Soft-output MIMO MMSE OSIC Detector under MMSE Channel Estimation

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***Abstract*-In practical wireless multiple-input multiple-output (MIMO) communication systems, the channel estimation must be imperfect. Unfortunately, the channel estimation errors have not been taken into account by existing soft-output MIMO minimum mean square error (MMSE) ordering successive interference cancellation (OSIC) detectors when calculating the log-likelihood ratio of each coded bit, i.e., the soft information. As a result, the system performance can be degraded. In this paper, we propose a novel soft-output MIMO MMSE OSIC detector when MMSE MIMO channel estimation is applied. Based on the basic statistic properties of MMSE MIMO channel estimation, this proposed detector takes the channel estimation error into account in the computation of the MMSE filter and LLR of each coded bit. When compared with existing MIMO MMSE OSIC detectors, our simulation results show that the proposed novel detector can obtain considerable performance gain at the cost of negligible increase of complexity.**

Keywords- multiple-input multiple-output, minimum mean square error, ordering successive interference cancellation, channel estimation, soft-output

I. INTRODUCTION

In practical wireless multiple-input multiple-output (MIMO) communication system, an error-correcting coder, i.e., channel coder, is usually concatenated with the space-time transmitter to obtain better bit-error-rate (BER) performance [1]. To achieve desirable BER performance, the MIMO detector should output the log-likelihood ratio (LLR), i.e., soft information, of each coded bit to the channel decoder, which results in a channel coded MIMO system. This class of detector is called soft-output MIMO detector.

For channel coded MIMO systems, the optimal soft detector for minimizing BER is maximum-likelihood (ML) detector [1], [2]. The main drawback of ML MIMO detector is that, it becomes prohibitively complex because its complexity increases exponentially with the transmitter antenna number and the modulation order. By compensating the residual decision error of previously detected symbols, [3] and [4] recently proposed a modified mean square error (MMSE) based ordering successive interference cancellation (OSIC) detector for Vertical Bell Lab Space Time (V-BLAST) MIMO system, which outperforms conventional MMSE OSIC detector significantly for channel coded MIMO system. In [5] and [6], this detector is improved through *a posteriori* symbol probability estimation. In [7], several reduced-complexity implementations of this detector are derived so that only one matrix inverse is needed to detect each transmitted symbol vector. Therefore, this class of detector can be a promising candidate in practical systems.

However, all the existing soft-output MIMO MMSE OSIC detectors are derived based on the assumption that the channel estimation is perfect. Unfortunately, the estimated MIMO channel coefficients matrix must be noisy and imperfect in practical application environments [9]- [13]. Therefore, these soft-output MIMO MMSE OSIC detectors will suffer from performance degradation under imperfect channel estimation.

When the channel estimation is imperfect, [11] investigated the ML MIMO symbol detection scheme which takes into consideration of the channel estimation error. Recently, [14] provided a MMSE based OSIC symbol detection algorithm for V-BLAST MIMO system when ML MIMO channel estimation is applied, which addresses the impact of the channel estimation error. However, no channel coding and decision error propagation compensation are considered in the scheme of [14].

To overcome the shortcomings of these existing soft-output MIMO MMSE OSIC detectors, we propose a novel soft-output MIMO MMSE OSIC detector which takes the channel estimation error into account in this paper. Specifically, we focus our investigation on MMSE MIMO channel estimation as it can achieve better performance than ML MIMO estimation [12]. Based on the statistical properties of MMSE MIMO channel estimation, we derive the MMSE filter for detecting each transmitted symbol and provide the method to compute the LLR of each coded bit. We also consider the compensation of the residual decision error through soft interference cancellation. When compared with existing soft-output MIMO MMSE OSIC detectors, our simulation results show that the proposed novel soft-output MIMO MMSE OSIC detectors can obtain considerable performance gain at the cost of negligible increase of complexity.

The rest of this paper is organized as follows. In Section II, we describe the system model used in this paper. The soft-output MIMO MMSE OSIC detector under perfect channel estimation is overviewed in Section III. In Section IV, we derived the soft-output MIMO MMSE OSIC detector under

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MMSE MIMO channel estimation. The simulation results and corresponding discussion are given in Section V. Finally, we conclude this paper in Section VI.

II. System Model

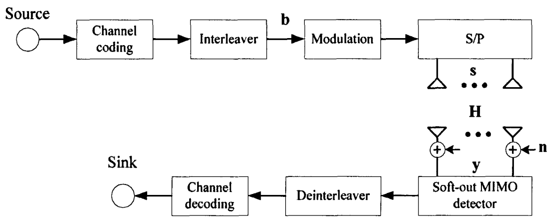

Figure 1. System model

In a MIMO system with N_T transmitter antennas and N_R receiver antennas illustrated in Fig. 1, the received signal can be modeled as follows,

$$\mathbf{y} = \mathbf{H}\mathbf{s} + \mathbf{n} = \sum_{i=1}^{N_T} \mathbf{h}_i s_i + \mathbf{n}, \tag{1}$$

where $\mathbf{y} = [y_1 \ \cdots \ y_{N_R}]^T$ is the received signal vector; $\mathbf{H} = [\mathbf{h}_1, \mathbf{h}_2, \cdots, \mathbf{h}_{N_T}]$ is the $N_R \times N_T$ MIMO channel coefficients matrix whose element $h_{i,j}$ denotes the channel fading coefficient between the jth transmitter antenna and the ith receiver antenna. We assume that the elements of $\mathbf{H}$ are independent identically distributed (i.i.d.) zero-mean circularly symmetric complex Gaussian (ZMCSCG) random variables (i.e., each random variable has independent real and imaginary parts with zero mean and same variance) with variance $\mathrm{E}\left\{\left|h_{i,j}\right|^2\right\} = \sigma_h^2$ and the notation '$\mathrm{E}(\cdot)$' denotes the expectation operator. In this paper, we assume that $\mathbf{H}$ is only known at the receiver. $\mathbf{s} = [s_1 \ \cdots \ s_{N_T}]^T$ is the $N_T \times 1$ complex signal vector whose element is taken from a complex modulation constellation $\mathcal{A}$, such as QPSK and 16-QAM, by mapping the coded bit vector $\mathbf{b}_i = \left\{b_{(i-1)\log_2(M)+1}, b_{(i-1)\log_2(M)+2}, \cdots, b_{i\log_2(M)}\right\}$ to one modulation symbol belonging to $\mathcal{A}$, i.e., $s_i = \mathrm{map}(\mathbf{b}_i) \in \mathcal{A}$. Meanwhile, we assume that each transmitted symbol is independently taken from the same modulation constellation and has the same mean energy. Therefore, we have $\mathrm{E}\left\{\mathbf{s}\mathbf{s}^H\right\} = E_S \mathbf{I}_{N_T}$. Finally, $\mathbf{n} = [n_1 \ \cdots \ n_{N_R}]^T$ is the i.i.d ZMCSCG noise vector with covariance matrix $\mathrm{E}\left[\mathbf{n}\mathbf{n}^H\right] = \sigma_n^2 \mathbf{I}_{N_R}$, which is independent of $\mathbf{H}$ and $\mathbf{s}$.

III. Soft-output MIMO MMSE OSIC Detector under Perfect Channel Estimation

Let $k_i \in \{1, 2, \cdots, N_T\}$ be the index of the ith detected spatial data stream according to the maximal post-detection signal-to-interference and noise ratio (SINR) ordering rule, the corresponding interference-cancelled received signal vector $\mathbf{y}_{k_i}$ is given as

$$\mathbf{y}_{k_i} = \mathbf{h}_{k_i} s_{k_i} + \underbrace{\sum_{j=k_{i+1}}^{k_{N_T}} \mathbf{h}_j s_j}_{\mathbf{I}_U} + \underbrace{\sum_{j=k_1}^{k_{i-1}} \mathbf{h}_j \left(s_j - \hat{s}_j\right)}_{\mathbf{I}_D} + \mathbf{n}, \tag{2}$$

where $\mathbf{I}_U$ is the interference from undetected spatial data streams and $\mathbf{I}_D$ is the interference due to the decision error of previously detected spatial data streams, $\hat{s}_j$ represents the estimation of s_j. The MMSE spatial filter $\mathbf{W}_i$ that is applied to suppress $\mathbf{I}_U$, $\mathbf{I}_D$ and $\mathbf{n}$ is given as

$$\mathbf{W}_i = E_S \mathbf{h}_{k_i}^H \left[E_s \mathbf{H}_{k_i:k_{N_T}} \mathbf{H}_{k_i:k_{N_T}}^H + \mathbf{R}_{\mathbf{I}_D} + \sigma_n^2 \mathbf{I}_{N_R} \right]^{-1} \tag{3}$$

where $\mathbf{H}_{k_i:k_{N_T}} = \left[\mathbf{h}_{k_i}, \mathbf{h}_{k_{i+1}}, \cdots, \mathbf{h}_{k_{N_T}}\right]$ is the sub-matrix of $\mathbf{H}$ by deleting the $k_1, k_2, \cdots, k_{i-1}$ columns. The covariance matrix $\mathbf{R}_{\mathbf{I}_D}$ is given as [3], [4]

$$\mathbf{R}_{\mathbf{I}_D} = E\left[\mathbf{I}_D \mathbf{I}_D^H\right] = \mathbf{H}_{k_1:k_{i-1}} \mathbf{Q}_i \mathbf{H}_{k_1:k_{i-1}}^H \tag{4}$$

where $\mathbf{Q}_i = \left[q_{u,v}^i\right]_{(i-1)\times(i-1)}$ is the residual interference cancellation error covariance matrix of previously detected spatial data streams, whose element is given as

$$q_{u,v}^i = E\left[\left(s_{k_u} - \hat{s}_{k_u}\right)\left(s_{k_v} - \hat{s}_{k_v}\right)^*\right] = \begin{cases} E\left[\left|s_{k_u} - \hat{s}_{k_u}\right|^2 \middle| \hat{s}_{k_u}\right] & ,u = v \\ E\left[\left(s_{k_u} - \hat{s}_{k_u}\right) \middle| \hat{s}_{k_u}\right] E\left[\left(s_{k_v} - \hat{s}_{k_v}\right)^* \middle| \hat{s}_{k_v}\right] & ,u \neq v \end{cases} \tag{5}$$

After MMSE filtering, the output corresponding to the transmitted symbol s_{k_i} is given by

$$\tilde{s}_i = \mathbf{W}_i \mathbf{y}_{k_i}, \tag{6}$$

According to Gaussian approximation of MMSE filter output [8] , (6) can be equivalently expressed as

$$\tilde{s}_{k_i} \approx \mu_{k_i} s_{k_i} + \eta_{k_i}, \tag{7}$$

where $\mu_{k_i} = \mathbf{W}_i \mathbf{h}_{k_i}$ and η_{k_i} is a zero-mean complex Gaussian (ZMCG) random variable with variance $\sigma_{\eta_{k_i}}^2 = \mu_{k_i} E_S - \mu_{k_i}^2 E_S$. According to (7) and with log-sum approximation, the LLR value corresponding to the λth bit of $\mathbf{b}_i$ can be obtained as

$$L\left(b_i^\lambda\right) \approx \frac{1}{\sigma_{\eta_{k_i}}^2}\left(\min_{a_i \in \mathcal{A}_\lambda^0}\left|\tilde{s}_{k_i} - \mu_{k_i} a_i\right|^2 - \min_{a_i \in \mathcal{A}_\lambda^1}\left|\tilde{s}_{k_i} - \mu_{k_i} a_i\right|^2\right), \tag{8}$$

where $\mathcal{A}_\lambda^0$ and $\mathcal{A}_\lambda^1$ denote the modulation constellation symbols subset of $\mathcal{A}$ whose λth bit equals 0 and 1, respectively. Then, the obtained LLR values of a channel coding block is de-interleaved and fed into the soft-input channel decoder to recover the transmitted information source bits.

We subsequently describe the method to compute $q_{u,v}^{i}$ based on *a posteriori* symbol probability. Following the equivalent approximate Gaussian expression of (7), the *a posteriori* probability of $\alpha_l \in \mathcal{A}$ conditioned on $\tilde{s}_{k_i}$ and μ_{k_i} is given as

$$p\left(s_{k_i}=\alpha_l \middle| \tilde{s}_{k_i},\mu_{k_i}\right)=\frac{p\left(\tilde{s}_{k_i} \middle| s_{k_i}=\alpha_l,\mu_{k_i}\right)p\left(s_{k_i}=\alpha_l\right)}{p\left(\tilde{s}_{k_i}\right)} \tag{9}$$

As each modulation constellation symbol is transmitted with equal probability, we have

$$p\left(s_{k_i}=\alpha_l \middle| \tilde{s}_{k_i},\mu_{k_i}\right)\propto \exp\left(-\left|\tilde{s}_{k_i}-\mu_{k_i}\alpha_l\right|^2 / \sigma_{\eta_{k_i}}^2\right) \tag{10}$$

While the equality $\sum_{\alpha_l\in\mathcal{A}} p\left(s_{k_i}=\alpha_l \middle| \tilde{s}_{k_i},\mu_{k_i}\right)=1$ stands, the *a posteriori* probability $p\left(s_{k_i}=\alpha_l \middle| \tilde{s}_{k_i},\mu_{k_i}\right),\alpha_l\in\mathcal{A}$ can therefore be computed. Considering soft interference cancellation [15], we set $\hat{s}_{k_i}=\bar{s}_{k_i}=\sum_{\alpha_l\in\mathcal{A}}\alpha_l p\left(s_{k_i}=\alpha_l \middle| \tilde{s}_{k_i},\mu_{k_i}\right)$ and have

$$\mathrm{E}\left[\left|s_{k_u}-\hat{s}_{k_u}\right|^2 \middle| \hat{s}_{k_u}\right]=\sum_{\alpha_l\in\mathcal{A}}\left|\alpha_l-\bar{s}_{k_u}\right|^2 p\left(s_{k_i}=\alpha_l \middle| \tilde{s}_{k_i},\mu_{k_i}\right) \tag{11}$$

Furthermore, it is evidently that $\mathrm{E}\left[\left(s_{k_u}-\hat{s}_{k_u}\right) \middle| \hat{s}_{k_u}\right]=0$ and $\mathbf{Q}_i$ is a diagonal matrix.

Note that if $\mathbf{Q}$ is set to be a zero matrix, the interference cancellation is assumed to be ideal and we obtain the conventional MMSE OSIC detection algorithm.

IV. Soft-output MMSE MIMO OSIC Detector under MMSE Channel Estimation

In this section, we derive the soft-output MMSE OSIC detection algorithm under MMSE channel estimation.

A. MMSE MIMO Channel Estimation

For MMSE based MIMO channel estimation, the estimated MIMO channel matrix can all be expressed as [12], [13]

$$\begin{aligned}\hat{\mathbf{H}}&=\mathbf{H}\mathbf{s}_p\mathbf{s}_p^H\left(\frac{\sigma_n^2}{\sigma_h^2}\mathbf{I}_{N_T}+\mathbf{s}_p\mathbf{s}_p^H\right)^{-1}+\mathbf{n}\mathbf{s}_p^H\left(\frac{\sigma_n^2}{\sigma_h^2}\mathbf{I}_{N_T}+\mathbf{s}_p\mathbf{s}_p^H\right)^{-1}\\&=\mathbf{H}-\Delta\mathbf{H},\end{aligned} \tag{12}$$

where $\mathbf{s}_p$ is a $N_T\times N_P$ pilot symbols matrix whose element has average energy E_p and $N_p\ge N_T$. $\Delta\mathbf{H}$ is the zero-mean channel estimation error matrix, which is uncorrelated with $\hat{\mathbf{H}}$ according to orthogonality principle. The optimal pilot symbols matrix minimizing MSE should satisfy [12], [13]

$$\mathbf{s}_p\mathbf{s}_p^H=N_pE_p\mathbf{I}_{N_T} \tag{13}$$

In this case, we have [12], [13]

$$\mathrm{E}\left[\Delta\hat{\mathbf{H}}\Delta\hat{\mathbf{H}}^H\right]=N_T\sigma_{\Delta h}^2\mathbf{I}_{N_R} \tag{14}$$

where

$$\sigma_{\Delta h}^2=\sigma_n^2\Big/\left(\sigma_n^2/\sigma_h^2+N_PE_P\right) \tag{15}$$

B. Computation of MMSE filter under MMSE channel estimation

When we consider the channel estimation error, (2) can be rewritten as

$$\begin{aligned}\tilde{\mathbf{y}}_{k_i}&=\mathbf{H}\mathbf{s}-\sum_{j=1}^{k_{i-1}}\hat{\mathbf{h}}_j\bar{s}_j+\mathbf{n}\\&=\sum_{j=k_i}^{N_T}\left(\hat{\mathbf{h}}_j+\Delta\mathbf{h}_j\right)s_j+\sum_{j=k_1}^{k_{i-1}}\hat{\mathbf{h}}_j\left(s_j-\bar{s}_j\right)+\sum_{j=k_1}^{k_{i-1}}\Delta\mathbf{h}_js_j+\mathbf{n}\end{aligned} \tag{16}$$

where $\hat{\mathbf{h}}_{k_i}$ and $\Delta\mathbf{h}_{k_i}$ represent k_i th column of $\hat{\mathbf{H}}$ and $\Delta\mathbf{H}$, respectively. Then, conditionally on $\hat{\mathbf{H}}$, the MMSE filter is given as [16]

$$\tilde{\mathbf{W}}_i=\mathrm{E}\left[s_{k_i}\tilde{\mathbf{y}}_{k_i}{}^H\middle|\hat{\mathbf{H}}\right]\left\{\mathrm{E}\left[\tilde{\mathbf{y}}_{k_i}\tilde{\mathbf{y}}_{k_i}{}^H\middle|\hat{\mathbf{H}}\right]\right\}^{-1}, \tag{17}$$

According to (16), the term $\mathrm{E}\left[\tilde{\mathbf{y}}_{k_i}\tilde{\mathbf{y}}_{k_i}{}^H\middle|\hat{\mathbf{H}}\right]$ can be expressed as

$$\begin{aligned}&\mathrm{E}\left[\tilde{\mathbf{y}}_{k_i}\tilde{\mathbf{y}}_{k_i}{}^H\middle|\hat{\mathbf{H}}\right]\\&=E_S\left(\sum_{j=k_i}^{N_T}\left(\hat{\mathbf{h}}_j\hat{\mathbf{h}}_j^H+\hat{\mathbf{h}}_j\mathrm{E}\left[\Delta\mathbf{h}_j^H\middle|\hat{\mathbf{H}}\right]+\mathrm{E}\left[\Delta\mathbf{h}_j\middle|\hat{\mathbf{H}}\right]\hat{\mathbf{h}}_j^H\right)+\right.\\&\left.\sum_{j=1}^{N_T}\left(\mathrm{E}\left[\Delta\mathbf{h}_j\Delta\mathbf{h}_j^H\middle|\hat{\mathbf{H}}\right]\right)\right)+\sigma_n^2\mathbf{I}_{N_R}+\\&\sum_{j=k_1}^{k_{i-1}}\left(\hat{\mathbf{h}}_j\hat{\mathbf{h}}_j^H+\hat{\mathbf{h}}_j\mathrm{E}\left[\Delta\mathbf{h}_j^H\middle|\hat{\mathbf{H}}\right]+\mathrm{E}\left[\Delta\mathbf{h}_j\middle|\hat{\mathbf{H}}\right]\hat{\mathbf{h}}_j^H\right)\mathrm{var}\left[s_j\right]\\&=E_S\sum_{j=k_i}^{N_T}\hat{\mathbf{h}}_j\hat{\mathbf{h}}_j^H+\sum_{j=k_1}^{k_i-1}\hat{\mathbf{h}}_j\hat{\mathbf{h}}_j^H\mathrm{var}\left[s_j\right]+\left(\sigma_n^2+N_TE_S\sigma_{\Delta h}^2\right)\mathbf{I}_{N_R}\end{aligned} \tag{18}$$

Note that the variance $\mathrm{var}\left[s_j\right]=q_{j,j}$ can be computed according to (11). The second step of (18) can be verified through the following relationship

$$\begin{aligned}&\mathrm{E}\left[\left(s_j-\bar{s}_j\right)s_j^*\right]=\mathrm{E}\left[s_j\left(s_j^*-\bar{s}_j^*\right)\right]=\mathrm{E}\left[\left|s_j\right|^2\right]-\left|\bar{s}_j\right|^2\\&=\mathrm{var}\left[s_j\right]\end{aligned} \tag{19}$$

The last step of (18) is because that $\hat{\mathbf{H}}$ and $\Delta\mathbf{H}$ is uncorrelated and the element of $\Delta\mathbf{H}$ has zero-mean based on the basic statistical properties of MMSE MIMO channel estimation described in the previous subsection, such as (15).

Meanwhile, we have

$$\mathrm{E}\left[s_{k_i}\tilde{\mathbf{y}}_{k_i}{}^H\middle|\hat{\mathbf{H}}\right]=E_S\hat{\mathbf{h}}_{k_i}^H \tag{20}$$

Finally, by combing (18) and (20) into (17), we can reach the MMSE filter conditionally on $\hat{\mathbf{H}}$ as

$$\begin{aligned}&\tilde{\mathbf{W}}_i=E_S\hat{\mathbf{h}}_{k_i}^H\\&\left(E_S\sum_{j=k_i}^{N_T}\hat{\mathbf{h}}_j\hat{\mathbf{h}}_j^H+\sum_{j=k_1}^{k_i-1}\hat{\mathbf{h}}_j\hat{\mathbf{h}}_j^H\mathrm{var}\left[s_j\right]+\left(\sigma_n^2+N_TE_S\sigma_{\Delta h}^2\right)\mathbf{I}_{N_R}\right)^{-1}\end{aligned} \tag{21}$$

C. Computation of LLR

By applying MMSE filter $\tilde{\mathbf{W}}_i$ to $\mathbf{y}_{k_i}$, we have the output associated with s_{k_i} as

$$\hat{s}_{k_i} = \tilde{\mathbf{W}}_i \tilde{\mathbf{y}}_{k_i} \tag{22}$$

According to the Gaussian approximation of the output of MMSE filter [8], we have

$$\hat{s}_{k_i} \approx \tilde{\mu}_{k_i} s_{k_i} + \tilde{\eta}_{k_i}, \tag{23}$$

where

$$\tilde{\mu}_{k_i} = \mathrm{E}\left[\tilde{\mathbf{W}}_i\left(\hat{\mathbf{h}}_{k_i} + \Delta\mathbf{h}_{k_i}\right)\middle|\hat{\mathbf{H}}\right] = \tilde{\mathbf{W}}_i \hat{\mathbf{h}}_{k_i} \tag{24}$$

And $\tilde{\eta}_{k_i}$ is a ZMCG random variable with variance

$$\begin{aligned}\mathrm{var}\left[\tilde{\eta}_{k_i}\right] &= \mathrm{E}\left[\tilde{\mathbf{W}}_i \tilde{\mathbf{y}}_{k_i} \tilde{\mathbf{y}}_{k_i}{}^H \tilde{\mathbf{W}}_i^H \middle| \hat{\mathbf{H}}\right] - \tilde{\mu}_{k_i}^2 E_S \\ &= E_S(1-\alpha)\hat{\mathbf{h}}_{k_i}^H \tilde{\mathbf{W}}_i^H - \tilde{\mu}_{k_i}^2 E_S \\ &= E_S\left(\tilde{\mu}_{k_i} - \tilde{\mu}_{k_i}^2\right)\end{aligned} \tag{25}$$

The last step of (25) is because $\tilde{\mu}_{k_i}$ is a real number.

Therefore, the LLR value of the coded bit b_i^{λ} can be given as

$$L\left(b_{k_i}^{\lambda}\right) \approx \frac{1}{E_S\left(\tilde{\mu}_{k_i} - \tilde{\mu}_{k_i}^2\right)}\left(\min_{a_i \in \mathcal{A}_\lambda^0}\left|\hat{s}_{k_i} - \tilde{\mu}_{k_i} a_i\right|^2 - \min_{a_i \in \mathcal{A}_\lambda^1}\left|\hat{s}_{k_i} - \tilde{\mu}_{k_i} a_i\right|^2\right) \tag{26}$$

D. Remarks

For simplicity of notation, we call the soft-output MMSE OSIC detector derived under perfect channel estimation as the conventional soft-output MMSE OSIC detector, the MMSE OSIC detector derived under perfect channel estimation without considering the residual interference cancellation error as the conventional MMSE OSIC hard detector, and the MMSE OSIC detector derived under imperfect channel estimation without considering the residual interference cancellation error as the improved MMSE OSIC hard detector hereafter.

1) Comparison with the conventional soft-output MMSE OSIC detector: It is obviously that $\sigma_{\Delta h}^2 = 0$ in (21) if the channel estimation is perfect. In this case, we have $\tilde{\mathbf{W}}_i = \mathbf{W}_i$, $\tilde{\mu}_i = \mu_i$ and $\mathrm{var}\left[\tilde{\eta}_{k_i}\right] = \sigma_{\eta_i}^2$. Not surprising, our proposed scheme is identical with conventional soft-output MMSE OSIC detector when the channel estimation is perfect, which manifests its generality.

On the other hand, by comparing the computation of $\tilde{\mathbf{W}}_i$ with $\mathbf{W}_i$, we noticed that the increased complexity in the computation of $\tilde{\mathbf{W}}_i$ is due to the computation of $N_T E_S \sigma_{\Delta h}^2$. As it is a scalar, the increase of complexity of our proposed scheme is negligible.

2) Comparison with the conventional MMSE OSIC hard detector: In the computation of MMSE filter, we can obtain the conventional MMSE OSIC hard detector by neglecting the items $\sum_{j=k_i}^{N_T} \Delta\mathbf{h}_j s_j$ and $\sum_{j=k_1}^{k_{i-1}} \hat{\mathbf{h}}_j\left(s_j - \bar{s}_j\right) + \sum_{j=k_1}^{k_{i-1}} \Delta\mathbf{h}_j s_j$ in (16). In this case, we have

$$\mathrm{E}\left[\tilde{\mathbf{y}}_{k_i}\tilde{\mathbf{y}}_{k_i}^H \middle| \hat{\mathbf{H}}\right] = E_S \sum_{j=k_i}^{N_T} \hat{\mathbf{h}}_j \hat{\mathbf{h}}_j^H + \sigma_n^2 \mathbf{I}_{N_R} \tag{27}$$

Then, compared with the conventional MMSE OSIC hard detector, it can be seen that the increased complexity of our proposed detector is mainly due to the computation of $\sum_{j=k_1}^{k_i-1} \hat{\mathbf{h}}_j \hat{\mathbf{h}}_j^H \mathrm{var}\left[s_j\right]$. Because the computation of $\hat{\mathbf{h}}_j \hat{\mathbf{h}}_j^H$ is required in both detectors, the increase of the complexity is due to the multiplying between the scalar $\mathrm{var}\left[s_j\right]$ and the matrix $\hat{\mathbf{h}}_j \hat{\mathbf{h}}_j^H$. The resulted complexity is N_R^2 complex multiplies. Meanwhile, note that

$$\sum_{j=k_1}^{k_{i-1}} \hat{\mathbf{h}}_j \hat{\mathbf{h}}_j^H \mathrm{var}\left[s_j\right] = \sum_{j=k_1}^{k_{i-2}} \hat{\mathbf{h}}_j \hat{\mathbf{h}}_j^H \mathrm{var}\left[s_j\right] + \hat{\mathbf{h}}_{k_{i-1}} \hat{\mathbf{h}}_{k_{i-1}}^H \mathrm{var}\left[s_{k_{i-1}}\right] \tag{28}$$

Then, the increase of complexity of the accumulation operation in the detection of each transmitted symbol vector is $N_R^2\left(N_T - 1\right)$ complex additions. Considering the main complexity of MMSE OSIC detector is due to the complex matrix inverse and its complexity is $\mathcal{O}\left(N_T N_R^3\right)$, the increase of our proposed detector is relatively small.

3) Comparison with the improved MMSE OSIC hard detector: Obviously, we can obtain the improved MMSE OSIC hard detector by neglecting the item $\sum_{j=k_1}^{k_{i-1}} \hat{\mathbf{h}}_j\left(s_j - \bar{s}_j\right)$ in (16). In this case, we have

$$\mathrm{E}\left[\tilde{\mathbf{y}}_{k_i}\tilde{\mathbf{y}}_{k_i}{}^H \middle| \hat{\mathbf{H}}\right] = E_S \sum_{j=k_i}^{N_T} \hat{\mathbf{h}}_j \hat{\mathbf{h}}_j^H + \left(\sigma_n^2 + N_T E_S \sigma_{\Delta h}^2\right)\mathbf{I}_{N_R} \tag{29}$$

As discussed above, compared with the improved MMSE OSIC hard detector, the increase of our proposed detector is relatively small.

V. Simulation Results

The setups of our simulations are as follows. We choose the 1/2 rate LDPC(Low Density Parity Check) code with a block length of 64800 bits, which is also adopted by DVB-S.2 standard [17]and implemented in MATLAB® module. QPSK and 16-QAM modulations with Gray mapping are adopted in a $N_T = N_R = 4$ MIMO system. Meanwhile, we set $\sigma_h^2 = 1$, $N_P = N_T$ and $E_P = E_S$.

Fig.2 and Fig. 3 show performance comparisons, in terms of BER of QPSK and 16-QAM, among our proposed soft-output MMSE OSIC MIMO detector (proposed detector), the conventional soft-output MMSE OSIC MIMO detector (conventional soft-output detector), the conventional MMSE

OSIC hard detector (conventional hard detector), and the improved MMSE OSIC hard detector (improved hard detector). From these two figures, it can be seen that our proposed detectors outperform all the existing MMSE OSIC detectors with considerable margin. The underlying reason of this improvement is that our proposed detector, by simultaneously taking the channel estimation error and residual interference cancellation error into account while computing LLR of each code bit, can output more reliable soft information to channel decoder.

VI. Conclusion

For MMSE MIMO channel estimation, we have proposed a novel soft-output MMSE OSIC detector which takes the channel estimation error and the residual interference cancellation error into account simultaneously in this paper. We derive a new method to compute the MMSE filter and LLR of each coded bit by considering the channel estimation error matrix and residual interference cancellation error. Compared with all existing MMSE OSIC detectors, simulation results show that this proposed detector can obtain considerable performance gain at the cost of negligible increase of complexity.

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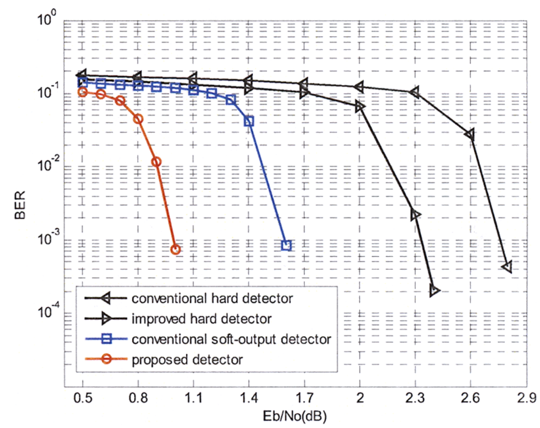

Figure 2. BER performance comparison between different MMSE OSIC detectors (QPSK)

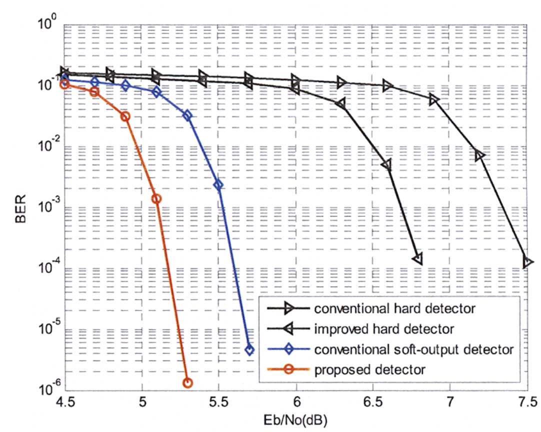

Figure 3. BER performance comparison between different MMSE OSIC detectors (16-QAM)