

Iterative Noncoherent Detection of Coded Differential Space-Time Modulation in Rayleigh Fading Channels

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Abstract—An iterative noncoherent detection method of coded and symbol interleaved differential space-time modulation (DSTM) is proposed in flat Rayleigh fading channels. Like differential phase shift keying (DPSK), DSTM can be considered as a recursive convolutional code. A soft-output a posteriori probability (APP) decoder of DSTM is proposed in flat Rayleigh fading channels. In the decoder, multiple-symbol differential detection (MSDD) is used to calculate the branch metric. Channel autocorrelations are considered in MSDD to mitigate the effects of channel variation, in the Rayleigh fading channels. Simulation results demonstrate that the proposed detection method has good performance in fast Rayleigh fading channels and the performance can be enhanced by increasing both the iterative times and the observation intervals.

Keywords—Differential space-time modulation, iterative decoding, noncoherent detection, fading channels, multiple-symbol differential detection.

I. INTRODUCTION

Differential space-time modulation (DSTM) [1]-[2] is an easily implemented and attractive transmit diversity method with multiple transmit antennas. With DSTM, no channel state information (CSI) is needed at both transmitter and receiver. This makes DSTM very competitive when fading channels change so rapidly that the CSI, which is necessary for coherent detection, cannot be got reliably.

DSTM can be seen as an extension of differential phase shift keying (DPSK). In [3], to improve the system performance of DPSK, serial concatenation of DPSK with a convolutional code is introduced. DPSK has been considered as a recursive convolutional code and the corresponding soft output a posteriori probability (APP) decoder has been proposed. Applying the proposed decoder in the receiver, an additional coding gain from the concatenation is shown to be obtained after iterative decoding processes.

Similarly, when DSTM is considered as a recursive convolutional code, coded DSTM is the serial concatenation of DSTM and a convolutional code, and an additional coding gain can also be expected. To take the additional coding gain, the research in [3] is generalized into the case of DSTM in this paper. A soft-output APP decoder of DSTM is proposed based on BCJR algorithm [4]. In the decoder, multiple-symbol differential detection (MSDD) [5] is applied to calculate the branch metric. Although in [3], the research is limited to the case of additive white Gaussian noise (AWGN) channels, flat Rayleigh fading channels are considered in the paper. Channel autocorrelations are considered in MSDD, to mitigate the effects of channel variation in the Rayleigh fading channels.

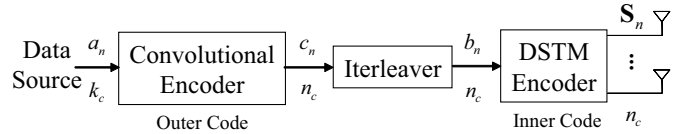


Fig. 1. The serial concatenated encoder of DSTM.

Several works on the same topic of iterative detection of coded DSTM can be found in [6] and [7]. In [6], noncoherent iterative decoding (NID) [8] using rectangular windowing (RW) or exponential decaying windowing (EDW) has been applied to get the detection schemes. But since NID with RW is developed for AWGN channels and NID with EDW is developed for slow fading channels, the schemes in [6] are not fit for fast fading channels. In [7], a detection method of DSTM has been proposed by employing soft output Viterbi algorithms whose branch metrics are got by modifying the decision metrics of MSDD. Since the channel autocorrelations are not considered, large observation interval can only lead to performance degradation, and thus only the minimum required observation interval is adopted in [7]. In this paper, differently from [6], the proposed detection method has good performance in fast fading channels. And differently from [7], large observation interval leads to significant performance gain and hence a proper observation interval can be chosen flexibly. Another major difference is that, instead of bit interleaving which is used in [6] and [7], the symbol interleaving is utilized in the paper to keep the code symbols intact.

The rest of this paper is organized as follows. Section II contains the system model. In Section III, focussed on the inner decoder, the iterative detection method is described. The performance of proposed detection method is analyzed by computer simulations in Section IV. Finally the conclusion is in Section V.

II. SYSTEM MODEL

The system model in [3] is generalized into the case of DSTM. The transmitter of coded and symbol interleaved DSTM is shown in Fig. 1. The information data are firstly convolutionally encoded, then after interleaving, the coded data are mapped into DSTM symbols and transmitted to the channel. Since symbol interleaver is used here, the information data are considered in symbols. Set every information symbol contains k_c information bits and the total number of the information symbols is N_a , the whole information data

can be denoted by $\underline{a}_1^{N_a}$, where $\underline{x}_n^m = \{x_n, x_{n+1}, \dots, x_m\}$. Accordingly, $\underline{c}_1^N$ is the codeword after the convolutionally encoding with rate k_c/n_c , where $N = N_a + L$ and L is the number of additional symbols at the end of the codeword to drive the convolutional encoder to zero state. And $\underline{b}_1^N$ is the interleaved codeword with $b_n \in \mathcal{M}$ and the code space $\mathcal{M}$ is $\{0, 1, \dots, M-1\}$. Assume M-ary phase-shift keying (MPSK) is used in DSTM, to make sure the code symbols intact after interleaving and modulation, it has $n_c = \log_2 M$. Set the number of transmit antennas as N_t , the $N_t \times N_t$ DSTM code matrix $\mathbf{S}_n$ is

$$\mathbf{S}_n = \begin{bmatrix} e^{j\frac{2\pi}{M}u_1d_n} & 0 & \dots \\ 0 & \ddots & 0 \\ 0 & \dots & e^{j\frac{2\pi}{M}u_{N_t}d_n} \end{bmatrix} \quad (1)$$

where d_n is the differential coded symbol of b_n , and u_m is the coefficient which is optimized to achieve maximum diversity product as show in [1]. Set the transmitted energy per symbol as E_s , then the transmitted energy per message bit E_b can be calculated as

$$E_b = \frac{N_a + L + 1}{N_a k_c N_t} E_s. \quad (2)$$

We consider a wireless communication system with N_r receive antennas and the channel between each transmit and receive antenna is assumed to be time-varying flat Rayleigh fading and uncorrelated mutually. At time $N_t\tau + k$, $0 \leq k \leq N_t - 1$, a symbol $s_\mu(N_t\tau + k)$ is transmitted by the μ th antenna. Then the received signal of the symbol at receive antenna ν can be expressed as

$$y_\nu(N_t\tau + k) = h_{\mu\nu}(N_t\tau + k)s_\mu(N_t\tau + k) + n_\nu(N_t\tau + k), \quad (3)$$

where $h_{\mu\nu}^l(t)$ which is a complex Gaussian random variable with mean zero and variance σ_h^2 is the subchannel gain between the μ th transmit antenna and the ν th receive antenna at time t . $n_\nu(t)$ is additive complex Gaussian noise with zero mean and variance σ_n^2 at receive antenna ν , and $\sigma_n^2 = N_0/2$ where N_0 is the one-sided power spectral density.

Since the space-time code matrix of transmitted symbols at τ th time block is $[\mathbf{S}_\tau]_{k\mu} = s_\mu(N_t\tau + k)$, where $[\cdot]_{ij}$ denotes the i, j th element of a matrix. Assume a block fading environment i.e.

$$h_{\mu\nu}(N_t\tau + k) = h_{\mu\nu}(N_t\tau + k') = h_{\mu\nu}(N_t\tau) \quad (4)$$

$$0 \leq k \leq k' \leq N_t - 1,$$

we can recast (2) to an equivalent matrix form as

$$\mathbf{Y}_\tau = \mathbf{S}_\tau \mathbf{H}_\tau + \mathbf{N}_\tau \quad (5)$$

where $\mathbf{Y}_\tau$, $\mathbf{H}_\tau$ and $\mathbf{N}_\tau$ are $N_t \times N_r$ matrices with $[\mathbf{Y}_\tau]_{k\nu} = y_\nu(N_t\tau + k)$, $[\mathbf{H}_\tau]_{\mu\nu} = h_{\mu\nu}(N_t\tau + k)$ and $[\mathbf{N}_\tau]_{k\nu} = n_\nu(N_t\tau + k)$ respectively.

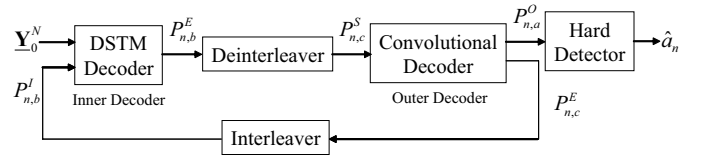


Fig. 2. Iterative detection of coded DSTM.

III. RECEIVER WITH ITERATIVE DETECTION

The optimal receiver by the mean of minimum symbol error, applies the maximum a posteriori probability (MAP) estimation, which chooses a_n as $\hat{a}_n$ when the APP $p\{a_n = \hat{a}_n | \mathbf{Y}_0^N\}$ is maximized. Since it is computationally prohibitive to calculate the APP's directly, utilization of suboptimal receivers to get the APP's is taken into account.

Considering the DSTM as a recursive convolutional code, a suboptimal receiver which is splitter into inner decoder and outer decoder and using the iterative decoding can be proposed as in Fig. 2. The processes of iterative decoding and outer decoder are very similar with those in [3], but the inner decoder should be generalized for multiple antennas and reconsidered for fast fading channels. Therefore, the process of inner decoder is the main point of this chapter. In the rest of this chapter, after a simple description of the whole iterative decoding process, we mainly focus on the process of inner decoder.

A. Iterative Decoding

A soft output DSTM decoder is used as the inner decoder to calculate the APP $P_{n,b}^O \cong p\{b_n = b | \mathbf{Y}_0^N\}$ for all possible values of $b \in \{0, 1, \dots, M-1\}$ and $n \in \{1, 2, \dots, N\}$. $P_{n,b}^O$ can be calculated with the method proposed in Sec. III-B using the received signals $\mathbf{Y}_0^N$ and a priori probability $p\{b_n = b\}$. At the very first time, $p\{b_n = b\}$ with equal probability can be used. After removing the a priori information by division, the inner decoder outputs the so-called extrinsic information $P_{n,b}^E = \frac{P_{n,b}^O}{p\{b_n = b\}}$, and the deinterleaved extrinsic information $P_{n,c}^S$ is passed to the outer decoder.

At the outer decoder, BCJR algorithm is used to decode the convolutional code. $P_{n,a}^O \cong p\{a_n = a | \mathbf{Y}_0^N\}$ and $P_{n,c}^O \cong p\{c_n = c | \mathbf{Y}_0^N\}$ are calculated based on $P_{n,c}^S$. Removed the extrinsic information from inner decoder, outer decoder outputs extrinsic information $P_{n,c}^E \cong \frac{P_{n,c}^O}{P_{n,c}^S}$ and $P_{n,c}^E$ is interleaved to $P_{n,b}^I$ to pass back to the inner decoder.

Then at the inner decoder, $P_{n,b}^I$ is used as the new a priori probability in place of $p\{b_n = b\}$. And the extrinsic information $P_{n,b}^E$ is recalculated with $P_{n,b}^I$ and the received signals $\mathbf{Y}_0^N$. Afterwards the new extrinsic information $P_{n,b}^E$ is passed to outer decoder and used to compute new $P_{n,a}^O$ and $P_{n,c}^E$.

Such an iterative process is repeated several times, and after a certain time of iterations, $P_{n,a}^O$ is input into a hard detector to make the decision of a_n .

B. Inner Decoder

Here, we generalize the inner decoder of DPSK with noncoherent demodulation in [3], which is considered in the AWGN channels, into the case of DSTM in the Rayleigh fading channels.

Like in [3], to calculate $P_{n,b}^O$, $p(\mathbf{Y}_n | b_1^n, \mathbf{Y}_0^{n-1})$ should be firstly calculated. Consider $\mathbf{Y}_0^n$ as a received signal sequence of MSDD with observation interval n , as in [9] the probability density function of $\mathbf{Y}_0^n$ given message b_1^n is,

$$p(\mathbf{Y}_0^n | b_1^n) = \frac{\exp\{-tr(\mathbf{Y}_0^{nH}(\Lambda_0^n)^{-1}\mathbf{Y}_0^n)\}}{(\pi^{(n+1)N_t} \det \Lambda_0^n)^{N_r}} \quad (6)$$

where 'tr' denotes the trace function. 'E' denotes expectation and the superscript 'H' denotes the Hermitian operation (transpose conjugation).

$$\Lambda_i^j = E[\mathbf{Y}_i^j \mathbf{Y}_i^{jH} | b_1^n] \quad (7)$$

is the covariance matrix of $\mathbf{Y}_i^j$. In Rayleigh fading channels, Λ_i^j can be written into [9]

$$\Lambda_i^j = \mathbf{D}_i^j \rho_{j-i+1} \mathbf{D}_i^{jH} + N_r \sigma_n^2 \mathbf{I}_{N_t(j-i+1)} \quad (8)$$

where $\mathbf{D}_i^j = \text{diag}\{\mathbf{S}_i, \mathbf{S}_{i+1}, \dots, \mathbf{S}_j\}$, $\mathbf{I}_M$ is an $M \times M$ identity matrix and ρ_M is a $M \times M$ matrix which considering the channel fading autocorrelation as in [10] and has elements as

$$[\rho_M]_{ij} = \sigma_h^2 \cdot J_0(2\pi f_D T_s N_t(i-j)). \quad (9)$$

where f_D is the maximum Doppler frequency, T_s is the sample period, and $J_0(\cdot)$ is the zeroth order Bessel function of the first kind. Thus $f_D T_s$ is the normalized maximum Doppler frequency. By considering the channel fading autocorrelation, the effects of channel variation can be mitigated.

From (6), we can get

$$\begin{aligned} p(\mathbf{Y}_n | b_1^n, \mathbf{Y}_0^{n-1}) &= \frac{p(\mathbf{Y}_0^n | b_1^n)}{p(\mathbf{Y}_0^{n-1} | b_1^n)} \\ &= \left(\frac{\det \Lambda_0^{n-1}}{\pi^{N_t} \det \Lambda_0^n} \right)^{N_r} \cdot \exp\{tr(\mathbf{Y}_0^{n-1H}(\Lambda_0^{n-1})^{-1}\mathbf{Y}_0^{n-1}) \\ &\quad - tr(\mathbf{Y}_0^{nH}(\Lambda_0^n)^{-1}\mathbf{Y}_0^n)\} \end{aligned} \quad (10)$$

As shown in (8), the calculation of Λ_0^n needs the information of b_1^n , and when n is big, it is too complex to be calculated. Therefore, it is hardly to use (10) directly. To solve this problem, truncation is also used here like in [3]. Set the number of previous samples used by the estimator as Z , and assume $p(\mathbf{Y}_n | b_1^n, \mathbf{Y}_0^{n-1}) = p(\mathbf{Y}_n | b_{n-Z+1}^n, \mathbf{Y}_{n-Z}^{n-1})$, (10) can be rewritten into

$$\begin{aligned} p(\mathbf{Y}_n | b_1^n, \mathbf{Y}_0^{n-1}) &= \left(\frac{\det \Lambda_{n-Z}^{n-1}}{\pi^{N_t} \det \Lambda_{n-Z}^n} \right)^{N_r} \cdot \exp\{tr(\mathbf{Y}_{n-Z}^{n-1H}(\Lambda_{n-Z}^{n-1})^{-1}\mathbf{Y}_{n-Z}^{n-1}) \\ &\quad - tr(\mathbf{Y}_{n-Z}^{nH}(\Lambda_{n-Z}^n)^{-1}\mathbf{Y}_{n-Z}^n)\}. \end{aligned} \quad (11)$$

Note since (11) has no meaning when $Z = 1$, the minimum possible value of Z is 2.

Define $s_n = \underline{b}_{n-Z+1}^{n-1}$ as the state at time n , accordingly $\text{ST}_Z[\underline{b}_{n-Z+1}^{n-1}, bn] = \underline{b}_{n-Z+2}^{n-1}$ is the state transition matrix, $\text{SG}_Z[\underline{b}_{n-Z+1}^{n-1}, bn] = \underline{b}_{n-Z+1}^n$ is the code symbol generation matrix, and the state space $\mathcal{S}$ has M^{Z-1} states. Thus the branch metric is

$$\begin{aligned} \mu_n(\tilde{\underline{b}}_{n-Z+1}^n) &= p(\mathbf{R}_n | \underline{b}_{n-Z+1}^n = \tilde{\underline{b}}_{n-Z+1}^n, \mathbf{R}_{n-Z}^{n-1}) \\ &= \left(\frac{\det \tilde{\Lambda}_{n-Z}^{n-1}}{\pi^{N_t} \det \tilde{\Lambda}_{n-Z}^n} \right)^{N_r} \cdot \exp\{tr(\mathbf{Y}_{n-Z}^{n-1H}(\tilde{\Lambda}_{n-Z}^{n-1})^{-1}\mathbf{Y}_{n-Z}^{n-1}) \\ &\quad - tr(\mathbf{Y}_{n-Z}^{nH}(\tilde{\Lambda}_{n-Z}^n)^{-1}\mathbf{Y}_{n-Z}^n)\} \end{aligned} \quad (12)$$

Afterwards the APP $P_{n,b}^O$ can be calculated as

$$P_{n,b}^O = \frac{p\{b_n = b\}}{\Omega_n} \sum_{s \in \mathcal{S}} \alpha_n(s) \mu_n(\text{SG}_Z[s, b]) \beta_{n+1}(\text{ST}_Z[s, b]) \quad (13)$$

where $\Omega_n = p(\mathbf{R}_n | \mathbf{R}_0^{n-1})$, $\alpha_n(s) = p(s_n = s | \mathbf{R}_0^{n-1})$, and $\beta_{n+1}(s') = \frac{p(\mathbf{R}_{n+1}^{N+1} | s_{n+1} = s', \mathbf{R}_0^n)}{p(\mathbf{R}_{n+1}^{N+1} | \mathbf{R}_0^n)}$. Using the BCJR algorithm, $\alpha_n(s)$ can be recursively computed by

$$\begin{aligned} \alpha_{n+1}(s') &= \frac{1}{\Omega_n} \sum_{s \in \mathcal{S}} \sum_{b \in \mathcal{M}} p(b_n = b) \alpha_n(s) \mu_n(\text{SG}_Z[s, b]) \\ &\quad \cdot p(s_{n+1} = s' | s_n = s, b_n = b), \end{aligned} \quad (14)$$

and $\beta_n(s)$ can be recursively computed by

$$\beta_n(s) = \frac{1}{\Omega_n} \sum_{b \in \mathcal{M}} p(b_n = b) \mu_n(\text{SG}_Z[s, b]) \beta_{n+1}(\text{ST}_Z[s, b]). \quad (15)$$

The recursion of $\alpha_n(s)$ is initialized by $\alpha_0(s) = 1$ when $s = 0$ and $\alpha_0(s) = 0$ when $s \neq 0$, and the recursion of $\beta_n(s)$ is initialized by $\beta_{N+1}(s) = \frac{1}{M^{Z-1}}$

1) *Fast Calculation Algorithm*: In (12), the computational complexity is mainly depended on the calculation of $(\Lambda_{n-Z}^{n-1})^{-1}$ and $(\Lambda_{n-Z}^n)^{-1}$. Note Λ_{n-Z}^{n-1} is actually a submatrix of Λ_{n-Z}^n , fast calculation algorithm (FCA) [11] can be applied.

In FCA, $\mathbf{A}_l$ is assumed to be an $l \times l$ reversible matrix and partitioned into four submatrices as

$$\begin{aligned} \mathbf{A}_l &= \left[\begin{array}{ccc|c} a_{11} & \cdots & a_{1(l-1)} & a_{1l} \\ \vdots & \ddots & \cdot & \vdots \\ a_{(l-1)1} & \cdot & a_{(l-1)(l-1)} & a_{(l-1)l} \\ \hline a_{l1} & \cdots & a_{ll(l-1)} & a_{ll} \end{array} \right] \\ &= \left[\begin{array}{cc} \mathbf{A}_{l-1} & \mathbf{A}_{1l} \\ \mathbf{A}_{l1} & a_{ll} \end{array} \right] \end{aligned} \quad (16)$$

Assuming $\mathbf{B}_l = \mathbf{A}_l^{-1}$ as the inverse matrix of $\mathbf{A}_l$, accordingly $\mathbf{B}_l$ is partitioned as

$$\mathbf{B}_l = \left[\begin{array}{cc} \mathbf{B}_{(l-1)(l-1)} & \mathbf{B}_{1l} \\ \mathbf{B}_{l1} & b_{ll} \end{array} \right] \quad (17)$$

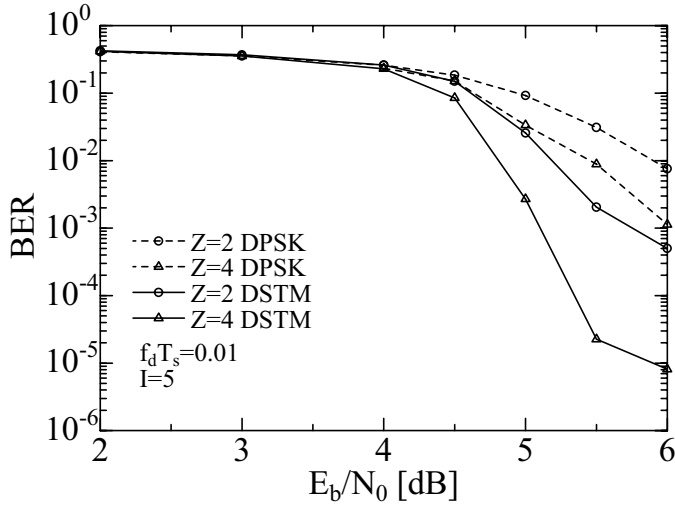


Fig. 3. BER performances of iterative detection of coded DPSK versus coded DSTM.

If $\mathbf{A}_l = \mathbf{A}_l^H$, the submatrices of $\mathbf{B}_l$ can be calculated as

$$\begin{aligned} b_{ll} &= (a_{ll} - \mathbf{A}_{l1} \mathbf{A}_{l-1}^{-1} \mathbf{A}_{1l})^{-1} \\ \mathbf{B}_{1l} &= -\mathbf{A}_{l-1}^{-1} \mathbf{A}_{1l} b_{ll} = \mathbf{B}_{l1}^H \\ \mathbf{B}_{(l-1)(l-1)} &= \mathbf{A}_{l-1}^{-1} - \mathbf{B}_{1l} \mathbf{A}_{l1} \mathbf{A}_{l-1}^{-1} \end{aligned} \quad (18)$$

Applying (14), $(\Lambda_{n-Z}^n)^{-1}$ can easily be calculated from $(\Lambda_{n-Z}^{n-1})^{-1}$. Therefore, the computational complexity of (12) can be reduced.

IV. SIMULATION RESULTS

In our simulations, a time-varying flat Rayleigh fading channel model is used. The numbers of transmit antennas N_t and receive antennas N_r in DSTM are set to 2 and 1 respectively. The transmit antennas are assumed to be independent with each other. A rate 1/2 convolutional code with generator $(135, 163)_8$ is used as outer code. Thus $n_c = 2$ and quadrature phase-shift keying (QPSK) is used in DSTM. An S-random [12] interleaver of size 1000 is used as the symbol interleaver.

In Fig. 3, the bit error rate (BER) performances of the iterative receiver of coded DPSK are compared with those of coded DSTM in fast Rayleigh fading channels. Since DPSK can be seen as a special case of DSTM when $N_t = 1$, to fit for the fast fading channels, the detection method proposed in this paper is also used for DPSK in place of the method in [3]. It is observed that in both cases of $Z = 2$ and $Z = 4$, DSTM has better BER performances than DPSK. Thus the effectiveness of transmit diversity is improved. We can also observe that, the performance improvement when $Z = 4$ is much bigger than that when $Z = 2$. That means with transmit diversity, the effects of increase the observation interval can be enhanced.

Figs. 4 and 5 show the BER performances of the receiver with different number of iteration I in a fast fading channel with $f_d T_s = 0.01$. Z is set to 2 in Fig. 4, and 3 in Fig. 5 respectively. It seems that these figures are very similar in

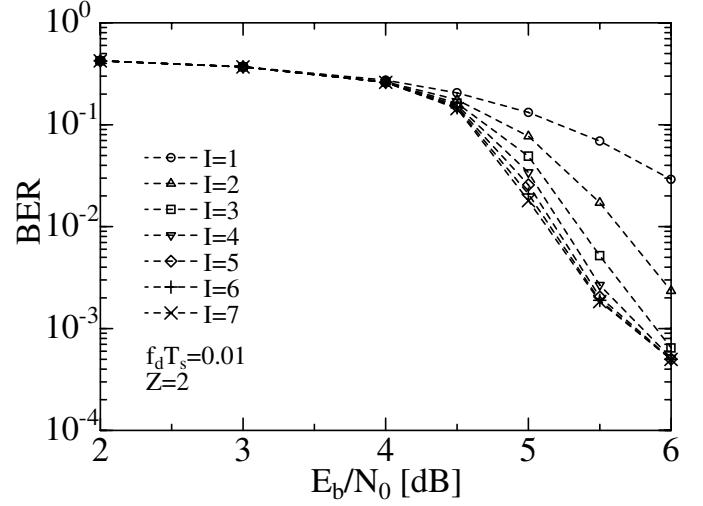


Fig. 4. BER performances of iterative detection of coded DSTM systems with $Z = 2$ and different number of iteration.

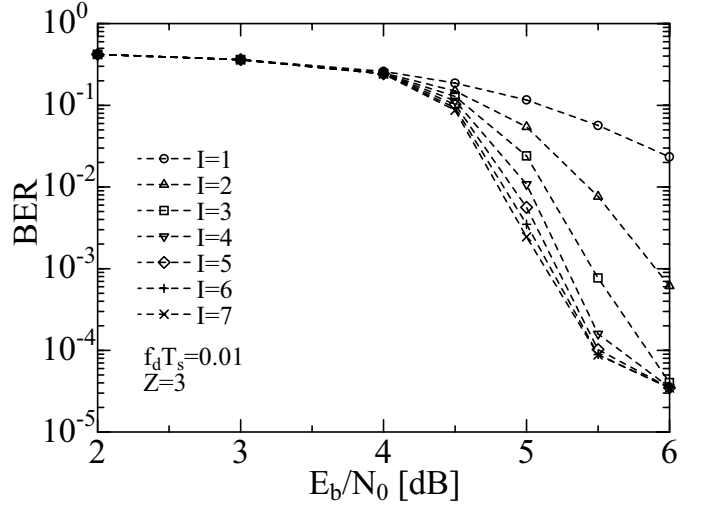


Fig. 5. BER performances of iterative detection of coded DSTM systems with $Z = 3$ and different number of iteration.

shape. That means with different Z , changing I has similar influences to the BER performances. It is observed from these figures that, at relatively low signal-to-noise ratio (SNR) ($E_b/N_0 \leq 4\text{dB}$), increasing the number of iteration can hardly lead to performance enhancement. At relatively high SNR, significant performance gain can be got by the first few iterations, although when I is big, the gain becomes marginal.

Figs. 6 and 7 show the bit error rate (BER) performances of the receiver with different Z in a fast fading channel with $f_d T_s = 0.01$. We set $I = 1$ in Fig. 6, and $I = 5$ in Fig. 7. In Fig. 6, it is shown that only very little performance enhancements is obtained by increasing Z . That means in this system, the effects of extending the observation interval on the performance improvements are extremely limited with-

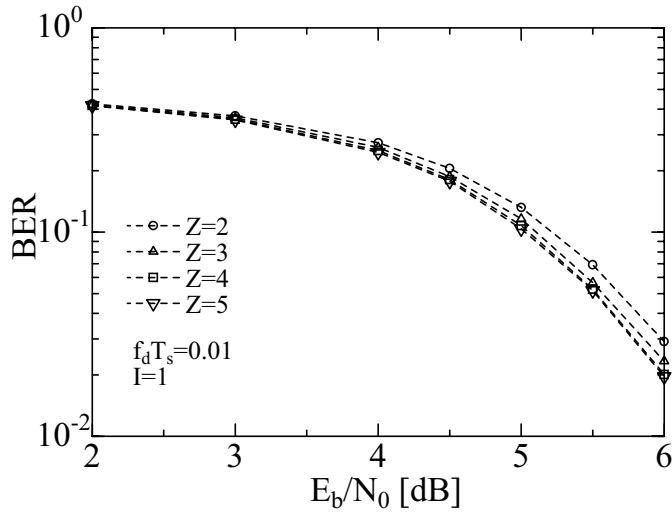


Fig. 6. BER performances of iterative detection of coded DSTM systems with $I = 1$ and different number of estimated previous samples.

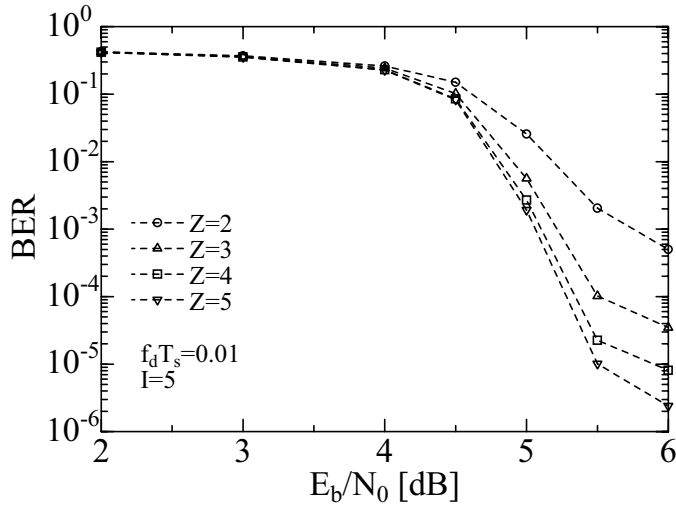


Fig. 7. BER performances of iterative detection of coded DSTM systems with $I = 5$ and different number of estimated previous samples.

out iteration. On the other hand, in Fig. 7, we can observe considerable performance enhancements by increasing Z at relatively high SNR. That means with iteration, it is effectively to improve the BER performance by extending the observation interval. Or in other words, the effects of extending the observation interval are enhanced by increasing I .

The BER performances of the receiver with different $f_D T_s$ at $E_b/N_0 = 6\text{dB}$ and $I = 5$ is given in Fig. 8. It is observed from this figure that, at very low $f_D T_s$ ($f_D T_s \leq 0.003$), performance with higher $f_D T_s$ is better and the best performance can be got around $f_D T_s = 0.003$. That is because, effects of time diversity can be got by using the interleaver. With the increase of $f_D T_s$, the autocorrelation of the channel becomes smaller and hence the effects of time diversity become bigger. Conversely, at relatively high $f_D T_s$,

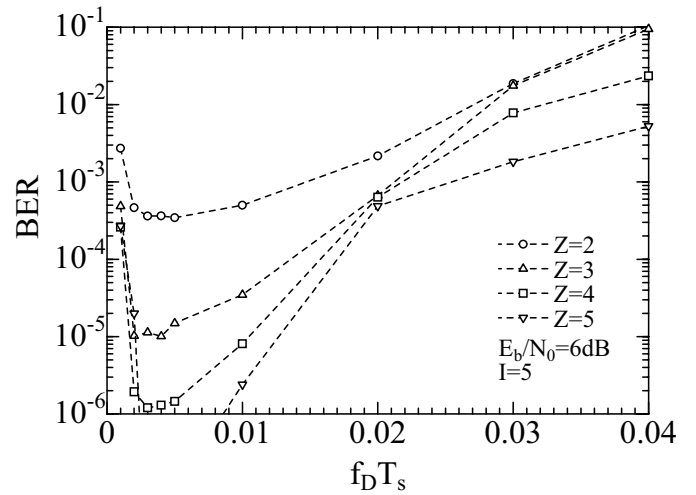


Fig. 8. BER performances of iterative detection of coded DSTM systems with different $f_D T_s$.

performances become worse when $f_D T_s$ becomes higher. That is because although the effects of time diversity are enhanced and lead to some performance improvements, the performance degradations brought by the faster channel variation are bigger and become dominated when $f_D T_s$ is big. We can also observe that, increasing Z always leads to better performances with any value of $f_D T_s$. That means application of the fading autocorrelation is effective to combat the fading channels.

V. CONCLUSION

By considering the coded DSTM as a serial concatenation of DSTM and a convolutional code, a noncoherent iterative receiver has been proposed for it. The key of the receiver is the soft-output decoder of DSTM, which is used as the inner decoder in the iterative process. Comparing with some other works in the same topic, the main feature of this paper is its good performance in fast fading channels. It is because that, channel autocorrelations are considered in MSDD to mitigate the effects of channel variation while computing the branch metrics in the DSTM decoder.

With computer simulations, the effects of transmit diversity have been confirmed firstly. Then, the effects of different iterative times and observation interval lengths have been studied in fast Rayleigh fading channels. It has been demonstrated that, extending observation interval lengths is very effective to improve the BER performances, especially when iterative times are large. Finally the effects of different maximized Doppler frequencies on performance have also been discussed. It has been shown that, since the channel autocorrelations are applied, longer observation interval can always lead to better BER performances.

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