EXIT 차트분석을 이용한 SC-MMSE기반 반복수신기의 성능 증대
Improving Iterative Detection and Decoding Based on SC-MMSE with EXIT Analysis

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Abstract

This paper aims to improve the design of iterative detection and decoding (IDD) based on the soft interference cancellation with minimum mean squared error (SC-MMSE) detector, which shows low performance compared to the maximum *a posteriori* (MAP) detector. By means of extrinsic information transfer (EXIT) chart analysis, such low performance may be attributed to that the "pure" (original) turbo principle is not ***always*** best for IDD. Thus, we propose a new IDD architecture based on the SC-MMSE detector which uses new ***a priori*** information. Simulation results show that the performance of the proposed IDD is very close to that of IDD based on the MAP detector.

I. Introduction

The optimum receiver to achieve the capacity of multiple-input multiple-output (MIMO) fast fading channels is joint detection and decoding which combines detector and channel code within an overall code frame (e.g., [1]). To approximate the joint detection and decoding with tractable complexity in an iterative fashion, the iterative detection and decoding (IDD) receiver has been paid great attention to in the past decade. The optimum detector for IDD is the maximum *a posteriori* (MAP) detector. As this detector has a prohibitive computational complexity, several suboptimal detectors have been proposed.

The list sphere detector (LSD) [2] limits a search space to a set of symbol vectors (so-called candidate list) for which the transmitted symbol vector lies within a sphere centered on the received symbol vector. For this reason, LSD can significantly lower complexity of the MAP detector, showing nearly identical performance to MAP provided that sphere radius and list size are sufficiently large. However, the complexity of LSD depends on the state of fading channels and noise, and exponential in M_c (the number of bits per symbol). To circumvent this problem, the iterative tree search (ITS) detector based on the breadth-first tree search algorithm, also called the *M*-algorithm, was proposed in [3]. With the aid of a multi-level bit mapping, the complexity of ITS becomes independent of the channel state and linear in M_c, respectively. The ITS detector can also approach the performance of MAP for a sufficiently large size of selected paths. Another suboptimal detector is SC-MMSE which uses soft interference cancellation (SC) followed by MMSE filtering to further suppress interference [4]-[7]. This simple MIMO detector has in general lower computational complexity than other suboptimal detectors. The performance of the SC-MMSE detector is, however, known to show a nontrivial loss compared with the MAP detector especially when many antennas and large symbol constellations are used.

In this paper, we reveal a reason for such a performance limit of SC-MMSE. The underlying principle of IDD is the celebrated turbo principle [8]. Through the principle, the detector and decoder exchange extrinsic information with each other, which means that the independence between detector and decoder is highly desirable. The use of this "pure extrinsic" information as well as a sufficiently large interleaver is critical to keep the independency over many iterations [10]. However, this paper shows the turbo principle is not optimum at least for IDD with the SC-MMSE detector, using the extrinsic information transfer (EXIT) chart analysis [11],[12]. By imposing some dependency between detector and decoder (i.e., some "impurity" on pure extrinsic information), we can significantly improve the performance of IDD with SC-MMSE. To do so, we propose a new IDD architecture based on the SC-MMSE detector. Although our IDD scheme employs the simple SC-MMSE, it is shown to have almost the same performance as IDD with the MAP detector achieving near-capacity, like suboptimal MAP detectors with much higher computational complexities (e.g., LSD [2] and ITS [3]).

Terminologies: Throughout this paper, L_{A_1}, L_{E_1} and L_{P_1} denote the *a priori*, extrinsic, and a posteriori LLR of the detector, respectively. Similarly, L_{A_2}, L_{E_2} and L_{P_2} denote those of the decoder. The subscript 1 of the detector is sometimes omitted if it does not lead to confusion.

II. Soft-Input Soft-Output MIMO Detection

We consider a space-time bit-interleaved coded modulation (ST-BICM) architecture with N_t transmit and N_r receive antennas [2],[5]. The information source is encoded by a rate-R_c turbo code, bit-wise interleaved. The interleaved bits are grouped into $N_c\times 1$ vectors, $\mathbf{x}_j=[x_{j,1},\cdots,\mathbf{x}_{j,M_c}]^T$, $j=1,\ldots,N_t$, and mapped onto $N_t\times 1$ vectors s whose entries are symbols chosen from a complex constellation S with $|S|=2^{M_c}$. The jth element of the transmitted symbol vector s is obtained by $s_j=\text{map}(\mathbf{x}_j)$ where map(•) is a mapping function like the gray mapping. The $N_r\times 1$ received vector signal in the MIMO system is then given by

$$\mathrm{y} = \mathrm{Hs} + \mathrm{n} \tag{1}$$

where the $N_r\times N_t$ channel matrix $\mathbf{H}$ with $\mathbb{E}[\mathbf{HH}^H]=1/N_t\mathbf{I}$ is supposed to be changing sufficiently rapidly that the channel can be viewed as ergodic, and known to the receiver, $\boldsymbol{s}=[s_1,s_2,\cdots,s_{N_t}]^T$ is the transmitted symbol vector with $\mathbb{E}[\boldsymbol{ss}^H]=E_s\mathbf{I}$, and $\mathbf{n}$ is a zero-mean circularly symmetric Gaussian noise with $\mathbb{E}[\mathbf{nn}^H]=2\sigma^2\mathbf{I}$, independent of $\mathbf{s}$. (Here, the superscript denotes the Hermitian transposition.) Hence, $\gamma=E_s/N_0=E_s/2\sigma^2$ becomes the average signal to noise ratio (SNR) at each receive antenna.

Although we focus on the MIMO system in (1) and do not consider any space-time code, the ideas in this paper can be readily applied to the iterative (turbo) equalizer and space-time codes as well, respectively.

In this paper, we will propose a new architecture for IDD based on the SC-MMSE detector and demonstrate its performance is very close to that of MAP. To this end, we briefly describe the MAP and SC-MMSE detectors in the sequel.

1) *MAP Detector*: Using a priori information of $\mathbf{x}=\{x_{j,k}; j=1,\ldots,N_t, k=1,\ldots,M_c\}$, from the soft-input soft-output decoder, the MAP detector computes the *a posteriori* log-likelihood ratio (LLR)

$$L_P(x_{j,k}|\mathrm{y}) = \ln\frac{\Pr(x_{j,k}=+1|y)}{\Pr(x_{j,k}=-1|y)}. \tag{2}$$

Using Bayes' rule and the independency of $x_{j,k}$'s due to ST-BICM, we can write the *a posteriori* LLR as [2]

$$L_P(x_{j,k}|\mathrm{y}) = L_A(x_{j,k}) +$$

$$\ln \frac{\sum_{\mathbf{x}\in\mathbb{X}_{j,k}^{+1}} p(\mathbf{y}|\mathbf{x})\exp\left(\frac{1}{2}\mathbf{x}_{[j,k]}^T\mathbf{L}_A\right)}{\sum_{\mathbf{x}\in\mathbb{X}_{j,k}^{-1}} p(\mathbf{y}|\mathbf{x})\exp\left(\frac{1}{2}\mathbf{x}_{[j,k]}^T\mathbf{L}_A\right)} \quad (3)$$

where $L_A(x_{j,k}) = \ln\frac{\Pr(x_{j,k}=+1)}{\Pr(x_{j,k}=-1)}$ denotes the *a priori* LLR of the code bit $x_{j,k}$, $\mathbb{X}_{j,k}^b$ is the set of $2^{N_tM_c-1}$ bit vectors of $\mathbf{x}$ with $x_{j,k}=b$, $b\in\{+1,-1\}$, $\mathbf{x}_{[j,k]}$ is the $2^{M_c}\times 1$ vector $\mathbf{x}$ with $x_{j,k}=0$, and $L_A=[L_A(x_{1,1}),\ldots,L_A(x_{N_t,M_c})]^T$ is the vector of *a priori* LLRs. The second term on the right-hand side denotes the extrinsic LLR of the detector.

To avoid the exponential and logarithm functions in (3) and reduce the computational complexity, we often use the max-log approximation [13]. Then the simplified form of the extrinsic LLR is given by [2]

$$\begin{aligned} L_E(x_{j,k}|\mathbf{y}) \simeq\ & \frac{1}{2}\max_{\mathbf{x}\in\mathbb{X}_{j,k}^{+1}}\left\{-\frac{1}{\sigma^2}\|\mathbf{y}-\mathbf{H}\mathbf{s}\|^2+\mathbf{x}_{[j,k]}^T\mathbf{L}_A\right\} \\ & -\frac{1}{2}\max_{\mathbf{x}\in\mathbb{X}_{j,k}^{-1}}\left\{-\frac{1}{\sigma^2}\|\mathbf{y}-\mathbf{H}\mathbf{s}\|^2+\mathbf{x}_{[j,k]}^T\mathbf{L}_A\right\}. \end{aligned} \quad (4)$$

In this paper, we will refer to the detectors using (3) and (4) as the ***exact-MAP*** and the ***max-log-MAP*** detector, respectively.

2) *List Sphere Detector*: The sphere detector (SD), also called the sphere decoder, finds an ML estimate by limiting the search space. However, the ML estimate is not necessarily the MAP estimate in (4). The LSD scheme in [2] modifies SD to yield a list $\mathcal{L}$ of N_{cand} points that includes the MAP estimate in (4). The resulting LLR is an approximation of (4) as follows

$$\begin{aligned} L_E(x_{j,k}|\mathbf{y}) \simeq\ & \frac{1}{2}\max_{\mathbf{x}\in\mathcal{L}\cap\mathbb{X}_{j,k}^{+1}}\left\{-\frac{1}{\sigma^2}\|\mathbf{y}-\mathbf{H}\mathbf{s}\|^2+\mathbf{x}_{[j,k]}^T\mathbf{L}_A\right\} \\ & -\frac{1}{2}\max_{\mathbf{x}\in\mathcal{L}\cap\mathbb{X}_{j,k}^{-1}}\left\{-\frac{1}{\sigma^2}\|\mathbf{y}-\mathbf{H}\mathbf{s}\|^2+\mathbf{x}_{[j,k]}^T\mathbf{L}_A\right\}. \end{aligned} \quad (5)$$

As seen from (5), LSD can significantly lower complexity of the MAP detector since the list size, N_{cand}, is far less than the entire search space, $2^{M\cdot M_c}$. It also shows nearly identical performance to MAP provided that sphere radius and list size N_{cand} are sufficiently large. However, the complexity of LSD depends on the state of fading channels and noise, and is exponential in M_c.

3) *Iterative Tree Search Detector*: Like LSD finding most likely candidates through SD, the ITS detector [3] uses a sequential tree searching algorithm known as the *M*-algorithm to search for the best paths through the tree structure generated by QR decomposition of $\mathbf{H}^H\mathbf{H}$. The *M*-algorithm chooses the best *M* paths (outgoing nodes) at each branch of the tree of depth N_t and deletes $M(2^{M_c}-1)$ paths. The ITS detector can become more computationally efficient with the aid of multilevel bit mapping such that its complexity is almost linear in M_c. The performance of ITS is near-optimum like LSD if the list size *M* is sufficiently large and the MIMO channel is not highly correlated.

4) *SC-MMSE Detector*: Given the *a priori* information of the code bits, $L_A(x_{j,k})$, we first compute the estimates of the mean and variance of the transmitted symbol, s_j, as follows

$$\bar{s}_j \triangleq E[s_j] = \sum_{s_j\in S} s_j P_A(s_j) \quad (6)$$

$$\text{var}(s_j) \triangleq \sum_{s_j\in S} |s_j|^2 P_A(s_j) - |\bar{s}_j|^2 \quad (7)$$

where $P_A(s_j) = \prod_{k=1,\cdots,M_c} P_A(x_{j,k})$ is the symbol *a priori* probability of s_j, and

$$P_A(x_{j,k}=\pm 1) = \frac{e^{\pm L_A(x_{j,k})}}{1+e^{\pm L_A(x_{j,k})}} \quad (8)$$

is the bit *a priori* probability of $x_{j,k}$.

Let $\bar{\mathbf{s}}_j$ denote the $N_t\times 1$ vector given by $\bar{\mathbf{s}}_j=[\bar{s}_1,\ldots,\bar{s}_{j-1},0,\bar{s}_{j+1},\ldots,\bar{s}_{N_t}]^T$. For each symbol s_j, after a soft interference cancellation on the received vector $\mathbf{y}$ using the estimates of interfering symbols, $\bar{\mathbf{s}}_j$, we have

$$\mathbf{y}_j = \mathbf{y} - \mathbf{H}\bar{\mathbf{s}}_j. \quad (9)$$

To further suppress the residual interference and noise, we perform the MMSE filtering of $\mathbf{y}_j$ yielding $s_j = \mathbf{w}_j^H \mathbf{y}_j$ where $\mathbf{w}_j$ can be written as [4]

$$\mathbf{w}_j = [\mathbf{H}\mathbf{R}_j\mathbf{H}^H + \gamma^{-1}\mathbf{I}]^{-1}\mathbf{h}_j \tag{10}$$

where $\mathbf{R}_j = E_s^{-1} \cdot \mathrm{diag}[\mathrm{var}(s_1)\cdots,\mathrm{var}(s_{j-1}),\ E_s,\ \mathrm{var}(s_{j+1}),\cdots,\ \mathrm{var}(s_{N_t})]$ is the covariance matrix of $\mathbf{s}_j$, and $\mathbf{h}_j$ is the jth column vector of $\mathbf{H}$.

In order to obtain the extrinsic LLR of $x_{j,k}$ based on SC-MMSE, we need first to compute the extrinsic probabilities of $\hat{s}_j$ using the Gaussian approximation [14]. The extrinsic probability of $\hat{s}_j$ conditioned on the transmitted symbol s_j is then given by

$$p(\hat{s}_j|s_j) \simeq \frac{1}{v_j^2\pi}\exp\left(-\frac{|\hat{s}_j - \mu_j s_j|^2}{v_j^2}\right) \tag{11}$$

where $\mu_j = \mathbf{w}_j^H \mathbf{h}_j$ and $v_j^2 = \mu_j E_s(1-E_s)$ are respectively the mean and variance of $\hat{s}_j$ due to the Gaussian approximation. Finally, we can approximate the extrinsic LLR of $x_{j,k}$

$$L_E(x_{j,k}|\mathbf{y}) \simeq \ln\frac{\sum_{s_j\in\mathbb{S}_j^{+1}} p(\hat{s}_j|s_j) \prod_{i=1,\ldots,M_c,\, i\neq k} P_A(x_{j,k})}{\sum_{s_j\in\mathbb{S}_j^{-1}} p(\hat{s}_j|s_j) \prod_{i=1,\ldots,M_c,\, i\neq k} P_A(x_{j,k})} \tag{12}$$

where $\mathbb{S}_j^b$ is the set of 2^{M_c-1} vectors of s_j with $x_{j,k} = b, b\in\{+1,-1\}$.

III. EXIT Chart

The EXIT chart [11] is a versatile tool to evaluate the convergence behavior of IDD or to design IDD as well as iterative decoders [12]. The essence of the EXIT chart is that we can separately obtain the EXIT charts of detector and decoder, assuming the independence between the detector and decoder (i.e., the *a priori* information of each component is statistically independent of its extrinsic information over many iterations). The behavior of IDD can then be predicted by only looking at the input/output relation of the EXIT charts of detector and decoder.

Throughout this paper, the turbo code has rate R_c=1/2, memory 2, and the number of iterations of 8 with feed-forward and feedback polynomials of $(5,7)_8$. The pseudorandom ST-interleaver is used. The channel matrix $\mathbf{H}$ is from the fast fading Rayleigh MIMO channel model such that the realizations of $\mathbf{H}$ are different at each symbol interval. The length of information bits is 2^{12} = 4096 for QPSK and 2^{13} = 8192 for 16QAM signaling with Gray mapping. The number of iterations, N_I, of IDD is allowed up to 10.

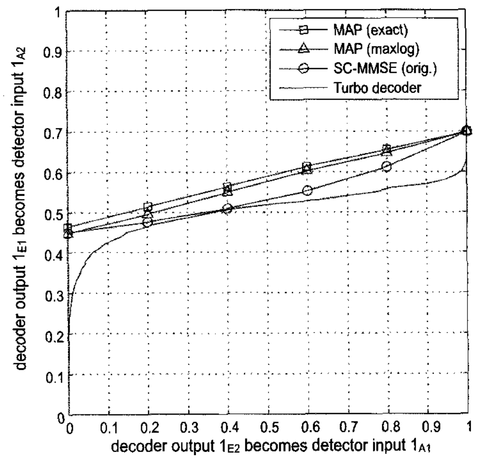

Fig. 1. EXIT charts of different detectors and turbo decoder

Fig. 1 shows the EXIT charts of the exact MAP, max-log MAP, and original SC-MMSE detectors as well as the turbo decoder. On the ordinate, the mutual information (MI) of the extrinsic output, I_{E_1}, of the detector becomes the MI of the a priori input, I_{A_2}, of the decoder. On the abscissa, the MI of the extrinsic output, I_{E_2}, of the decoder becomes the MI of the a priori input, I_{A_1}, of the detector. This figure clearly shows why the original SC-MMSE detector suffers from a significant performance degradation over the MAP detector. Note that there is a bottleneck around I_{E_2} = 0.3, where the tunnel between the EXIT charts of SC-MMSE and turbo decoder is closed.

We can expect from the observation above, that IDD with SC-MMSE would get better performance if the bottleneck of the tunnel is open. In the following section, we will present a new design of IDD with SC-MMSE to improve the performance and EXIT analysis of the new IDD scheme will be given.

IV. A New Architecture for IDD with SC-MMSE

The original SC-MMSE detector [4], [5] for IDD follows the turbo principle that postulates the inner MAP detector and the outer MAP decoder. However, this suboptimal detector does not *explicitly* originate from the MAP rule, in contrast to other suboptimal MAP detectors like the LSD and ITS detectors. The SC-MMSE detector is rather based on the multiuser detection [4]. From the viewpoint of the soft interference cancellation in (9), the higher the reliability of decision feedback, the larger the reduction in interference becomes. For instance, it may be better to use L_{P_2} as the *a priori* information of the SC-MMSE detector, L_{A_1}, instead of L_{E_2}, since $\mathbb{E}|L_{P_2}| \geq \mathbb{E}|L_{E_2}|$ in general. It was found in [7] that using L_{P_2} gives a gain over using L_{E_2}, which will be further discussed in Section V.

On the other hand, using L_{P_2} as the *a priori* information of the detector clearly breaks the independence between the extrinsic information of the detector and decoder imposed by the turbo principle. Furthermore, it violates the MAP rule of (3) or (4), which incurs a serious performance loss. To our best knowledge, however, it has not been rigorously studied that the SC-MMSE detector in the form of (12) is also the case. Therefore, we need to closely investigate the effect of different forms of the *a priori* information, more importantly, whether or not the turbo principle is really optimal for IDD with SC-MMSE. (It should be pointed out that the turbo principle does not always assume the MAP rule for both inner and outer components, as can be seen from applications in [9].) The more detailed description will be given in Section IV.

For a new architecture for IDD with SC-MMSE, we first define the new *a priori* LLR of the SC-MMSE detector as

$$L_{A_1} = \prod\left(L_{E_2} + (1-\beta)L_{A_2}\right) = L_{A_{1,O}} + L_{A_{1,I}} \qquad (13)$$

where $\prod(\bullet)$ is a bit-wise interleaving function, and β is a weighting factor with 0 † β † 1. Note that (13) becomes the *a priori* information of the original SC-MMSE detector [4], [5] if $\beta = 1$. In the opposite case of $\beta = 0$, it is similar to that in [7]. Here, is the original a priori LLR coming from L_{E_2}, and is $L_{A_{1,I}}$ an increment from $(1-\beta)L_{A_2}$. We will see in the next section that the weighting factor β is an important design parameter of IDD with SC-MMSE.

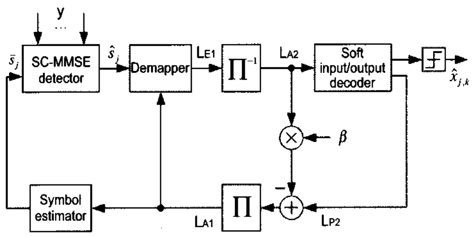

Fig. 2. The new architecture of IDD based on SC–MMSE.

In order to accept the *a priori* information of (13), we illustrate a new receiver architecture for IDD based on the SC-MMSE detector in Fig. 2. The transmitter uses the ST-BICM scheme as mentioned in Section II. The symbol estimator serves to compute the estimates of the mean and variance of the transmitted symbol, s_j, as shown in (6) and (7). The demapper computes the bit extrinsic LLR, L_{E_1}, $x_{j,k}$ of by using (11) and (12). Note that the demapper in [7] is fed by the extrinsic LLR, L_{E_2}. In contrast, we may use the same *a priori* LLR, L_{A_1}, for both the symbol estimator and the demapper. Since using (13) already breaks the pure turbo principle, we need not to insist on the principle. Moreover, there is empirically no difference between the performances of the two choices.

In what follows, we would like to analyze the proposed IDD scheme with the EXIT chart. The idea of the EXIT chart is to predict the behavior of IDD by only looking at the input/output relation of the EXIT charts of detector and decoder. However, the use of the *a priori* LLR of (13) unfortunately breaks the independency, and hence the detector and decoder become now mutually dependent in the new architecture of IDD, which makes our analysis too complicate. Note that, nevertheless, the detector and decoder are independent at least at the 1st iteration. Except for this case, we have to resort to an empirical method.

Apart from the exceptional case, we make use of the following empirical data to obtain an EXIT-like chart (this terminology is intended to stress that the obtained chart is not the EXIT chart as the information exchanged between detector and decoder is no longer pure extrinsic to each other in the new IDD scheme). In this paper, the new chart will be referred to henceforth as the mutual information transfer (MIT) chart in a more general terminology.

As mentioned earlier, we cannot separately obtain the MIT charts of the detector and decoder due to the dependence between the two components. Thus, our analysis is restricted to outline the MIT chart only via trajectories of mutual information (MI) of the detector and decoder obtained by simulation at each iteration. Let $I_{E,i,j}$ denote the MI of outputs of detector or decoder at the ith iteration during the jth data stream transmission. The average trajectory of $I_{E,i,j}$ over N_J data streams is written as

$$\overline{I_{E,j}} = \frac{1}{N_J}\sum_{j=1}^{N_J} I_{E,i,j}. \tag{14}$$

Fig. 3 outlines the MIT charts of the SC-MMSE detectors with different weighting factors by the average trajectory of (14), in which $\beta = 1$ corresponds to the original SC-MMSE [4], [5], [7], and $E_s / N_0 = 9.0$ dB. This figure shows that using (13) as the *a priori* information to SC-MMSE makes the tunnel between the corresponding MIT charts open, yielding a better performance than the original SC-MMSE. The observation of Fig. 1 and 3 gives us the answer that the turbo principle is not best at least for IDD based on SC-MMSE. Moreover, we can see that the output MI, L_{E_1}, of SC-MMSE at the 2nd iteration is a crucial factor dominating the entire performance. Fortunately, as the MI at the 2nd

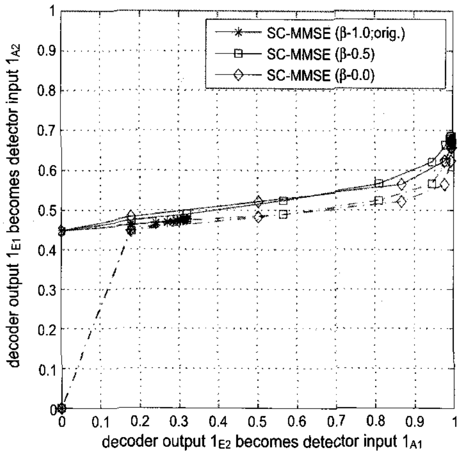

Fig. 3 MIT charts (average trajectories) of the SC-MMSE detectors for different weighting factors; 4x4 MIMO, 16QAM; the dashed lines denote the MIT charts of the turbo decoder.

iteration belongs to the aforementioned exceptional case, a numerical method to obtain it can be found in [15].

V. Simulation Results

In order to more accurately assess the performance of IDD, we define the asymptotic performance measure as

$$\in \triangleq \lim_{i\to\infty} P_{e,i} \tag{15}$$

where $P_{e,i}$ is the bit error rate (BER) of IDD at the ith iteration. A reason to introduce the measure is that we are intended to differentiate the performance with convergence rate. That is, it is possible that one IDD scheme can converge to $\in$ faster than the other, but has the same $\in$. However, we limited here N_I up to 10 as no improvement empirically took place beyond this value in most cases.

Fig. 4 compares the BER performances of IDD schemes based on the exact MAP, max-log MAP, and SC-MMSE detectors with different β's for 4×4 QPSK and 16QAM. We can see that optimizing IDD with SC-MMSE significantly reduces the performance gap between IDD with MAP and IDD with the original SC-MMSE roughly by one decibel. The

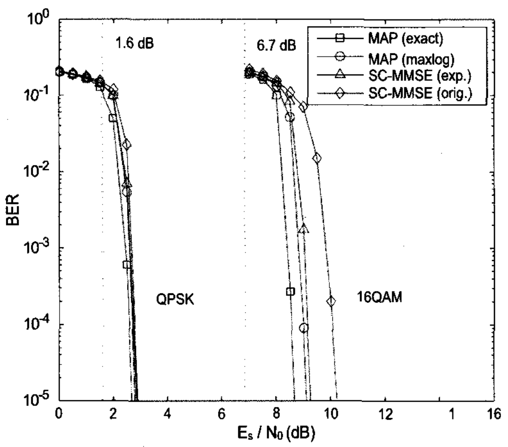

Fig. 4 BER curves of IDD schemes based on various detectors with the turbo code; the dotted lines mean capacity limits of QPSK and 16QAM at half rate encoding.

proposed IDD scheme with $\beta_i = (0.85)^{i-1}$ is only 0.16 dB from IDD with the max-log MAP for 4×4 16QAM, aside from the exact MAP for practical reasons as usual [2],[3].

When a convolutional code is employed, it should be further pointed out that the SC-MMSE detector with $\beta = 0$ similar to [7] shows faster convergence rate than the original SC-MMSE, but the two have almost the same $\in$. Fig. 5 shows the convergence rates of the two cases with a half rate convolutional code, in which no performance

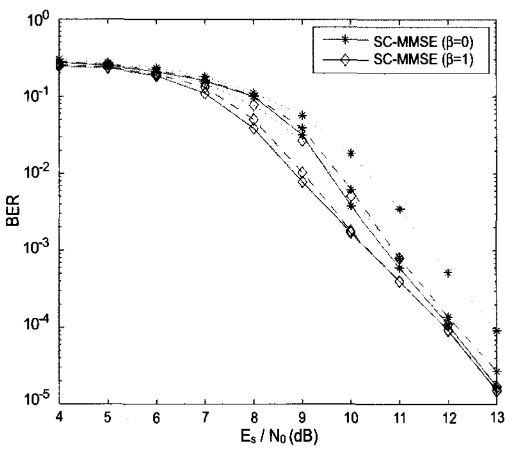

Fig. 5 Convergence rates of IDD schemes based on SC-MMSE with half rate convolutional code of (5,7); the dotted, dashed and solid lines indicate N_I = 3,5,7, respectively.

improvement occurred beyond $N_I = 7$. A reason for the same $\in$ is that the output MI of detector at the tail of EXIT now becomes a more dominant factor than that at the head, as a convolutional code has a smoothly increasing tail compared to a turbo code. It is then seen from Fig. 3 that the case of $\beta = 0$ with relatively small MI at the tail loses its advantage over the original case.

VI. Conclusion

We have shown that the turbo principle is not always best at least for IDD based on the SC-MMSE detector. Our IDD scheme employs the previous output of SC-MMSE as a part of the a priori information of SC-MMSE itself, which is the traditional way of the soft or successive interference cancellation. An EXIT-like chart has shown that benefits of such "impure" ***a priori*** information outweigh impairments due to the transgression of the independence between the detector and decoder (i.e., the turbo principle). The remarkable result is that the proposed IDD architecture based on the simple SC-MMSE detector with low complexity can exhibit almost the same performance as the IDD with the max-log MAP detector achieving near-capacity. However, the deviation from the "pure" turbo principle pays the cost of slow convergence rate, which comes to be negligible for the number of iterations of $N_I \geq 5$.

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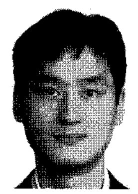
약 력



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