Data Detection in MIMO Systems with Co-Channel Interference

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Abstract— **The Bell Labs Layered Space-Time (BLAST) architecture has been proposed to achieve high spectral efficiency on multi-input multi-output (MIMO) channels. Most studies of the BLAST algorithm consider spatially and temporally white noise and interference at the receiver. In this paper, we study channel estimation and data detection of a MIMO system under both spatially and temporally colored interference. We derive maximum likelihood (ML) estimates of channel and spatial interference correlation matrices. By exploiting known temporal interference correlation, we extend one-time-slot ordered minimum mean-squared error (MMSE) nulling detection to a multi-time-slot version. We evaluate the symbol error rate of an uncoded QPSK MIMO system under independent Rayleigh fading. The results show that by exploiting both spatial and temporal interference correlation, we achieve about 2dB gain in SIR for a 4×4 MIMO system.**

I. Introduction

The Bell Labs Layered Space-Time (BLAST) architecture was proposed to achieve high channel capacity on multi-input multi-output (MIMO) channels [1]. Most studies of the BLAST algorithm consider temporally and spatially white noise or interference at the receiver. However, in cellular and/or multiple access systems, due to co-channel or multiple access interference, the interference is in general spatially and temporally colored. In [2] and [3], one-time-slot [1] zero-forcing and minimum mean-squared error (MMSE) detection with optimal ordering have been studied, respectively. Spatially and temporally white noise and perfect channel knowledge at the receiver were assumed in [2] and [3]. In [4], maximum likelihood (ML) estimate of channel using training sequences was studied assuming temporally and spatially white noise.

In this paper, we study channel estimation and data detection of a MIMO system with one co-channel interferer under slow flat fading in an interference-limited environment. The interference is shown to be both temporally and spatially colored. The temporal correlation may be due to fading and/or intersymbol interference, and can be determined a priori by the interfering user's delay and pulse shaping factor. In the training period, by decomposing the interference covariance matrix into a Kronecker product of temporal and spatial correlation matrices, we derive ML estimates of channel parameters and interference spatial correlation lags. By exploiting known temporal interference correlation, we extend the one-time-slot ordered MMSE detection [3] to a multi-time-slot version. Monte-Carlo simulation is used to evaluate the symbol error rate of an uncoded QPSK MIMO system in independent Rayleigh fading. A special case of high temporal interference correlation is examined. The results quantify the benefits of utilizing known temporal interference correlation in channel estimation and data detection.

[1]The term one-time-slot will be explained in Section IV.

II. System Model

We consider a single-user link with one co-channel interferer. We assume the desired user has N_1 transmit antennas, the interfering user has L transmit antennas, and there are N_2 receive antennas. The desired user transmits data frame by frame. Each frame has M data vectors. The first N data vectors are for training, and the remaining data vectors are for information transmission. The desired and the interfering users transmit data at the same rate. Assuming thermal noise is small relative to interference, we ignore thermal noise. In a slow flat fading environment, assuming perfect synchronization for the desired user, as we sample the matched filter output at the receiver at time jT, we obtain

$$\boldsymbol{y}_j = \sqrt{\frac{P_s T}{N_1}} \boldsymbol{H} \boldsymbol{x}_j + \underbrace{\sqrt{\frac{P_I T}{L}} \boldsymbol{H}_I \sum_{k=-\infty}^{\infty} \boldsymbol{b}_k g(jT - kT - \tau)}_{\boldsymbol{n}_j}$$
$$j = 0, \ldots, M-1,$$

where $g(t)$ is the combined impulse response of the transmitter and receiver which has a raised cosine spectrum with rolloff factor β [5]. The data transmission rate is $1/T$. The symbols in data vectors $\boldsymbol{x}_k$ $(N_1 \times 1)$ and $\boldsymbol{b}_k$ $(L \times 1)$ are mutually independent, zero-mean and with unit variance. The delay of the interfering user is τ. Matrices $\boldsymbol{H}$ $(N_2 \times N_1)$ and $\boldsymbol{H}_I$ $(N_2 \times L)$ are channel matrices of the desired and the interfering users, respectively. The channel matrices are fixed over one frame, and have independent realizations from frame to frame. The elements in $\boldsymbol{H}$ and $\boldsymbol{H}_I$ are assumed independent, identically distributed (i.i.d.) zero-mean complex Gaussian with unit variance. This implies independent Rayleigh fading. We denote P_s and P_I as the transmit powers of the desired and the interfering users, respectively.

Since $\boldsymbol{b}_k$ is zero-mean, the interference vector $\boldsymbol{n}_j$ is zero-mean as well. During the training period, we further assume $\boldsymbol{n}_j$ is circularly symmetric complex Gaussian. It can be shown that the cross correlation between interference vectors at time jT and qT is

$$E\left\{\boldsymbol{n}_j\boldsymbol{n}_q^\dagger\right\} = \underbrace{\left(\frac{P_I T}{L}\boldsymbol{H}_I\boldsymbol{H}_I^\dagger\right)}_{\boldsymbol{R}_0}\underbrace{\sum_{k=-\infty}^{\infty}\left\{g(jT-kT-\tau)g(qT-kT-\tau)\right\}}_{\lambda_0(j,q)},$$

where $\dagger$ denotes transpose conjugate, and $\lambda_0(j,q)$ depends on $|j-q|$, delay τ and rolloff factor β.

During the training period, we stack the interference vectors into a long vector, $\bar{\boldsymbol{n}} = [\boldsymbol{n}_0^T \cdots \boldsymbol{n}_{N-1}^T]^T$, where N is the training length and T denotes transpose. The covariance matrix of this long interference vector can be expressed as a Kronecker product,

$$\begin{aligned} E\left\{\bar{\boldsymbol{n}}\bar{\boldsymbol{n}}^\dagger\right\} &= \boldsymbol{R}_0 \otimes \boldsymbol{\Lambda}_0 \quad (1)\\ &= \begin{bmatrix} \boldsymbol{\Lambda}_{0(0,0)}\boldsymbol{R}_0 & \cdots & \boldsymbol{\Lambda}_{0(0,N-1)}\boldsymbol{R}_0 \\ \vdots & & \vdots \\ \boldsymbol{\Lambda}_{0(N-1,0)}\boldsymbol{R}_0 & \cdots & \boldsymbol{\Lambda}_{0(N-1,N-1)}\boldsymbol{R}_0 \end{bmatrix}, \end{aligned}$$

where $\otimes$ denotes Kronecker product, $\boldsymbol{\Lambda}_{0(i,j)}$ denotes the (i,j)th element of matrix $\boldsymbol{\Lambda}_0$, and $\boldsymbol{\Lambda}_{0(i,j)} = \lambda_0(i,j)$. In (1), $\boldsymbol{R}_0$ ($N_2 \times N_2$) captures the spatial correlation of interference which is determined by the channel matrix of the interfering user, while $\boldsymbol{\Lambda}_0$ ($N \times N$) captures the temporal correlation of interference. With the knowledge of delay τ and rolloff factor β, the temporal correlation matrix $\boldsymbol{\Lambda}_0$ can be calculated a priori. In the following sections, we rely only on a spatial-temporal correlation structure given by a Kronecker product as in (1). That is, the spatial and temporal interference statistics are separable.

III. ML Estimates of Channel and Spatial interference Correlation

During the training period, given observations

$$\boldsymbol{y}_j = \sqrt{\frac{P_s T}{N_1}}\boldsymbol{H}\boldsymbol{x}_j + \boldsymbol{n}_j, j = 0, \cdots, N-1 \quad (2)$$

where $\boldsymbol{x}_j$'s are known training vectors, we would like to find ML estimates of channel and spatial correlation matrix of $\boldsymbol{n}_j$. The estimates will facilitate data detection after the training period.

A. General case: interference is both spatially and temporally colored

Let $\bar{\boldsymbol{y}} = [\boldsymbol{y}_0^T \cdots \boldsymbol{y}_{N-1}^T]^T$ and $\bar{\boldsymbol{x}} = [\boldsymbol{x}_0^T \cdots \boldsymbol{x}_{N-1}^T]^T$, the observations in (2) can be re-written as

$$\bar{\boldsymbol{y}} = \sqrt{\frac{P_s T}{N_1}}(\boldsymbol{H} \otimes \boldsymbol{I}_N)\bar{\boldsymbol{x}} + \bar{\boldsymbol{n}}$$

where $\boldsymbol{I}_N$ is an $N \times N$ identity matrix.

If the covariance matrix of $\bar{\boldsymbol{n}}$ in (1) is $\boldsymbol{R} \otimes \boldsymbol{\Lambda}$, assuming that $\boldsymbol{R}$ and $\boldsymbol{\Lambda}$ are nonsingular, the conditional probability density function (pdf) of $\bar{\boldsymbol{y}}$ given $\boldsymbol{H}$ and $\boldsymbol{R}$ is

$$\begin{aligned} &p(\bar{\boldsymbol{y}}|\boldsymbol{H},\boldsymbol{R}) \\ &= \frac{1}{\pi^{N\cdot N_2}|\boldsymbol{R}\otimes\boldsymbol{\Lambda}|}\exp\left\{-\left[\bar{\boldsymbol{y}} - \sqrt{\frac{P_s T}{N_1}}(\boldsymbol{H}\otimes\boldsymbol{I}_N)\bar{\boldsymbol{x}}\right]^\dagger\right. \\ &\qquad \left.(\boldsymbol{R}\otimes\boldsymbol{\Lambda})^{-1}\left[\bar{\boldsymbol{y}} - \sqrt{\frac{P_s T}{N_1}}(\boldsymbol{H}\otimes\boldsymbol{I}_N)\bar{\boldsymbol{x}}\right]\right\} \quad (3) \end{aligned}$$

where $|\cdot|$ denotes matrix determinant. The ML estimate $(\hat{\boldsymbol{H}}, \hat{\boldsymbol{R}})$ is the one maximizing the conditional pdf in (3).

With the identities [6] $|\boldsymbol{R}\otimes\boldsymbol{\Lambda}| = |\boldsymbol{R}|^N|\boldsymbol{\Lambda}|^{N_2}$ ($\boldsymbol{R}$ is of dimension $N_2 \times N_2$, $\boldsymbol{\Lambda}$ is of dimension $N \times N$) and $(\boldsymbol{R}\otimes\boldsymbol{\Lambda})^{-1} = \boldsymbol{R}^{-1}\otimes\boldsymbol{\Lambda}^{-1}$, maximizing (3) is equivalent to minimizing

$$\begin{aligned} f(\boldsymbol{H},\boldsymbol{R}) = \ln|\boldsymbol{R}| + \frac{1}{N}&\left[\bar{\boldsymbol{y}} - \sqrt{\frac{P_s T}{N_1}}(\boldsymbol{H}\otimes\boldsymbol{I}_N)\bar{\boldsymbol{x}}\right]^\dagger \\ &\left(\boldsymbol{R}^{-1}\otimes\boldsymbol{\Lambda}^{-1}\right)\left[\bar{\boldsymbol{y}} - \sqrt{\frac{P_s T}{N_1}}(\boldsymbol{H}\otimes\boldsymbol{I}_N)\bar{\boldsymbol{x}}\right]. \end{aligned}$$

Denoting the elements of $\boldsymbol{\Lambda}^{-1}$ as

$$\begin{bmatrix} \alpha_{0,0} & \cdots & \alpha_{0,N-1} \\ \vdots & & \vdots \\ \alpha_{N-1,0} & \cdots & \alpha_{N-1,N-1} \end{bmatrix} = \boldsymbol{\Lambda}^{-1},$$

we re-write $f(\boldsymbol{H},\boldsymbol{R})$ as

$$\begin{aligned} f(\boldsymbol{H},\boldsymbol{R}) = \ln|\boldsymbol{R}| + \mathrm{trace}&\left\{\boldsymbol{R}^{-1}\frac{1}{N}\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}\alpha_{i,j}\right. \\ &\left.\left(\boldsymbol{y}_i - \sqrt{\frac{P_s T}{N_1}}\boldsymbol{H}\boldsymbol{x}_i\right)\left(\boldsymbol{y}_j - \sqrt{\frac{P_s T}{N_1}}\boldsymbol{H}\boldsymbol{x}_j\right)^\dagger\right\}. \end{aligned} \quad (4)$$

By setting $\partial f(\boldsymbol{H},\boldsymbol{R})/\partial\boldsymbol{R} = 0$, we obtain

$$\hat{\boldsymbol{R}} = \frac{1}{N}\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}\alpha_{i,j}\left(\boldsymbol{y}_i - \sqrt{\frac{P_s T}{N_1}}\boldsymbol{H}\boldsymbol{x}_i\right)\left(\boldsymbol{y}_j - \sqrt{\frac{P_s T}{N_1}}\boldsymbol{H}\boldsymbol{x}_j\right)^\dagger.$$

Substituting $\hat{\boldsymbol{R}}$ into (4), the estimate of $\boldsymbol{H}$ is determined by minimizing

$$\begin{aligned} &f_1(\boldsymbol{H}) \\ &= \left|\frac{1}{N}\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}\alpha_{i,j}\left(\boldsymbol{y}_i - \sqrt{\frac{P_s T}{N_1}}\boldsymbol{H}\boldsymbol{x}_i\right)\left(\boldsymbol{y}_j - \sqrt{\frac{P_s T}{N_1}}\boldsymbol{H}\boldsymbol{x}_j\right)^\dagger\right|. \end{aligned} \quad (5)$$

It can be shown that [7]

$$\hat{\boldsymbol{H}} = \boldsymbol{R}_{xy}^\dagger\boldsymbol{R}_{xx}^{-1}, \quad (6)$$

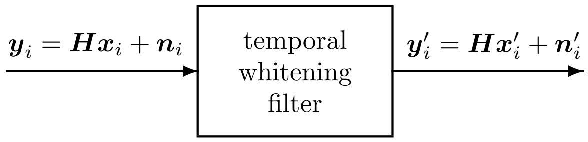

Fig. 1. At the output of the filter, interference $\boldsymbol{n}'_0, \ldots, \boldsymbol{n}'_{N-1}$ are i.i.d. random vectors.

where

$$\boldsymbol{R}_{yy} = \frac{1}{N}\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}\alpha_{i,j}\boldsymbol{y}_i\boldsymbol{y}_j^{\dagger} \tag{7}$$

$$\boldsymbol{R}_{xy} = \frac{1}{N}\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}\sqrt{\frac{P_sT}{N_1}}\alpha_{i,j}\boldsymbol{x}_i\boldsymbol{y}_j^{\dagger} \tag{8}$$

$$\boldsymbol{R}_{xx} = \frac{1}{N}\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}\frac{P_sT}{N_1}\alpha_{i,j}\boldsymbol{x}_i\boldsymbol{x}_j^{\dagger}. \tag{9}$$

Using (6)-(9), the estimate of $\boldsymbol{R}$ can be expressed as

$$\hat{\boldsymbol{R}} = \boldsymbol{R}_{yy} - \hat{\boldsymbol{H}}\boldsymbol{R}_{xy}. \tag{10}$$

Let us interpret (7)-(9). If we pass observations $\boldsymbol{y}_0, \ldots, \boldsymbol{y}_{N-1}$ through a filter which temporally whitens the interference as shown in Fig. 1, it can be shown that $\boldsymbol{R}_{yy}$, $\boldsymbol{R}_{xy}$ and $\boldsymbol{R}_{xx}$ in (7)-(9) are the auto- and cross-correlation of $\boldsymbol{x}'_i$ and $\boldsymbol{y}'_i$, respectively. The temporal whitening filter is determined by the temporal correlation matrix $\boldsymbol{\Lambda}$.

B. Special cases

B.1 Interference is spatially colored, but temporally white ($\boldsymbol{n}_i$ is independent of $\boldsymbol{n}_j$ for $i \neq j$)

The covariance matrix of $\bar{\boldsymbol{n}}$ in (1) has the form $\boldsymbol{R} \otimes \boldsymbol{I}_N$. Substituting $\boldsymbol{\Lambda} = \boldsymbol{I}_N$ into (7)-(9), we obtain

$$\boldsymbol{R}_{yy1} = \frac{1}{N}\sum_{i=0}^{N-1}\boldsymbol{y}_i\boldsymbol{y}_i^{\dagger} \tag{11}$$

$$\boldsymbol{R}_{xy1} = \frac{1}{N}\sum_{i=0}^{N-1}\sqrt{\frac{P_sT}{N_1}}\boldsymbol{x}_i\boldsymbol{y}_i^{\dagger} \tag{12}$$

$$\boldsymbol{R}_{xx1} = \frac{1}{N}\sum_{i=0}^{N-1}\frac{P_sT}{N_1}\boldsymbol{x}_i\boldsymbol{x}_i^{\dagger}. \tag{13}$$

Substituting (11)-(13) into (6) and (10) yields the estimates of the channel and spatial interference correlation matrix.

B.2 Interference is both spatially and temporally white

The covariance matrix of $\bar{\boldsymbol{n}}$ in (1) has the form $\sigma^2\boldsymbol{I}_{N_2} \otimes \boldsymbol{I}_N$. Substituting $\boldsymbol{R} = \sigma^2\boldsymbol{I}_{N2}$ and $\boldsymbol{\Lambda} = \boldsymbol{I}_N$ into (4), it can be shown that $\hat{\boldsymbol{H}}$ in (6) is replaced by

$$\hat{\boldsymbol{H}}_w = \boldsymbol{R}_{xy1}^{\dagger}\boldsymbol{R}_{xx1}^{-1},$$

while

$$\hat{\sigma}^2 = \frac{1}{N_2}\text{trace}\Big\{\boldsymbol{R}_{yy1} - \hat{\boldsymbol{H}}_w\boldsymbol{R}_{xy1}\Big\}.$$

IV. Data Detection with Estimated Channel and Interference

During the data transmission period, with estimates of the channel and spatial interference correlation matrix, MMSE nulling with optimal ordering can be used to detect data at the receiver. Without loss of generality, we present two data detection schemes, which we refer to as one-time-slot and two-time-slot detection. In one-time-slot detection, we ignore temporal correlation of interference, and detect $\boldsymbol{x}_i$ using only $\boldsymbol{y}_i$. While in two-time-slot detection, we utilize the known temporal interference correlation, as well as $(\boldsymbol{y}_i, \boldsymbol{y}_{i+1})$, to detect $(\boldsymbol{x}_i, \boldsymbol{x}_{i+1})$.

A. One-time-slot data detection

Suppressing the time dependence, the observation is $\boldsymbol{y} = \sqrt{\frac{P_sT}{N_1}}\boldsymbol{H}\boldsymbol{x} + \boldsymbol{n}$. The linear MMSE estimate $\hat{\boldsymbol{x}} = \boldsymbol{Q}\boldsymbol{y}$ chooses the matrix $\boldsymbol{Q}$ such that trace[cov$(\boldsymbol{x} - \boldsymbol{Q}\boldsymbol{y})$] is minimized. With the estimates $\hat{\boldsymbol{H}}$ and $\hat{\boldsymbol{R}}$,

$$\boldsymbol{Q} = \sqrt{\frac{P_sT}{N_1}}\hat{\boldsymbol{H}}^{\dagger}\left(\frac{P_sT}{N_1}\hat{\boldsymbol{H}}\hat{\boldsymbol{H}}^{\dagger} + \hat{\boldsymbol{R}}\right)^{-1}.$$

The covariance matrix of the estimation error is

$$\begin{aligned}\boldsymbol{P} &\triangleq E\left\{(\boldsymbol{x} - \hat{\boldsymbol{x}})(\boldsymbol{x} - \hat{\boldsymbol{x}})^{\dagger}\right\} \\ &= \boldsymbol{I}_{N_1} - \frac{P_sT}{N_1}\hat{\boldsymbol{H}}^{\dagger}\left(\frac{P_sT}{N_1}\hat{\boldsymbol{H}}\hat{\boldsymbol{H}}^{\dagger} + \hat{\boldsymbol{R}}\right)^{-1}\hat{\boldsymbol{H}}.\end{aligned}$$

MMSE nulling with optimal ordering using perfect channel knowledge under spatially white interference is given in [3]. Modifying the algorithm in [3], we give the steps of MMSE nulling with optimal ordering using an estimated channel under spatially colored interference.

1. $k = 1$, $\boldsymbol{H}_k = \hat{\boldsymbol{H}}$.
2. Calculate $\boldsymbol{P}_k = \boldsymbol{I} - \frac{P_sT}{N_1}\boldsymbol{H}_k^{\dagger}\left(\frac{P_sT}{N_1}\boldsymbol{H}_k\boldsymbol{H}_k^{\dagger} + \hat{\boldsymbol{R}}\right)^{-1}\boldsymbol{H}_k$, and find that the jth diagonal entry of $\boldsymbol{P}_k$ is the smallest.
3. Estimate the jth element in $\boldsymbol{x}$ from $\boldsymbol{Q}_j\boldsymbol{y}$, where $\boldsymbol{Q}_j$ is the jth row of $\boldsymbol{Q}$ and $\boldsymbol{Q} = \sqrt{\frac{P_sT}{N_1}}\boldsymbol{H}_k^{\dagger}\left(\frac{P_sT}{N_1}\boldsymbol{H}_k\boldsymbol{H}_k^{\dagger} + \hat{\boldsymbol{R}}\right)^{-1}$.
4. Subtract the effect of the jth element of $\boldsymbol{x}$ from $\boldsymbol{y}$.
5. $k = k + 1$, form $\boldsymbol{H}_{k+1}$ by deleting the jth column of $\boldsymbol{H}_k$. Go to Step 2 until all the data in $\boldsymbol{x}$ are detected.

B. Two-time-slot data detection

When interference is not temporally white, we use $\boldsymbol{y}_{N+1}, \ldots, \boldsymbol{y}_M$ to detect data symbols $\boldsymbol{x}_{N+1}, \ldots, \boldsymbol{x}_M$ jointly. Due to the complexity of using all observations, we consider a simplified algorithm using only $(\boldsymbol{y}_i, \boldsymbol{y}_{i+1})$ to detect $(\boldsymbol{x}_i, \boldsymbol{x}_{i+1})$. It can be shown that

$$\underbrace{\begin{bmatrix}\boldsymbol{y}_i \\ \boldsymbol{y}_{i+1}\end{bmatrix}}_{\tilde{\boldsymbol{y}}} = \sqrt{\frac{P_sT}{N_1}}\underbrace{\begin{bmatrix}\boldsymbol{H} & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{H}\end{bmatrix}}_{\tilde{\boldsymbol{H}}}\underbrace{\begin{bmatrix}\boldsymbol{x}_i \\ \boldsymbol{x}_{i+1}\end{bmatrix}}_{\tilde{\boldsymbol{x}}} + \underbrace{\begin{bmatrix}\boldsymbol{n}_i \\ \boldsymbol{n}_{i+1}\end{bmatrix}}_{\tilde{\boldsymbol{n}}}.$$

An estimate of $\tilde{\boldsymbol{H}}$, $\hat{\tilde{\boldsymbol{H}}}$, can be obtained through the estimate of $\boldsymbol{H}$. Using the estimated spatial correlation matrix of $\boldsymbol{n}_i$ and the known temporal interference correlation, we are able to estimate the covariance matrix of $\tilde{\boldsymbol{n}}$, $\hat{\tilde{\boldsymbol{R}}}$. Replacing $\boldsymbol{x}$, $\boldsymbol{y}$, $\hat{\boldsymbol{H}}$ and $\hat{\boldsymbol{R}}$ in the one-time-slot detection algorithm by $\tilde{\boldsymbol{x}}$, $\tilde{\boldsymbol{y}}$, $\hat{\tilde{\boldsymbol{H}}}$ and $\hat{\tilde{\boldsymbol{R}}}$, respectively, we obtain the two-time-slot detection algorithm.

V. Data Detection without channel and interference estimation

During the training period, instead of estimating the channel and the spatial interference correlation matrix, a matrix $\boldsymbol{M}$ which minimizes $\sum_{i=0}^{N-1} |\boldsymbol{x}_i - \boldsymbol{M}\boldsymbol{y}_i|^2$, where N is the training length, may be estimated. It can be shown that

$$\boldsymbol{M} = \boldsymbol{R}_{xy3}\boldsymbol{R}_{yy3}^{-1}, \tag{14}$$

where

$$\boldsymbol{R}_{xy3} = \frac{1}{N}\sum_{i=0}^{N-1} \boldsymbol{x}_i \boldsymbol{y}_i^{\dagger}, \tag{15}$$

$$\boldsymbol{R}_{yy3} = \frac{1}{N}\sum_{i=0}^{N-1} \boldsymbol{y}_i \boldsymbol{y}_i^{\dagger}. \tag{16}$$

During the data transmission period, the data vector is estimated by $\hat{\boldsymbol{x}}_i = \boldsymbol{M}\boldsymbol{y}_i$.

VI. Simulation Results

We assume that both desired and interfering users have 4 transmit antennas and there are 4 receiver antennas. The training sequences are columns of an FFT matrix [3]. This guarantees that the training sequences from different transmit antennas are orthogonal. Both desired and interfering users employ uncoded QPSK. Monte-Carlo simulation is used to evaluate the symbol error rate, and $\text{SIR(dB)} \equiv 10\log\frac{P_s}{P_I}$. We examine a special case of high temporal interference correlation with $\beta = 1$, $T = 1$ and $\tau = 1/2$, where the temporal interference correlation matrix $\boldsymbol{\Lambda}_0$ in (1) is a symmetric Toeplitz matrix with elements

$$\boldsymbol{\Lambda}_{0(i,j)} = \begin{cases} 0.5 & i = j \\ 0.25 & |i-j| = 1 \\ 0 & \text{otherwise} \end{cases} \quad \text{for} \ \ 0 \le i, j \le N-1.$$

Figs. 2 to 4 show symbol error rates for different training lengths. In each figure, symbol error rates with different estimates of channel and spatial interference correlation matrices and different data detection schemes are shown:

- channel and interference are estimated assuming the interference is both spatially and temporally colored (Section III-A), with one-time-slot (curve 1) or two-time-slot (curve 2) detection;
- channel and interference are estimated assuming the interference is spatially colored but temporally white (Section III-B.1), with one-time-slot detection (curve 3);
- channel and interference are estimated assuming the interference is both temporally and spatially white (Section III-B.2), with one-time-slot detection (curve 4).

For reference, we show results for the cases of

- perfectly known channel parameters and interference statistics, with one-time-shot and two-time-shot detection;
- no channel and interference estimation (Section V) (curve 5).

Comparing curves 4 and 5 in Figs. 2 to 4, it is obvious that much lower symbol error rates can be achieved by estimating the channel and interference statistics. In Fig. 2, we observe that with a short training length, it is better to estimate channel and interference statistics by assuming the interference is both spatially and temporally white.

By comparing curves 3 and 4 in Figs. 3 and 4, we see that much gain can be obtained by considering the interference as spatially colored in estimating the channel and interference statistics, and this gain increases as the training length increases.

By examining curves 1 and 3 in Figs. 3 and 4, we observe that the improvement by taking account of temporal interference correlation in *channel estimation* is not significant, and this improvement decreases as the training length increases.

By comparing curves 1 and 2 in Figs. 3 and 4, we observe that the improvement of using two-time-slot detection over one-time-slot detection is not significant either, but this improvement increases as the training length increases. This implies that not much gain can be achieved by taking account of temporal interference correlation in *data detection*.

Fig. 3 shows that, by comparing curves 2 and 4, there is about 2dB gain in SIR by assuming spatially colored interference and taking explicit advantage of known temporal interference correlation in channel estimation and data detection. Most of the savings are due to the estimation of spatial interference correlation.

VII. Conclusions

We have quantified the benefit of taking account of spatial and temporal interference correlation in channel estimation and data detection in a MIMO system. The results show that the improvements in symbol error rates by exploiting temporal interference correlation in channel estimation and data detection are not significant. However, more significant gains may be achieved by estimating the spatial correlation of the interference.

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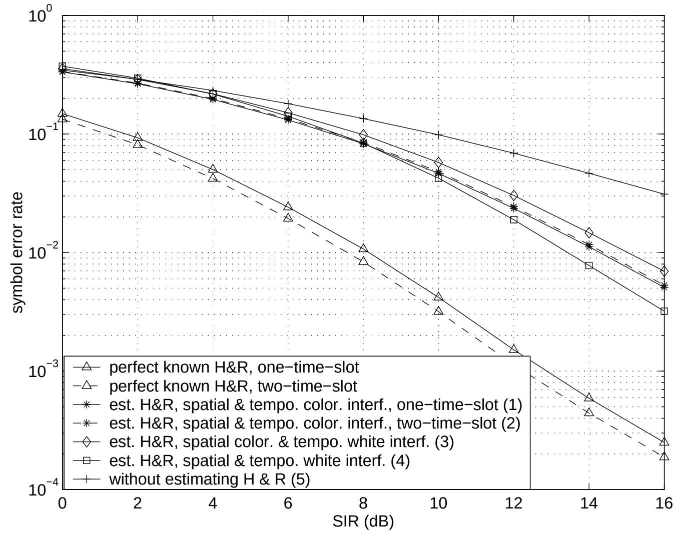

Fig. 2. Symbol error rate versus SIR. The training length is 8, twice the number of transmit antennas.

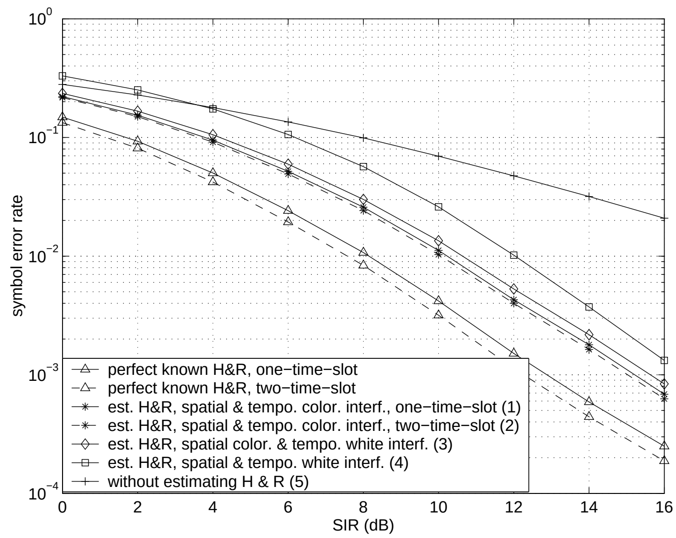

Fig. 3. Symbol error rate versus SIR. The training length is 16, four times the number of transmit antennas.

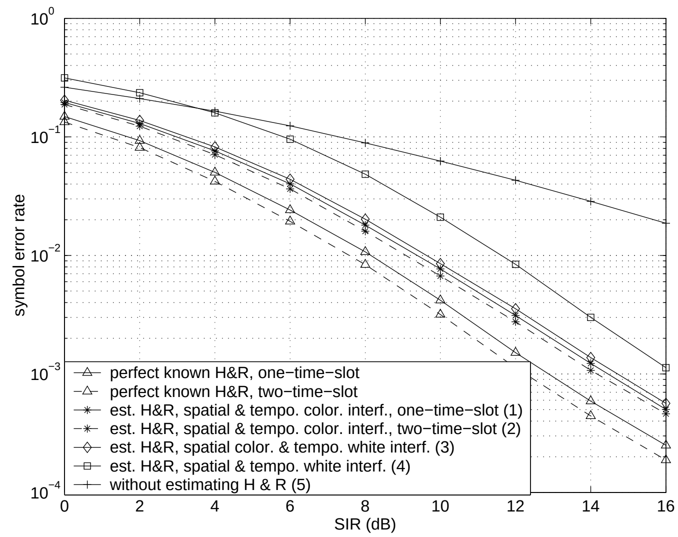

Fig. 4. Symbol error rate versus SIR. The training length is 24, six times the number of transmit antennas.

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