The channel is caracterized as a MIMO system which introduces dispersion in both the spatial and temporal dimensions.

Figure 2 shows the block diagram of a ST Turbo receiver. After matched-filtering and sampling at symbol rate, it is obtained a sequence of observations $\tilde{\mathbf{x}} = [\mathbf{x}^T(0)\ \mathbf{x}^T(1)\ \cdots\ \mathbf{x}^T(K-1)]^T$,

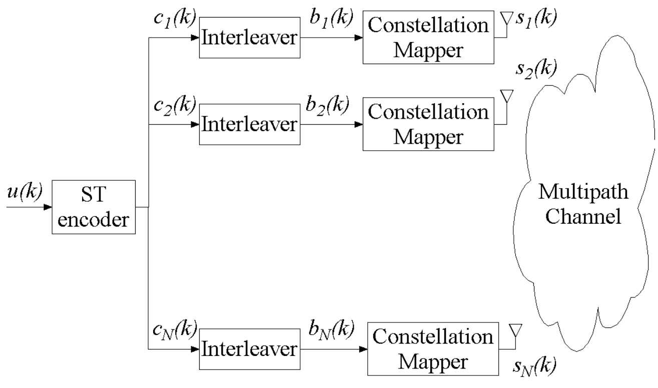

Fig. 1. Transmitter model

where the observations corresponding to the k-th sampling interval, $\mathbf{x}(k)$, have the form

$$\mathbf{x}(k) = \mathbf{H}\mathbf{z}(k) + \mathbf{g}(k), \;\; k = 0, 1, ..., K-1 \tag{1}$$

where $\mathbf{H} = [H(m-1)\; H(m-2)\; \cdots\; H(0)]$ represents the overall dispersive MIMO channel with memory length m. Each matrix $H(i)$ contains the fading coefficients that affect the symbol vector $\mathbf{s}(k-i)$. The vector $\mathbf{z}(k)$ results from stacking the source vectors $\mathbf{s}(k)$, i.e., $\mathbf{z}(k) = [\mathbf{s}^T(k-m+1)\; \mathbf{s}^T(k-m+2)\; \cdots\; \mathbf{s}^T(k)]^T$. The component $\mathbf{g}(n)$ is a vector of independent samples of white Gaussian noise.

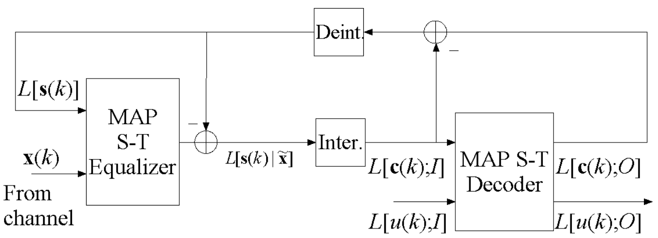

Fig. 2. Receiver model

The MAP ST equalizer computes the logarithm of the *a posteriori* probabilities of $\mathbf{s}(k)$ conditioned to the overall sequence of observations, i.e., $L[\mathbf{s}(k)|\tilde{\mathbf{x}}]$, from the set of available observations, $\tilde{\mathbf{x}}$, and the sequence of *a priori* log-probabilities about the source symbol vectors, $L[\mathbf{s}(k)]$. Whatever kind of MAP equalizer is employed, it can always be shown that the *a posteriori* log-probabilities take the form $L[\mathbf{s}(k)|\tilde{\mathbf{x}}] = L[\mathbf{s}(k)] + L_e[\mathbf{s}(k)]$. Only the latter term, called *extrinsic* information in the Turbo coding literature, is forwarded to the decoder to avoid statistical dependences with the results of the previous iteration. Similarly, the MAP ST decoder computes the *a posteriori* probabilities for both source symbols, $u(k)$, and coded symbol vectors, $\mathbf{c}(k)$. The latter are forwarded to the equalizer via an interleaver after substracting its *a priori* component.

Optimum MAP detection can be carried out by the BCJR (Bahl-Cocke-Jelinek-Raviv) algorithm [4], which exactly computes the *a posteriori* log-probabilities $L[\mathbf{s}(k)|\tilde{\mathbf{x}}]$. Let $e_k = (s_{k-1}, \mathbf{s}(k), s_k)$ be a transition of the finite-state machine that describes the ISI channel, where s_{k-1} is the previous state, $\mathbf{s}(k) = L_{in}[e_k]$ the input, $\mathbf{s}(k) = L_{out}[s_{k-1}, \mathbf{s}(k)]$ the associated output and s_k the next state. Having in mind that

$$L[\mathbf{s}(k)|\tilde{\mathbf{x}}] = L[\mathbf{s}(k), \tilde{\mathbf{x}}] + h_s \tag{2}$$

where h_s is the constant that makes $P[\mathbf{s}(k)|\tilde{\mathbf{x}}]$ being a probability density, the algorithm reduces to compute

$$L[\mathbf{s}(k), \tilde{\mathbf{x}}] = \log \sum_{e_k : L_{in}[e_k] = \mathbf{s}(k)} \exp L[e_k, \tilde{\mathbf{x}}] \tag{3}$$

The problem behind optimum MAP detection is that the complexity of the BCJR algorithm is exponential in both the number of transmitting antennas and the channel ISI. To overcome this problem we present a suboptimal scheme that esentially computes $L[\mathbf{s}(k)|\tilde{\mathbf{x}}]$ after removing the co-channel and the intersymbol interferences via a DFE designed using a novel criterion explained in subsequent sections.

3. DECISION FEEDBACK EQUALIZER BASED ON THE MAXIMUM LIKELIHOOD PRINCIPLE

Let us consider the following model for our DFE

$$\mathbf{y}(k) = \mathbf{W}^H \mathbf{x}_m(k) + \mathbf{V}^H \hat{\mathbf{s}}_v(k), \;\; k = 0, 1, ..., K-1 \tag{4}$$

where $\mathbf{y}(k) = [y_1(k)\; y_2(k)\; \cdots\; y_N(k)]^T$ is the filtered vector, $\mathbf{W}$ the forward filter, $\mathbf{V}$ the backward filter, $\mathbf{x}_m(k) = [\mathbf{x}^T(k)\; \mathbf{x}^T(k+1)\; \cdots\; \mathbf{x}^T(k+m-1)]^T$ the observations that contain information about the transmitted symbol vector $\mathbf{s}(k)$, and $\hat{\mathbf{s}}_v(k) = [\hat{\mathbf{s}}^T(k-m+1)\; \hat{\mathbf{s}}^T(k-m+2)\; \cdots\; \hat{\mathbf{s}}^T(k-1)]^T$ estimations of the symbols that interfere with symbol $\mathbf{s}(k)$.

In order to derive the expression of the equalizer filters, we will start considering that there exist linear filters $\mathbf{W}_*$ and $\mathbf{V}_*$ that completely remove co-channel and intersymbol interferences. Under such assumption, we have

$$\mathbf{y}(k) = \mathbf{s}(k) + \mathbf{g}_f(k), \;\; k = 0, 1, ..., K-1 \tag{5}$$

where $\mathbf{g}_f(k)$ is the channel AWGN. For simplicity reasons, we will assume that $E[\mathbf{g}_f(k)\mathbf{g}_f(k-n)^H] = \sigma_f^2 \mathbf{I}\delta(n)$ which enables us to write the pdf of the filtered vector $\mathbf{y}(k)$ as follows [6]

$$\begin{aligned} f_{\mathbf{y}(k);\boldsymbol{\Theta}_*}(\mathbf{y}(k)) &= E_{\mathbf{s}(k)}\left[f_{\mathbf{y}(k)|\mathbf{s}(k);\boldsymbol{\Theta}_*}(\mathbf{y}(k))\right] \\ &\propto E_{\mathbf{s}(k)}\left[\exp\left\{-\frac{1}{\sigma_f^2}\|\mathbf{y}(k) - \mathbf{s}(k)\|^2\right\}\right] \end{aligned}$$

where $\boldsymbol{\Theta}_* = [\mathbf{W}_*, \mathbf{V}_*]$ represents the optimum filter coefficients. The joint pdf of the filtered vectors $\tilde{\mathbf{y}} = [\mathbf{y}^T(0)\; \mathbf{y}^T(1)\; \cdots\; \mathbf{y}^T(K-1)]^T$ is the product of marginal densities, i.e.,

$$\begin{aligned} f_{\tilde{\mathbf{y}};\boldsymbol{\Theta}_*}(\tilde{\mathbf{y}}) &= \prod_{k=0}^{K-1} f_{\mathbf{y}(k);\boldsymbol{\Theta}_*}(\mathbf{y}(k)) \\ &\propto \prod_{k=0}^{K-1} E_{\mathbf{s}(k)}\left[\exp\left\{-\frac{1}{\sigma_f^2}\|\mathbf{y}(k) - \mathbf{s}(k)\|^2\right\}\right] \end{aligned}$$

The optimum filter coefficients can now be estimated according to the Maximum Likelihood principle

$$\begin{aligned} \hat{\boldsymbol{\Theta}} &= \arg\max_{\boldsymbol{\Theta}_*} \log f_{\tilde{\mathbf{y}};\boldsymbol{\Theta}_*}(\tilde{\mathbf{y}}) \\ &= \arg\max_{\boldsymbol{\Theta}_*} \sum_{k=0}^{K-1} \log E_{\mathbf{s}(k)}\left[\exp\left\{-\frac{1}{\sigma_f^2}\|\mathbf{y}(k) - \mathbf{s}(k)\|^2\right\}\right] \end{aligned}$$

This is an optimization problem without closed-form solution. In the next section we will show how can be solved using an iterative method termed the SAGE algorithm.

4. THE SAGE ALGORITHM

The Space-Alternating Generalized-EM (SAGE) algorithm [7] is a variation of the EM algorithm, less complex and with faster convergence, that is useful when the set of parameters to be estimated can be partitioned into disjoint subsets. Using the usual terminology employed in the EM algorithm, we define the "complete" data set as $\tilde{\mathbf{y}}_e = [\mathbf{s}^T(0)\,\mathbf{y}^T(0)\,\mathbf{s}^T(1)\,\mathbf{y}^T(1)\,\cdots\,\mathbf{s}^T(K-1)\,\mathbf{y}^T(K-1)]^T$, being the "incomplete" data set the observations $\tilde{\mathbf{y}}$.

Before proceeding with the application of the SAGE algorithm, it should be mentioned that the noise variance after filtering, σ_f^2, has to be considered as a parameter to be estimated since it is a function of $\mathbf{W}_*$, which is not *a priori* known. Therefore, we redefine our set of parameters as $\mathbf{\Theta}_* = [\mathbf{W}_*, \mathbf{V}_*, \sigma_f^2]$, where $\mathbf{W}_*$, $\mathbf{V}_*$ and σ_f^2 are considered disjoint through the estimation process. According to the SAGE algorithm formulation, the $(i+1)$-th estimate of $\mathbf{W}_*$ is obtained by solving the following optimization problem

$$\hat{\mathbf{W}}_{i+1} = \arg\max_{\mathbf{W}_*} E_{\tilde{\mathbf{y}}_e|\tilde{\mathbf{y}};[\hat{\mathbf{W}}_i,\hat{\mathbf{V}}_i,\hat{\sigma}^2_{f,i}]}\left[\log f_{\tilde{\mathbf{y}}_e;[\mathbf{W}_*,\hat{\mathbf{V}}_i,\hat{\sigma}^2_{f,i}]}(\tilde{\mathbf{y}}_e)\right] \tag{6}$$

After some calculus we arrive at

$$\begin{aligned}\hat{\mathbf{W}}_{i+1} = \arg\min_{\mathbf{W}_*} \sum_{k=0}^{K-1} &\mathbf{x}_m^H(k)\mathbf{W}_*\mathbf{W}_*{}^H\mathbf{x}_m(k)\\ &+ \mathbf{x}_m^H(k)\mathbf{W}_*\hat{\mathbf{V}}_i^H\hat{\mathbf{s}}_v(k) + \hat{\mathbf{s}}_v^H(k)\hat{\mathbf{V}}_i^H\mathbf{W}_*^H\mathbf{x}_m(k)\\ &- \mathbf{x}_m^H(k)\mathbf{W}_*E_{ii}[\mathbf{s}(k)] - E_{ii}[\mathbf{s}^H(k)]\mathbf{W}_*^H\mathbf{x}_m(k)\end{aligned} \tag{7}$$

where

$$E_{ij}[g(\mathbf{s}(k))] = E_{\mathbf{s}(k)|\mathbf{y}(k);[\hat{\mathbf{W}}_i,\hat{\mathbf{V}}_j,\hat{\sigma}^2_{f,i}]}[g(\mathbf{s}(k))] \tag{8}$$

being $g(\mathbf{s}(k))$ an arbitrary function of $\mathbf{s}(k)$. Note that this expectation can be computed using Bayes' rule as

$$E_{ij}[g(\mathbf{s}(k))] = \frac{E_{\mathbf{s}(k)}\left[g(\mathbf{s}(k))\exp\left\{-\frac{1}{\hat{\sigma}^2_{f,i}}\|\mathbf{y}_{ij}(k)-\mathbf{s}(k)\|^2\right\}\right]}{E_{\mathbf{s}(k)}\left[\exp\left\{-\frac{1}{\hat{\sigma}^2_{f,i}}\|\mathbf{y}_{ij}(k)-\mathbf{s}(k)\|^2\right\}\right]} \tag{9}$$

where

$$\mathbf{y}_{ij}(k) = \hat{\mathbf{W}}_i^H\mathbf{x}_m(k) + \hat{\mathbf{V}}_j^H\hat{\mathbf{s}}_v(k) \tag{10}$$

Equation (7) represents a quadratic optimization problem with an exact solution given by

$$\hat{\mathbf{W}}_{i+1} = \hat{\mathbf{R}}_x^{-1}(\hat{\mathbf{R}}_{xs} - \hat{\mathbf{R}}_{xv}\hat{\mathbf{V}}_i) \tag{11}$$

where

$$\hat{\mathbf{R}}_x = \sum_{k=0}^{K-1}\mathbf{x}_m(k)\mathbf{x}_m^H(k) \tag{12}$$

$$\hat{\mathbf{R}}_{xs} = \sum_{k=0}^{K-1}\mathbf{x}_m(k)E_{ii}\left[\mathbf{s}^H(k)\right] \tag{13}$$

$$\hat{\mathbf{R}}_{xv} = \sum_{k=0}^{K-1}\mathbf{x}_m(k)\mathbf{s}_v^H(k) \tag{14}$$

Once $\hat{\mathbf{W}}_{i+1}$ has been computed, we obtain the $(i+1)$-th estimation of $\mathbf{V}_*$ solving the following optimization problem

$$\hat{\mathbf{V}}_{i+1} = \arg\max_{\mathbf{V}} E_{\tilde{\mathbf{y}}_e|\tilde{\mathbf{y}};[\hat{\mathbf{W}}_{i+1},\hat{\mathbf{V}}_i,\hat{\sigma}^2_{f,i}]}\left[\log f_{\tilde{\mathbf{y}}_e;[\hat{\mathbf{W}}_{i+1},\mathbf{V}_*,\hat{\sigma}^2_{f,i}]}(\tilde{\mathbf{y}}_e)\right] \tag{15}$$

Again, this is a quadratic optimization problem with the following exact solution

$$\hat{\mathbf{V}}_{i+1} = \hat{\mathbf{R}}_v^{-1}(\hat{\mathbf{R}}_{vs} - \hat{\mathbf{R}}_{xv}^H\hat{\mathbf{W}}_{i+1}) \tag{16}$$

where

$$\hat{\mathbf{R}}_v = \sum_{k=0}^{K-1}\hat{\mathbf{s}}_v(k)\hat{\mathbf{s}}_v^H(k) \tag{17}$$

$$\hat{\mathbf{R}}_{vs} = \sum_{k=0}^{K-1}\hat{\mathbf{s}}_v(k)E_{i+1i}\left[\mathbf{s}^H(k)\right] \tag{18}$$

(19)

Finally, given $\hat{\mathbf{W}}_{i+1}$ and $\hat{\mathbf{V}}_{i+1}$, we can compute $\hat{\sigma}^2_{f,i}$ as

$$\hat{\sigma}^2_{f,i} = \arg\max_{\sigma_f^2} E_{\tilde{\mathbf{y}}_e|\tilde{\mathbf{y}};[\hat{\mathbf{W}}_{i+1},\hat{\mathbf{V}}_{i+1},\hat{\sigma}^2_{f,i}]}\left[\log f_{\tilde{\mathbf{y}}_e;[\hat{\mathbf{W}}_{i+1},\hat{\mathbf{V}}_{i+1},\sigma^2_{f,i}]}(\tilde{\mathbf{y}}_e)\right] \tag{20}$$

whose solution is

$$\hat{\sigma}^2_{f,i} = \frac{1}{KN}\sum_{k=0}^{K-1}E_{i+1i+1}\left[\|\mathbf{y}_{i+1i+1}(k)-\mathbf{s}(k)\|^2\right] \tag{21}$$

5. DECISION FEEDBACK TURBO EQUALIZER

As mentioned in Section 2, the MAP ST equalizer must compute $L[\mathbf{s}(k)|\tilde{\mathbf{x}}]$. In our DFE we compute these log-probabilities after removing co-channel and intersymbol interferences from the observations, i.e., $L[\mathbf{s}(k)|\tilde{\mathbf{x}}] \approx L[\mathbf{s}(k)|\tilde{\mathbf{y}}]$. Taking into account the structure of $\mathbf{y}(k)$ given by (5) and using Bayes' rule, we have

$$\begin{aligned}L[\mathbf{s}(k)|\tilde{\mathbf{y}}] &= L[\mathbf{s}(k)|\mathbf{y}(k)] = L[\mathbf{y}(k)|\mathbf{s}(k)] + L[\mathbf{s}(k)] - L[\tilde{\mathbf{y}}]\\ &= -\frac{1}{\sigma_f^2}\|\mathbf{y}(k)-\mathbf{s}(k)\|^2 + L[\mathbf{s}(k)] + h_s\end{aligned} \tag{22}$$

where h_s is the constant that makes $P[\mathbf{s}(k)|\tilde{\mathbf{y}}]$ being a pdf. Clearly, the *extrinsic* information to be forwarded to the outer decoder is $L_e[\mathbf{s}(k)] = -\frac{1}{\sigma_f^2}\|\mathbf{y}(k)-\mathbf{s}(k)\|^2$.

Let us make some comments about how the information provided by the decoder is used in our DFE. It is apparent from (9) that the *a priori* values, $L[\mathbf{s}(k)]$, fed back from the decoder play a key role in computing the DFE parameters. Thus, in each decoding iteration, one (or more) iterations of the SAGE algorithm can be performed in order to obtain more refined estimations of $\mathbf{W}_*$, $\mathbf{V}_*$ and σ_f^2. Furthermore, the backward filter $\mathbf{V}_*$ can be fed with estimations of the transmitted symbols that come from the decoder, since they are supposed to be more accurate than those obtained at the output of the equalizer. For instance, if BPSK is used, we can estimate the transmitted symbols by $\hat{\mathbf{s}}(k) = sign\left\{E_{\mathbf{s}(k)}[\mathbf{s}(k)]\right\}$.

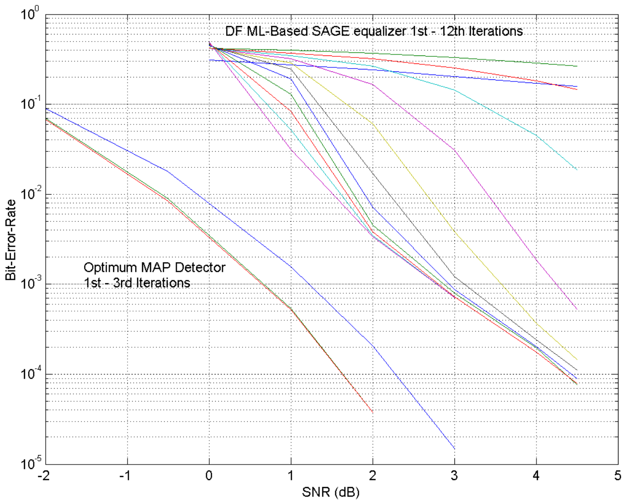

Fig. 3. Comparison between Optimum MAP Detector and DF ML-Based SAGE Equalizer

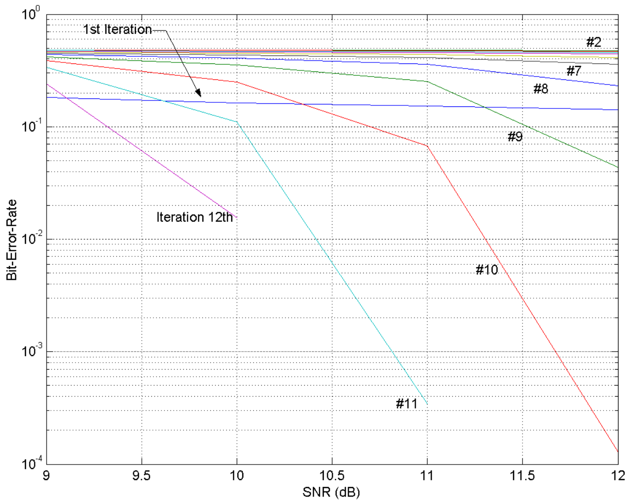

Fig. 4. Performance Results of the DF ML-Based SAGE Equalizer in a severe ISI scenario

6. SIMULATION RESULTS

Computer simulations were carried out to illustrate the performance of the proposed ST equalizer. Figure 3 shows a comparison between the results obtained with the optimum MAP detector and those obtained with the DF SAGE Equalizer for a dispersive channel with memory $m = 2$. The chosen modulation format is BPSK and the number of transmitting and receiving antennas is $N = L = 2$. The ST encoder is a rate 1/2 full diversity convolutional binary code given by the generator matrix $\mathbf{G} = [46, 72]$ in octal representation [1]. The interleaver size is 20800 bits. Data are processed in blocks of size 233 out of which $M = 25$ symbols correspond to a deterministic pilot sequence that is known *a priori* at the receiver. For the channel coefficients, we have assumed a spatially uncorrelated, Rayleigh distributed, flat fading model where the elements in matrix $\mathbf{H}$ are constituted by i.i.d. complex Gaussian random variables. The channel changes in each transmitted block. We have considered that in each decoding iteration, only one iteration of the SAGE algortihm is performed to obtain a more refined estimate of the equalizer parameters. Figure 3 shows how the Bit-Error-Rate (BER) diminishes through decoding iterations when the DF ML-Based SAGE Equalizer is employed. In this case Optimum MAP Detection does not yield significant improvement in BER beyond the 3rd decoding iteration. At the twelveth iteration, the difference with respect to the optimum MAP detector is about 2.1 dB for a BER of 10^{-3} and about 2.7 dB for a BER of 10^{-4}.

Figure 4 shows the performance of the DF ML-Based Equalizer in a more severe ISI environment where the channel memory is $m = 5$. Data are processed in blocks of size 248 out of which the pilot sequence occupies $M = 40$ symbols. The remaining simulation parameters are the same that were used in Figure 3.

7. CONCLUSIONS

We have presented a novel Turbo equalization structure for Space-Time Coded systems based on performing channel equalization via a Decision Feedback Equalizer (DFE). The computational cost of our approach is considerably less than the optimum MAP detector whereas simulation results show that the performance is only slightly worse.

8. REFERENCES

[1] A. R. Hammons, H. El Gamal, “On the theory of space-time codes for PSK modulation”, in *IEEE Trans. on Comm.*, vol. 46, no. 2, pp. 524-542, March 2000.

[2] V. Tarokh, N. Seshadri, A. R. Calderbank, “Space-Time codes for high data rate wireless communication: performance criterion and code construction”, in *IEEE Trans. on Inf. Theory*, vol. 44, no. 2, pp. 744-765, March 1998.

[3] C. Berrou, A. Glavieux, P. Thitimajshima, “Near Shannon limit error correcting coding and decoding: Turbo codes”, in *Proc. ICC’93*, pp. 1064-1070, Geneva, Switzerland, May 1993.

[4] S. Benedetto, D. Divsalar, G. Montorsi, F. Pollara, “A soft-input soft-output APP module for iterative decoding of concatenated codes”, in *IEEE Commun. Lett.*, vol. 1, pp. 22-24, January 1997.

[5] C. Laot, A. Glavieux, J. Labat, “Turbo Equalization: Adaptive Equalization and Channel Decoding Jointly Optimized”, in *IEEE Journal on Selected Areas In Comm.*, vol. 19, pp. 1744-1752, September 2001.

[6] M. F. Bugallo, J. Míguez, L. Castedo, “Decision-Feedback Semiblind Channel Equalization in Space-Time Coded Systems”, in *Proc. ICASSP’2002*, Orlando (Florida, USA), May 2002.

[7] J. A. Fessler, A. O. Hero, “Space-Alternating Generalized Expectation-Maximization Algorithm”, in *IEEE Trans. on Signal Processing*, vol. 42, no. 10, pp. 2664-2677, October 1994.