the output $\tilde{\boldsymbol{y}}_1(t)$ in (33) is the output of a system that has $n-1$ inputs and m outputs. Therefore, by the calculation of Step 6, the number of inputs becomes deflated by one.

VI. Conclusions

We have proposed a deflationary SEM for solving the BSS problem, in which the solutions of the problem $\tilde{\boldsymbol{w}}_l$'s satisfying (4) are found one by one. The proposed SEM is not sensitive to Gaussian noise, which is referred to as a robust super-exponential method (RSEM). This is a novel property of the proposed method, whereas the conventional methods do not posses it. It was shown from the simulation results that the proposed RSEM was robust to Gaussian noise and could successfully solve the BSS problem.

Appendix
Derivation of (16)

From the properties of the cumulant (see [6]), cum$\{y_q(t), y_r(t), y_i(t), y_j(t)\}$ in (14) becomes

$$\begin{aligned}\text{cum}\,&\{y_q(t), y_r(t), y_i(t), y_j(t)\}\\ &= \sum_{l_1,l_2,l_3,l_4} h_{ql_1}h_{rl_2}h_{il_3}h_{jl_4}\text{cum}\{s_{l_1}(t), s_{l_2}(t), s_{l_3}(t), s_{l_4}(t)\}\\ &\quad + \text{cum}\,\{n_q(t), n_r(t), n_i(t), n_j(t)\} \qquad (34)\\ &= \sum_{l=1}^{n} h_{ql}h_{rl}h_{il}h_{jl}\gamma_l = \boldsymbol{h}_q^T\boldsymbol{\Lambda}_{\gamma h_{ij}}\boldsymbol{h}_r \qquad (35)\end{aligned}$$

where the second equality comes from assumptions A2) and A3) and the fact that the fourth-order cumulant of Gaussian noises $n_i(t)$'s are equal to zero, $\boldsymbol{h}_q := [h_{q1}, h_{q2}, \cdots, h_{qn}]^T$, $\boldsymbol{\Lambda}_{\gamma h_{ij}}$ is a diagonal matrix defined by

$$\boldsymbol{\Lambda}_{\gamma h_{ij}} = \begin{bmatrix} \gamma_1 h_{i1}h_{j1} & 0 & \cdots & 0\\ 0 & \gamma_2 h_{i2}h_{j2} & \cdots & 0\\ \vdots & \vdots & \ddots & \vdots\\ 0 & 0 & \cdots & \gamma_n h_{in}h_{jn}\end{bmatrix}$$

and $\boldsymbol{h}_r := [h_{r1}, h_{r2}, \cdots, h_{rn}]^T$. From (35), we obtain

$$\sum_{i,j=1}^{m} \beta_{ij}\text{cum}\,\{y_q(t)y_r(t)y_i(t)y_j(t)\} = \boldsymbol{h}_q^T\boldsymbol{\Lambda}_{\gamma\Sigma h_{ij}}\boldsymbol{h}_r \qquad (36)$$

where $\boldsymbol{\Lambda}_{\gamma\Sigma h_{ij}}$ is a diagonal matrix defined by

$$\begin{bmatrix} \gamma_1\sum_{i,j} h_{i1}h_{j1} & 0 & \cdots & 0\\ 0 & \gamma_2\sum_{i,j} h_{i2}h_{j2} & \cdots & 0\\ \vdots & \vdots & \ddots & \vdots\\ 0 & 0 & \cdots & \gamma_n\sum_{i,j} h_{in}h_{jn}\end{bmatrix}.$$

It can be seen that (36) expresses the (q,r)th element of $\boldsymbol{H}\tilde{\boldsymbol{\Lambda}}\boldsymbol{H}^T$. Therefore, (16) holds true.

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Iterative Decoding of Wrapped Space-Time Codes

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***Abstract*—We study the iterative decoding of Wrapped Space-Time Codes (WSTCs) employing per-survivor-processing with the soft-output Viterbi-algorithm (SOVA). We use a novel receiver scheme that incorporates extrinsic information delivered by the SOVA. The decision metric of the SOVA is developed, and the performance is analyzed.**

***Index Terms*—Iterative decoding, MIMO, SOVA, space-time codes.**

I. Introduction

In recent years, the goal of providing high-speed wireless data services has generated a great amount of interest among the research community. Recent information-theoretic results have demonstrated that the capacity of the system in the presence of Rayleigh fading improves significantly with the use of multiple transmit and receive antennas [1], [2].

Diagonal Bell Labs Layered Space-Time (DBLAST), which is an architecture that theoretically achieves a capacity for such multiple-input

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multiple-output (MIMO) channels, has been proposed by Foschini in [3]. However, the high complexity of the algorithm implementation is its substantial drawback. Vertical BLAST (VBLAST), which is a simplified and suboptimal version of the BLAST architecture using ordered successive nulling and interference cancellation at the receiver, is capable of achieving high capacity at low complexity. A drawback of VBLAST is the effect of error propagation caused by incorrect estimations of transmitted signals. To avoid this drawback, many iterative schemes with high complexity have been proposed in the literature, e.g., [4], [5].

Another approach to reduce the effect of error propagation and to improve the performance significantly was proposed by Caire *et al.* in [6]. They proposed a low-complexity space-time scheme called Wrapped Space-Time Coding (WSTC) for Rayleigh fading channels to achieve high spectral efficiencies [6]. In this scheme, only a single encoder is used. The coded data is diagonally interleaved and transmitted over the n_T transmit antennas. At the receiver, the nulling and cancellation steps are integrated into a Viterbi algorithm employing per-survivor processing [7]. In this work, we apply the coding and decoding technique from [6] as inner coding and decoding components, respectively. However, instead of the receiver used in [6], which provides only hard decisions over the information bits, we employ a SOVA providing soft decisions to the outer decoder. Since we need the data estimations at the inner decoder for the interference cancellation with a minimum amount of delay, the application of optimum soft-input soft-output (SISO) maximum *a posteriori* (MAP) algorithms [8] is not feasible. Further on, we apply an outer code at the transmitter and couple this with an iterative decoding process in order to improve the performance of the architecture and in order to achieve the capacity promised by the information-theoretic results. The performance of our scheme is evaluated by simulations and compared to the scheme proposed in [6].

The rest of this paper is organized as follows. In Section II, we introduce the system model and establish notation. The novel receiver scheme is described in Section III. Section IV gives simulation results, followed by some concluding remarks in Section V.

II. System Model

We consider a wireless multiple-input-multiple-output (MIMO) system with n_T transmit and n_R receive antennas, as depicted in Fig. 1. The transmitter consists of two systematic, recursive convolutional codes (CCs), which are denoted as FEC_1 and FEC_2 in Fig. 1, concatenated in serial via a pseudorandom interleaver. Codes of such a structure are known as serially concatenated convolutional codes (SCCCs). This interleaver is used in order to uncorrelate the log-likelihoods of adjacent bits and distribute the error events due to a deeply faded block during a transmission. We can obtain different spectral efficiencies by puncturing the parity bits of the component encoders. After encoding the whole information bit sequence with FEC_1 and interleaving, the coded bit sequence is divided into τ blocks. Each block is encoded separately. Let a block of coded bits be $\{c_1, c_2, \ldots, c_{L_B}\}$, where L_B is the block length. This coded bits are then mapped onto symbols from a given constellation, e.g., binary phase shift keying (BPSK) and interleaved via a diagonal (channel) interleaver, which is different from the interleaver used for concatenation of the SCCC code component encoders. The channel is constant during the transmission of one block and changes independently from block to block.

Our system model is defined by

$$\mathbf{Y} = \sqrt{\frac{\rho}{n_T}}\mathbf{H}\mathbf{X} + \mathbf{N} \tag{1}$$

where $\mathbf{X}$ is the $(n_T \times T)$ transmit matrix, $\mathbf{Y}$ is the $(n_R \times T)$ receive matrix, $\mathbf{H} = [\mathbf{h}_1, \mathbf{h}_2, \ldots, \mathbf{h}_{n_T}]$ is the $(n_R \times n_T)$ flat fading channel

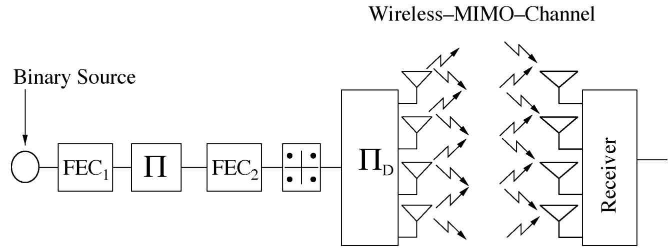

Fig. 1. System model with binary source, SCCC encoder, modulation, diagonal interleaving (cf. Fig. 2), Rayleigh MIMO-channel, and receiver (cf. Section III, Fig. 3).

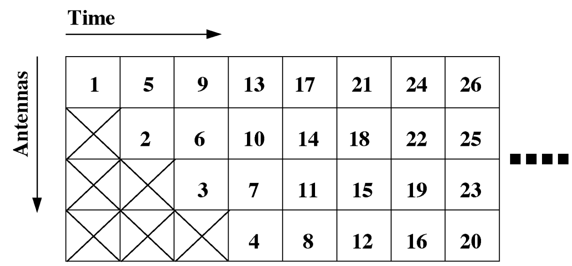

Fig. 2. Diagonal interleaver for a system with $n_T = 4$ transmit antennas. The entries in the cells indicate the index k of the symbols in the current codeword. A cross in a cell means that at this time the given antenna is not active.

matrix, and $\mathbf{N}$ is the $(n_R \times T)$ additive white Gaussian noise (AWGN) matrix, where an entry $\{n_i\}$ of $\mathbf{N}$ $(1 \leq i \leq n_R)$ denotes the complex noise at the ith receiver for a given time $t(1 \leq t \leq T)$ (for clarity, we dropped the time index). The real and imaginary parts of n_i are independent and normal $\mathcal{N}(0, 1/2)$ distributed.

An entry of the channel matrix is denoted by $\{h_{ij}\}$. This represents the complex gain of the channel between the jth transmitter $(1 \leq j \leq n_T)$ and the ith receiver $(1 \leq i \leq n_R)$, where the real and imaginary parts of the channel gains are independent and normal distributed random variables with $\mathcal{N}(0, 1/2)$ per dimension. Throughout the paper, it is assumed that the channel matrix is independent and identically distributed (i.i.d.) and that every channel realization of the channel is independent, i.e., the channel is memoryless. The expected signal-to-noise ratio (SNR) at each receive antenna is independent of n_T and is denoted as ρ in (1). It is further assumed that the transmitter has no channel state information (CSI) and that the receiver has perfect CSI. To obtain the transmit matrix $\mathbf{X}$, we use a special interleaver, as illustrated in Fig. 2.

With the index k of the symbols in the current codeword, we get the right cell position in $\mathbf{X}$ as follows:

$$r = k - \left\lfloor \frac{k-1}{n_T} \right\rfloor n_T \tag{2}$$

$$c = k - \left\lfloor \frac{k-1}{n_T} \right\rfloor (n_T - 1) \tag{3}$$

where $[\mathbf{X}]_{r,c}$ is the current cell of $\mathbf{X}$. Herein, c corresponds to the column and r to the row of $\mathbf{X}$.

III. Receiver With Iterative Decoding

A. Receiver Structure

Fig. 3 shows the structure of the receiver, which consists of two stages: the space-time SOVA (STS) decoder described in Section III-B, and a MAP SISO channel decoder. The two stages are separated by deinterleavers and interleavers. The receiver works as follows: Assuming equally likely bits, the resulting *a priori* information $\lambda_{A,\text{STS}}$ is zero in the first iteration. Therefore, the switch in Fig. 3 is in

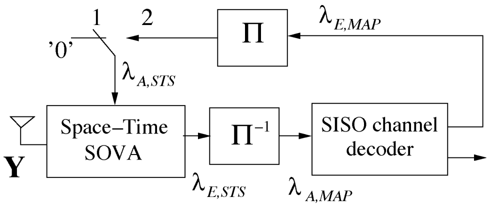

Fig. 3. Model of the proposed SISO receiver with Space-Time SOVA decoder, channel decoder, interleaver, and deinterleaver.

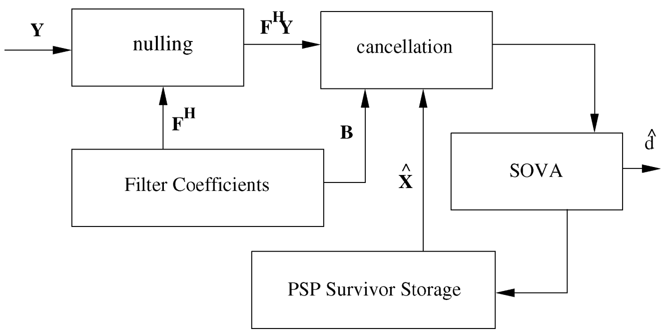

Fig. 4. Model of the proposed receiver with PSP, joint decoding, and channel estimating.

position 1. Now, the ST SOVA decoder has to compute the extrinsic information $\lambda_{E,\mathrm{STS}}$ only from the observations of the channel output. The extrinsic information $\lambda_{E,\mathrm{STS}}$ is now deinterleaved and fed into the MAP decoder as *a priori* information $\lambda_{A,\mathrm{MAP}}$. Based on this *a priori* information and the trellis structure of the channel code, the MAP-Decoder computes the extrinsic information $\lambda_{E,\mathrm{MAP}}$. After interleaving, this extrinsic information $\lambda_{E,\mathrm{MAP}}$ is fed back to the ST SOVA decoder as *a priori* information $\lambda_{A,\mathrm{STS}}$ for the following iterations. After the first iteration, the switch in Fig. 3 is the on position 2.

At the receiver, decoding is done by processing the receive matrix according to the diagonal interleaver structure. In Fig. 4, the variable $\widehat{\mathbf{X}}$ represents the estimated transmit matrix with entries up to the current decoding step k in the trellis diagram of the SOVA, which is obtained from the survivor terminating in the code trellis state τ at decoding step k. According to the Zero-Forcing (ZF) or the Minimum Mean-Square Error (MMSE) criterion for the filter design [6], [9], we have for the feedforward (or interference nulling) filter $\mathbf{F} = [\mathbf{f}_1, \mathbf{f}_2, \ldots, \mathbf{f}_{n_T}]$

$$\mathbf{f}_r = \begin{cases} \mathbf{q}_r \\ \frac{1}{\sqrt{\mathbf{h}_r^H \mathbf{S}_r^{-1} \mathbf{h}_r}} \mathbf{S}_r^{-1} \mathbf{h}_r \end{cases} \quad (4)$$

where

$$\mathbf{S}_r = (\mathbf{H\Gamma})(\mathbf{H\Gamma})^H + \left(\frac{n_T}{\rho}\right)\mathbf{I}_{n_r} = \sum_{i=1}^{r-1} \mathbf{h}_i \mathbf{h}_i^H + \left(\frac{n_T}{\rho}\right)\mathbf{I}_{n_r} \quad (5)$$

and

$$\mathbf{\Gamma} = \begin{bmatrix} \mathbf{I}_{\mathrm{r}-1} \\ \mathbf{0}_{(\mathrm{n_T}-\mathrm{r}+1)\times(\mathrm{r}-1)} \end{bmatrix}. \quad (6)$$

The vector $\mathbf{q}_r$ is obtained from the $\mathbf{QR}$-factorization of the channel matrix $\mathbf{H}$, where the the matrix $\mathbf{R}$ is an upper triangular $n_T \times n_T$ matrix, and $\mathbf{Q} = [\mathbf{q}_1, \mathbf{q}_2, \ldots, \mathbf{q}_{n_T}]$ is an $n_R \times n_T$ unitary matrix with $\mathbf{Q}^H\mathbf{Q} = \mathbf{I}$. The superscript $(\cdot)^H$ denotes matrix conjugate transpose. For the feedback (interference cancellation) filter $\mathbf{B} = [\mathbf{b}_1^T, \mathbf{b}_2^T, \ldots, \mathbf{b}_{n_T}^T]^T$, $\mathbf{b}_r^T = [\mathbf{0}_{1\times r}, \tilde{\mathbf{b}}_r^T]$, we have

$$\tilde{\mathbf{b}}_r^T = \mathbf{f}_r^H \mathbf{H} \begin{bmatrix} \mathbf{0}_{\mathrm{r}\times(\mathrm{n_T}-\mathrm{r})} \\ \mathbf{I}_{\mathrm{n_T}-\mathrm{r}} \end{bmatrix}. \quad (7)$$

Note that we have to compute the filter coefficients only once during a channel realization. At each trellis step, the module called "per-survivor processing (PSP) survivor storage" gets, for each trellis state, the hard decisions of the data sequence corresponding to the survivor at that state from the SOVA. With this input, the estimated transmit matrix $\widehat{\mathbf{X}}$ is constructed for the trellis update leaving each state. This update is done by the cancellation module, which takes $\widehat{\mathbf{X}}$ and computes the interference for the current decoding step in the trellis diagram for each trellis state. Note that we need soft-decisions for the iterative decoding, but only hard-decisions of the data sequence for the cancellation, since the PSP estimates are based on (hard) hypothesized paths, leading to the given trellis state. The nulling module takes the matrix $\mathbf{F}^H$, which is obtained by the filter coefficients module to null out the interference from not-yet-decoded codeword symbols.

B. ST SOVA Decoder

In order to obtain the path metric for the ST SOVA decoder in the presence of interference from the other layers, we use the matrices $\mathbf{F}$ and $\mathbf{B}$ for nulling out the impact of the upper (not-yet-detected) layers, and combine this with PSP for cancelling the interference of the lower (already-detected) layers. To improve the decoding process, we also need *a priori* information about the transmitted signals in the modified path metric. Let $\mathbf{y}_k$ be the receive vector corresponding to the symbols in $\mathbf{Y}$, and let $\widehat{\mathbf{x}}_k$ be the interference vector corresponding to the symbols in $\widehat{\mathbf{X}}$ at decoding time k, respectively. Furthermore, let the signal-to-interference plus noise ratio at the output of the cancellation module given by

$$\mu_r = \begin{cases} [\mathbf{R}]_{r,r} \\ \sqrt{\mathbf{h}_r^H \mathbf{S}_r^{-1} \mathbf{h}_r} \end{cases} \quad (8)$$

where $\mathbf{S}_r$ is given in (5), and $[\mathbf{R}]_{r,r}$ is the rth row and column entry of the upper triangular matrix $\mathbf{R}$. Then, the modified path metric $\mathrm{M}_k(\tau)$ of the path terminating in a state τ in the code trellis at the decoding time k is given by

$$\mathrm{M}_k(\tau) = \min_{\nu\in P(\tau)} \{\mathrm{M}_{k-1}(\nu) + \log p_k(\nu,\tau) + \left|\mathbf{f}_r^H \mathbf{y}_k - \mathbf{b}_r^T \widehat{\mathbf{x}}_k - \mu_r z_{\nu\tau}\right|\} \quad (9)$$

where $P(\tau)$ denotes the set of parent states of τ, $z_{\nu\tau}$ denotes the modulated symbol on the trellis transition $\nu \to \tau$, $M_{k-1}(\nu)$ is the smallest metric of the path connected to the trellis state ν, and $\log p_k(\nu\tau)$ is the logarithm of the *a priori* probability of the bit c_k corresponding to the trellis transition $\nu \to \tau$. The *a priori* probability is obtained from the SISO channel decoder. The ST SOVA decoder stepwise decodes the symbols at each stage of the code trellis diagram, storing the survivor terminating in each state of the trellis and, use the survivors to cancel their impact as interference on the following decoding steps. The soft output of the ST SOVA is an approximate log-likelihood ratio of the *a posteriori* probabilities of the information bits. The soft output can be approximately expressed as the metric difference between the maximum-likelihood path and its strongest competitor at each decoding step. The strongest competitor of the maximum-likelihood path is the path that has the minimum path metric among a given set of paths. This set is obtained by taking all paths, which have, at the current decoding step, the symbol on their trellis transition complementary to the one on the maximum likelihood path. The ST SOVA decoder provides soft information, which can be expressed as

$$\begin{aligned}\Lambda(c_k) &= \log \frac{P(c_k = 0|\mathbf{Y})}{P(c_k = 1|\mathbf{Y})} \\ &= \log \frac{P(z_{\nu\tau} = +1|\mathbf{Y})}{P(z_{\nu\tau} = -1|\mathbf{Y})} \\ &= M_k^{-1} - M_k^{+1} \end{aligned} \quad (10)$$

where M_k^{-1} is the minimum path metric corresponding to $z_{\nu\tau} = -1$, and M_k^{+1} is the minimum path metric corresponding to $z_{\nu\tau} = +1$. We can split the soft output of the SOVA into two parts: the extrinsic information $\lambda_{E,\mathrm{STS}}(c_k)$ and the intrinsic or *a priori* information $\lambda_{A,\mathrm{STS}}$,

$$\Lambda(c_k) = \lambda_{A,\mathrm{STS}}(c_k) + \lambda_{E,\mathrm{STS}}(c_k) \quad (11)$$

where the *a priori* information is given as

$$\Lambda_{A,\mathrm{STS}}(c_k) = \log \frac{p_k(0)}{p_k(1)}. \quad (12)$$

Therefore, the extrinsic information, which is fed into the MAP decoder after deinterleaving is obtained from (11) and (12) as

$$\lambda_{E,\mathrm{STS}}(c_k) = \Lambda(c_k) - \lambda_{A,\mathrm{STS}}(c_k). \quad (13)$$

Some simulation results of the proposed scheme and their interpretation are presented in the following section.

IV. Numerical Simulation

In this section, we illustrate the bit error performance of our proposed scheme, which we call WSTC with iterative decoding (WSTC-ID) in the remainder of the paper, and compare it with the performance of the WSTC in [6] and [10]. In Fig. 5, we present the bit error rate (BER) of the WSTC-ID scheme for a system with $n_T = n_R = 4$ transmit-and-receive antennas and quadrature phase shift keying (QPSK) modulation. The outer coding is performed over multiple block fading channels. After encoding with the outer code and interleaving, we divide the whole sequence into $\tau = 8$ blocks. Each block has a length of $L_B = 128$ bits after encoding with the inner code. We assume that the channel is constant for the transmission for each block and change independently from block to block. As component codes, we use the binary linear feedback systematic convolutional code $\mathrm{CC}(7,5)_8$, where the generator polynomials are given in octal numbers with feedback polynomial $G_r = 7$ and feedforward polynomial $G_f = 5$. The overall code rate of our scheme is $R_{\mathrm{WSTC-ID}} = 1/4$. For reference, the simulated BER performance of the WSTC for BPSK modulation are also shown. As channel code for WSTC, we used the convolutional code $\mathrm{CC}(7,5)_8$ with code rate $R_{\mathrm{WSTC}} = 1/2$. By comparing the curves of our proposed scheme with the one of WSTC, we observe that although the performance at the first iteration is relatively worse, there is a significant improvement with further iterations, especially for higher SNR values. Furthermore, simulation results show that there occurs a saturation of the improvement beyond iteration 3. This behavior can be explained by the fact that after each iteration, the extrinsic output of the receiver components tends to a Gaussian distribution according to the central limit theorem, but the correlation between the extrinsic information and the channel output increases after each iteration [11].

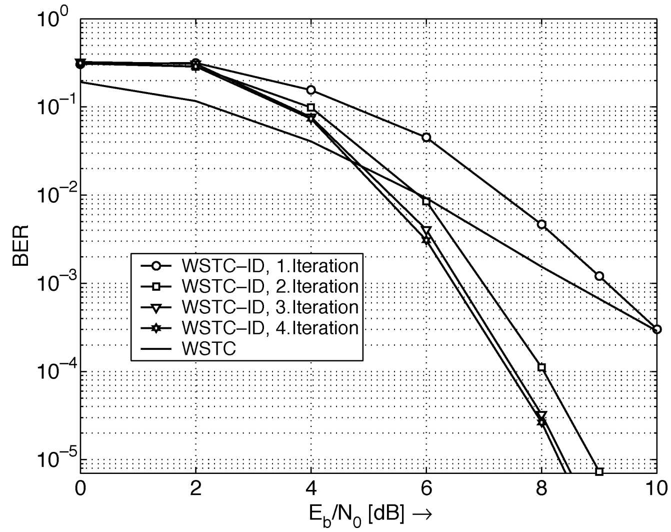

Fig. 5. Bit error rates, ZF receiver, $n_T = n_R = 4$ antennas, WSTC-ID with coded QPSK modulation with inner and outer code $\mathrm{CC}(5,7)_8$, $R_{\mathrm{WSTC-ID}} = 1/4$, and WSTC with BPSK and $R_{\mathrm{WSTC}} = 1/2$.

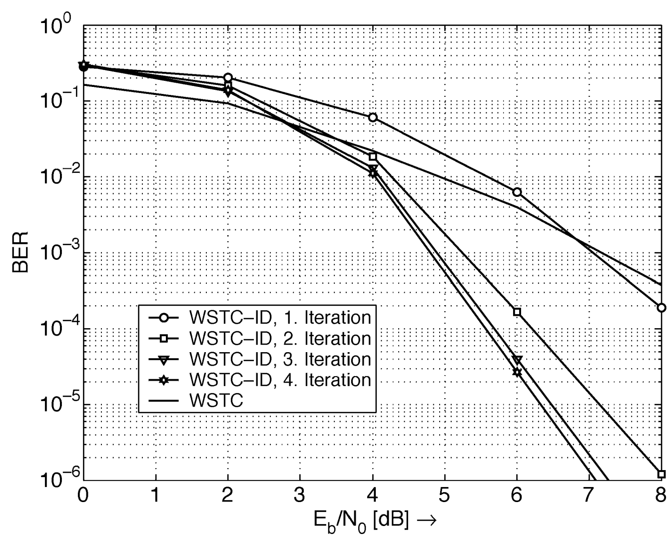

Fig. 6. Bit error rates, MMSE receiver, $n_T = n_R = 4$ antennas, WSTC-ID with coded QPSK modulation with inner and outer code $\mathrm{CC}(5,7)_8$, code rate $R_{\mathrm{WSTC-ID}} = 1/4$, and WSTC with BPSK and $R_{\mathrm{WSTC}} = 1/2$.

Hence, the improvement of the BER performance diminishes after each iteration. Even at the first iteration, we observe that the WSTC have a diversity loss in comparison to the the new WSTC-ID scheme. The loss is due to the inability of the ZF-or MMSE Decision Feedback Equalization (DFE) within the WSTC to achieve full diversity with given coded modulation over finite alphabets. The diversity gain (or change of slope) of the new WSTC-ID scheme is mainly achieved due to soft decisions used for the iterative decoding and the distribution of error events (with interleaving) due to a deeply faded block during a transmission. Note that the improvement to WSTC can further enhanced with a bigger τ and through the enlargement of the whole information bit length. In addition to the BER for the ZF solution, we present the BER for the MMSE case in Fig. 6. From the figure, we observe that the new scheme outperforms the WSTC scheme. We also observe that the improvement in comparison to WSTC is higher, as in the ZF case.

V. Conclusion

In conclusion, we proposed a novel iterative receiver scheme for a low-complexity space-time architecture called WSTC. The receiver consists of the serial concatenation of two stages: A Space-Time (ST) SOVA decoder and a MAP decoder. We developed the decision metric for the ST SOVA decoder employing per-survivor processing. Furthermore, we analyzed the performance of our proposed scheme in terms of numerical simulations and compared it with the noniterative WSTC scheme in [10]. It is shown that the proposed scheme has significantly better performance in terms of bit error rates.

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