PERFORMANCE ANALYSIS FOR PILOT-EMBEDDED DATA-BEARING APPROACH IN SPACE-TIME CODED MIMO SYSTEMS

Chaiyod Pirak[1,2], *Z. Jane Wang*[1], *and K. J. Ray Liu*[1]

[1]University of Maryland College Park
Department of Electrical & Computer Engineering
College Park, MD, USA. 20742
Email: chaiyod@umd.edu,
wangzhen@glue.umd.edu, kjrliu@eng.umd.edu

Somchai Jitapunkul[2]

[2]Chulalongkorn University
Department of Electrical Engineering
Bangkok, Thailand 10320
Email: somchai.j@chula.ac.th

ABSTRACT

This paper evaluates the performance of the data-bearing approach for pilot-embedding for joint data detection and channel estimation in space-time (ST) coded multiple-input multiple-output (MIMO) systems. Performance measures, such as the minimum mean-squared error (MMSE) of channel estimation, Cramer-Rao lower bound (CRLB), and the Chernoff's bound of the estimated-channel bit error rate (BER) for ST codes, are explored to examine the proposed scheme. The power allocation problem for data and pilot parts is also addressed by optimizing the probability-of-error upper-bound (PEUB) mismatched factor subject to certain constraints. Three kinds of data bearer and pilot structures are investigated via simulations, including time- multiplexing (TM)-based, ST-block-code (STBC)-based, and code- multiplexing (CM)-based data bearer and pilot matrices. Among these three structures, the CM-based scheme provides superior detection performance over the TM-based and the STBC-based schemes for nonquasi-static flat Rayleigh fading channels, while the performances of these three structures are quite close for quasi-static flat Rayleigh fading channels.

1. INTRODUCTION

Recently, the space-time (ST) codes have been studied for MIMO communications [10, 11], where the bit error rate (BER) of the communication systems is significantly improved without increasing transmission power by exploiting transmit diversity [10]. A major challenge in wireless ST communications employing a coherent detector is channel state information acquisition. Typically, the channel state information is acquired or estimated by using a pilot or training signal, a known signal transmitted from the transmitter to the receiver. This technique has been widely applied because it is feasible to implement, and it allows a channel estimator with a low computational complexity [2]. One nonblind or pilot-based MIMO channel estimation were proposed in [1, 9].

Our purpose here is to design a novel pilot-embedding approach for ST coded MIMO systems with affordable computational cost and better fast-fading channel acquisition. The basic idea is to simplify channel estimation and data detection processes by taking advantage of the null-space and orthogonality properties of the data-bearer and pilot matrices. The data-bearer matrix is used for projecting the ST data matrix onto the orthogonal subspace of the pilot matrix. By the virtue of the null-space and orthogonality properties, in our proposed data-bearing approach for pilot-aiding, a block of data matrix is added into a block of pilot matrix, that are mutually orthogonal to each other. The benefit that we are able to expect from this approach is better channel estimation performance, since the estimator can take into account the channel variation in the transmitted data block. We also provide performance analysis of this approach. The minimum mean-squared error (MMSE) of the channel estimation, Cramer-Rao lower bound (CRLB), and the Chernoff's bound of the estimated-channel bit error rate (BER) for ST codes are analyzed for examining the performance of the proposed scheme. The optimum power allocation for the data and the pilot parts is also determined by optimizing the probability-of-error upper-bound (PEUB) mismatched factor subject to a constant block power and an acceptable threshold of the MMSE of the channel estimation.

The rest of this paper is organized as follows. In Section 2, we present MIMO channel and system models first, and then we present the proposed data-bearing approach for pilot-embedding, including channel estimator and data detector. In section 3, performance analysis for the proposed scheme is presented, and the optimum power allocation scheme is discussed in Section 4. The simulation results are shown in Section 5, and we conclude this paper in Section 6.

2. THE DATA-BEARING APPROACH FOR PILOT-EMBEDDING

2.1. MIMO Channel and System Models

We briefly describe the MIMO channel and system models used in this paper. We consider the MIMO communication system with L_t transmit antennas and L_r receive antennas. In general, for a given block index t, a ST symbol matrix $\mathbf{U}(t)$ is an $L_t \times M$ codeword matrix transmitted across the transmit antennas in M time slots. The received symbol matrix $\mathbf{Y}(t)$ at the receiver front-end can be described as follows [10],

$$\mathbf{Y}(t) = \mathbf{H}(t)\mathbf{U}(t) + \mathbf{N}(t), \tag{1}$$

where $\mathbf{H}(t)$ is the $L_r \times L_t$ channel coefficient matrix and $\mathbf{N}(t)$ is the $L_r \times M$ additive complex white Gaussian noise matrix with zero mean and variance $\frac{\sigma^2}{2}\mathbf{I}_{(ML_r \times ML_r)}$ per real dimension. The elements of channel coefficient matrix $\mathbf{H}(t)$ are assumed to be independent complex Gaussian random variables with zero mean and variance 0.5 per real dimension. Or equivalently, an independent Rayleigh fading channel is assumed. Our problems are to estimate the channel coefficient matrix $\mathbf{H}(t)$ and the ST symbol matrix $\mathbf{U}(t)$ by using the pilot or training signal embedded in the ST symbol matrix $\mathbf{U}(t)$.

2.2. The Proposed Scheme

In what follows, we summarize the data-bearing approach for pilot-embedding proposed in [6]. In this approach, the pilot signal is firstly added into the ST data, and then regard this signal combination as the ST symbol. Our motivation of this approach is to distribute the pilot signal onto the ST data in order to capture the variation of the channel at every instant for achieving a better channel estimate. The proposed pilot-embedded ST symbol matrix $\mathbf{U}(t)$ can be expressed as follows,

$$\mathbf{U}(t) = \mathbf{D}(t)\mathbf{A} + \mathbf{P}, \tag{2}$$

This work was supported in part by University Staff Development Scholarship, Commission on Higher Education, Ministry of Education, Thailand.

where $\mathbf{D}(t) \in \mathbb{C}^{L_t \times N}$ is the ST data matrix, $\mathbf{A} \in \mathbb{R}^{N \times M}$ is the data bearer matrix with N being the data time slots, and $\mathbf{P} \in \mathbb{R}^{L_t \times M}$ is the pilot matrix. The necessary properties for the proposed data-bearing approach for pilot-embedding are as follows,

$$\mathbf{A}\mathbf{P}^T = \mathbf{0} \in \mathbb{R}^{N \times L_t}, \mathbf{P}\mathbf{A}^T = \mathbf{0} \in \mathbb{R}^{L_t \times N}, \\ \mathbf{A}\mathbf{A}^T = \beta\mathbf{I} \in \mathbb{R}^{N \times N}, \mathbf{P}\mathbf{P}^T = \alpha\mathbf{I} \in \mathbb{R}^{L_t \times L_t}, \quad (3)$$

where β is a real-valued data-power factor for controlling the data-part power, α is a real-valued pilot-power factor for controlling the pilot-part power, $\mathbf{0}$ stands for an all-zero-element matrix, and $\mathbf{I}$ stands for an identity matrix.

There are three possible structures of data-bearer and pilot matrices, in which the elements of these matrices are real numbers, that satisfy the properties in (3) as follows.

1.) Time-Multiplexing (TM)-Based Matrices

The structures of these matrices are given as

$$\mathbf{A} = \sqrt{\beta}\left[\mathbf{0}_{(N \times L_t)}; \mathbf{I}_{(N \times N)}\right], \\ \mathbf{P} = \sqrt{\alpha}\left[\mathbf{I}_{(L_t \times L_t)}; \mathbf{0}_{(L_t \times N)}\right],\ M = N + L_t, \quad (4)$$

where ; stands for matrix combining. In this structure, the $L_t \times L_t$ identity matrix $\mathbf{I}$ is used as a pilot or training symbol. In addition, this structure are similar to the PSAM concept in [2], because it employs the time-multiplexing structure for pilot and data allocation, and has been used in many literatures [9]. Therefore, the existing PSAM technique is subsumed in the proposed general idea in (2).

2.) ST-Block-Code (STBC)-Based Matrices

The structures of these matrices are given as

$$\mathbf{A} = \sqrt{\beta}\left[\mathbf{0}_{(N \times \tau)}; \mathbf{I}_{(N \times N)}\right], \\ \mathbf{P} = \sqrt{\alpha}\left[\text{STBC}_{(L_t \times \tau)}; \mathbf{0}_{(L_t \times N)}\right],\ M = N + \tau, \quad (5)$$

where τ is the number of time slots used for transmitting one ST block code. In this structure, the major difference from the TM-based structure is that it employs the normalized known ST block code [11] as the pilot symbol instead of using the identity matrix. It also inherits the time-multiplexing structure in pilot and data allocation. This kind of data bearer and pilot matrices have been used in [3], for instance.

3.) Code-Multiplexing (CM)-Based Matrices

The structures of these matrices are given as

$$\mathbf{A} = \sqrt{\beta}\text{WH}[1:N]_{(N \times M)}, \\ \mathbf{P} = \sqrt{\alpha}\text{WH}[N+1:M]_{(L_t \times M)},\ M = N + L_t, \quad (6)$$

where WH$[x:y]$ denotes a sub-matrix created by splitting the $M \times M$ normalized Walse-Hadamard matrix [4] starting from x^{th}-row to y^{th}-row. Unlike the time-multiplexing structure employed for pilot and data allocation in the TM-based and the STBC-based structures, in this structure, the code-multiplexing structure is employed instead. Due to the even distribution inherited from the code-multiplexing structure over the transmitted ST symbol block, we are able to expect superior channel estimation performance over the other two structures. The disadvantage of this structure is the limitation of dimensionality of Walse-Hadamard matrix, which has a dimension proportionally to $2^n,\ n \in \mathbb{I}$. In addition, this structure provides an instructive example of the proposed general idea in (2) for pilot-embedding.

2.2.1. Channel Estimation

The channel estimation procedure can be summarized as follows (please refer to [6]):

1.) Post-multiplying the received symbol matrix $\mathbf{Y}(t)$ in (1), in which (2) is substituted, by the transpose of the pilot matrix $\mathbf{P}^T$; dividing the result by α; and using the properties in (3) to arrive at

$$\mathbf{y}(t) = \mathbf{h}(t) + \mathbf{n}(t), \quad (7)$$

where $\mathbf{y}(t) \triangleq \mathbf{vec}(\frac{\mathbf{Y}(t)\mathbf{P}^T}{\alpha}),\ \mathbf{h}(t) \triangleq \mathbf{vec}(\mathbf{H}(t)),\ \mathbf{n}(t) \triangleq \mathbf{vec}$ $(\frac{\mathbf{N}(t)\mathbf{P}^T}{\alpha})$ with $\mathbf{vec}(\cdot)$ being vectorizing conversion. The second-order statistics of the pilot-projected noise vector $\mathbf{n}(t)$ can be expressed as follows,

$$\boldsymbol{\mu}_{\mathbf{n}(t)} = \mathbf{0}_{(L_t L_r \times 1)},\ \mathbf{V}_{\mathbf{n}(t)} = \frac{\sigma^2}{2\alpha}\mathbf{I}_{(L_t L_r \times L_t L_r)}. \quad (8)$$

where $\boldsymbol{\mu}_{\mathbf{n}(t)}$ and $\mathbf{V}_{\mathbf{n}(t)}$ stand for the mean vector and the covariance matrix of the pilot-projected noise vector $\mathbf{n}(t)$ per real dimension, respectively.

2.) The maximum-Likelihood (ML) channel estimator that maximizes the log-likelihood function $\ln(p(\mathbf{y}(t)|\mathbf{h}(t)))$ is given by

$$\hat{\mathbf{h}}(t) = \mathbf{y}(t) \text{ or } \hat{\mathbf{H}}(t) = \frac{\mathbf{Y}(t)\mathbf{P}^T}{\alpha}. \quad (9)$$

2.2.2. Data Detection

Based on [6], the decoding procedure can be summarized as follows:

1.) Post-multiplying the received symbol matrix $\mathbf{Y}(t)$ in (1), in which (2) is substituted, by the transpose of the data bearer matrix $\mathbf{A}^T$; dividing the result by β; and using the properties in (3) to arrive at

$$\mathbf{Y}_1(t) = \mathbf{H}(t)\mathbf{D}(t) + \mathbf{N}_1(t), \quad (10)$$

where $\mathbf{Y}_1(t) = \frac{\mathbf{Y}(t)\mathbf{A}^T}{\beta}$ and $\mathbf{N}_1(t) = \frac{\mathbf{N}(t)\mathbf{A}^T}{\beta}$. The second-order statistics of the data-bearer-projected noise vector $\mathbf{n}'(t) = \mathbf{vec}(\mathbf{N}_1(t))$ can be expressed as follows,

$$\boldsymbol{\mu}_{\mathbf{n}'(t)} = \mathbf{0}_{(L_r N \times 1)},\ \mathbf{V}_{\mathbf{n}'(t)} = \frac{\sigma^2}{2\beta}\mathbf{I}_{(L_r N \times L_r N)}, \quad (11)$$

where $\boldsymbol{\mu}_{\mathbf{n}'(t)}$ and $\mathbf{V}_{\mathbf{n}'(t)}$ stand for the mean vector and the covariance matrix of the data-bearer-projected noise vector $\mathbf{n}'(t)$ per real dimension, respectively.

2.) The ML receiver is employed by computing the decision matric and deciding the codeword that minimizes this decision matric [10],

$$\{\hat{d}_t^i\} = \min_{\{d_t^i\}}\left\{\sum_{t=1}^{N}\sum_{j=1}^{L_r}|y_t^j - \sum_{i=1}^{L_t}\hat{h}_{j,i}d_t^i|^2\right\}, \\ \forall d_t^i,\ i \in \{1,\ldots,L_t\},\ t \in \{1,\ldots,N\}, \quad (12)$$

where y_t^j denotes the j^{th}-row t^{th}-column element of $\mathbf{Y}_1(t)$ in (10), $\hat{h}_{j,i}$ denotes the j^{th}-row i^{th}-column element of $\hat{\mathbf{H}}(t)$ in (9), and $\hat{d}_t^i$ denotes the i^{th}-row t^{th}-column element of the estimated ST data matrix $\hat{\mathbf{D}}(t)$.

3. THE PERFORMANCE ANALYSIS FOR THE PROPOSED SCHEME

3.1. Channel Estimation Performance Analysis

We analyze the channel estimation error first, and then compare it to the Cramer-Rao lower bound (CRLB), which is widely accepted for performance evaluation of the estimator.

3.1.1. Channel Estimation Error

A channel estimation error vector can be evaluated as follows,

$$\tilde{\mathbf{h}}(t) = \mathbf{h}(t) - \hat{\mathbf{h}}(t). \quad (13)$$

Substituting (9) into (13), the variance matrix of the channel estimation error is given by

$$\text{Var}\left[\tilde{\mathbf{h}}(t)\right] = \mathbf{V}_{\mathbf{n}(t)}. \quad (14)$$

The minimum mean-squared error (MMSE) of the channel estimation is given by

$$\text{MMSE} = \text{trace}\left\{\text{Var}\left[\tilde{\mathbf{h}}(t)\right]\right\} = \frac{\sigma^2 L_t L_r}{\alpha}. \quad (15)$$

3.1.2. Unbiasedness and Cramer-Rao lower bound (CRLB)

Using (9) and $\boldsymbol{\mu}_{\mathbf{n}(t)}$ obtained in (8), the unbiasedness of our proposed channel estimator is given by

$$\mathrm{E}[\hat{\mathbf{h}}(t)] = \mathrm{E}\left[\mathbf{h}(t) + \mathbf{n}(t)\right] = \boldsymbol{\mu}_{\mathbf{h}(t)} \quad (16)$$

where $\boldsymbol{\mu}_{\mathbf{h}(t)}$ represents the mean vector of $\mathbf{h}(t)$. It is clear that our estimator is unbiased, where the expectation vector of our estimator is equal to the mean vector of the channel coefficient vector $\mathbf{h}(t)$.

The CRLB for an unbiased estimator is defined as [8]

$$\begin{aligned}\mathrm{Var}\left[\hat{\mathbf{h}}(t) - \mathbf{h}(t)|\mathbf{h}(t)\right] &= \left[-\mathrm{E}\left[\frac{\partial^2 \ln(p(\mathbf{y}(t)|\mathbf{h}(t)))}{\partial \mathbf{h}^2(t)}\right]\right]^{-1} \\ &= \mathbf{V}_{\mathbf{n}(t)}. \end{aligned} \quad (17)$$

One can see that the channel estimator achieves the desired properties of a good estimator that is unbiased, and achieves the CRLB, i.e. the trace of (17) is equal to (15).

3.2. Data Detection Performance Analysis

Assuming full rank ST codes are employed, which can be relaxed in general, and considering independent Rayleigh distributions of the channel, the Chernoff's upper bound of the average probability of transmitting a codeword $\mathbf{d} \triangleq (d_1^1 d_1^2 \cdots d_1^{L_t} \cdots d_N^1 d_N^2 \cdots d_N^{L_t})^T$ and deciding in favor of a different codeword $\mathbf{e} \triangleq (e_1^1 e_1^2 \cdots e_1^{L_t} \cdots e_N^1 e_N^2 \cdots e_N^{L_t})^T$ is given by [7] (see also [6]),

$$P(\mathbf{d} \to \mathbf{e})_{\hat{\mathbf{H}}(t)} \leq \left(\prod_{i=1}^{L_t} \lambda_i\right)^{-L_r} \left(\frac{\sigma_Q^2}{4\left(\frac{1}{\beta} + \frac{1}{\alpha}\right)\sigma^2}\right)^{-L_t L_r}, \quad (18)$$

where λ_i is the eigenvalue of the code-error matrix $\mathbf{C}(\mathbf{d}, \mathbf{e})$ defined as $C_{p,q} = \mathbf{x}_q^H \mathbf{x}_p$ where $\mathbf{x}_p = (d_1^P - e_1^P, \ldots, d_N^P - e_N^P)^T$ and $\sigma_Q^2 = 1 + \frac{\sigma^2}{\alpha}$ is the variance of the element of the estimated channel coefficient vector $\hat{\mathbf{h}}(t)$.

Notice that (18) involves the variance of the channel estimation error, i.e. $\frac{\sigma^2}{\alpha}$, and the data-bearer-projected noise, i.e. $\frac{\sigma^2}{\beta}$, into its expression; therefore, it completely reveals the underlined effects of pilot- and data-power factors on the probability of error. Hence, this probability of error can be reasonably used as a cost function for optimum power allocation problem.

Let us define the probability of error upper bound (PEUB) mismatched factor between the estimated channel coefficient case and the ideal case where channel coefficients are known [10] as follows,

$$\eta = \ln\left(\frac{P(\mathbf{d}\to\mathbf{e})_{\hat{\mathbf{H}}(t)}}{P(\mathbf{d}\to\mathbf{e})_{\mathbf{H}(t)}}\right) = L_t L_r \ln\left(\frac{P_s\left(\frac{1}{\beta}+\frac{1}{\alpha}\right)}{(1+\frac{\sigma^2}{\alpha})}\right), \quad (19)$$

where P_s is the normalized power allocated to the data part when the channel coefficients are known.

This PEUB mismatched factor is used for performance measure in order to optimally allocate the power to the data and the pilot parts.

4. OPTIMUM POWER ALLOCATION

We now address the power allocation problem in order to optimally allocate the power to the data and the pilot parts. To yield a fair comparison, we assume the constant block power case, where the power of the pilot-embedded ST symbol matrix $\mathbf{U}(t)$ is remained the same for different approaches. We show that the normalized power allocated to the pilot-aided ST symbol matrix $\mathbf{U}(t)$, which is normalized by the transmit antenna numbers L_t, can be expressed as follows,

$$P_s = \frac{\mathrm{E}\left[\|\mathbf{D}(t)\mathbf{A}\|^2\right]}{L_t} + \frac{\mathrm{E}\left[\|\mathbf{P}\|^2\right]}{L_t} = P_s^{'} + P_p = \beta + \alpha, \quad (20)$$

where $P_s^{'} = \beta$ is the normalized power allocated to the data part and $P_p = \alpha$ is the normalized power allocated to the pilot part.

The objective is to minimize the PEUB mismatched factor η in (19) with respect to the pilot-power factor α subject to the constant block power and the acceptable MMSE of the channel estimation constraints. In addition, the acceptable MMSE of the channel estimation is a threshold that indicates the acceptable channel estimation error of the reliable channel estimates, which in turn yield the good probability of error performances. Substituting $\beta = P_s - \alpha$ into (19), the problem formulation is given by

$$\min_{\alpha} \ln\left(\frac{P_s^2}{(\alpha + \sigma^2)(P_s - \alpha)}\right), \quad (21)$$

where MMSE $\leq T$ with T being the acceptable threshold of the MMSE of the channel estimation.

In summary, we propose to determine the optimum pilot-power factor α^* under different signal-to-noise ratio (SNR) scenarios as follows (see also [6]),

$$\alpha^* = \begin{cases} \frac{L_t L_r P_s}{T + 2L_t L_r}; & \text{SNR} < 1 + \frac{2L_t L_r}{T} \\ \frac{P_s - \sigma^2}{2}; & \text{Otherwise.} \end{cases} \quad (22)$$

The acceptable threshold T for the MMSE of channel estimation is usually small and is determined by practice, e.g. the simulation results (in Section 5).

5. SIMULATION RESULTS

We now demonstrate the performance of the proposed data-bearing approach based on simulations. Without loss of generality, we examine a 4×3 orthogonal ST block code of [11]. Three data bearer and pilot structures proposed in Section 2.2 are investigated. The setting parameters of our experiments are: the normalized pilot-embedded ST symbol power is 1 watt/pilot-embedded ST symbol block; the time slots are 8 time slots/pilot-embedded ST symbol block; and the number of transmit antennas is 3. For the nonoptimum power allocation, the data part's power is constantly allocated 80% and the pilot part's power is constantly allocated 20% of the normalized pilot-embedded ST symbol power, according to the results in [9] that the maximum transmission rate is achieved. In addition, 4-PSK modulation is employed in these experiments and the acceptable threshold of the MMSE of the channel estimation is 0.5.

5.1. The Quasi-Static Flat Rayleigh Fading Channel

In this situation, the channel coefficients of the channel coefficient matrix $\mathbf{H}(t)$ in (1) are assumed to be independent complex Gaussian random variables with zero mean and variance 0.5 per real dimension.

In Fig.1, we plot BERs of the pilot-embedded MIMO system with applying the optimum and the nonoptimum power allocation strategies, in comparison with the ideal-channel MIMO system, when 1 and 2-received antennas are employed. In the ideal channel case, the channel coefficients are assumed known, thus it serves as a performance bound. Notice that the optimum power allocation scheme provides better performance than the nonoptimum power allocation scheme. For instance, at BER = 10^{-3}, the SNR differences are about 2 dB for both the 1 and 2-received antenna scenarios. Furthermore, the SNR differences between the case of ideal-channel and the pilot-embedded optimum-power-allocated MIMO systems are about 2.5 dB for both the 1 and 2-received antenna scenarios.

In Fig.2, we plot MMSEs of the channel estimation of the pilot-embedded MIMO system with applying the optimum and the nonoptimum power allocation strategies, when 1 and 2-received antennas are employed. Notice that the MMSEs of the optimum power allocation scheme is less than that of the nonoptimum power allocation scheme for all SNRs. In addition, the MMSEs of the channels estimation of the 2-received antenna scenario are larger than that of the 1-received antenna scenario as explained by referring to (15). Three types of data bearer and pilot matrices yield the same MMSE which coincides with the trace of the CRLB.

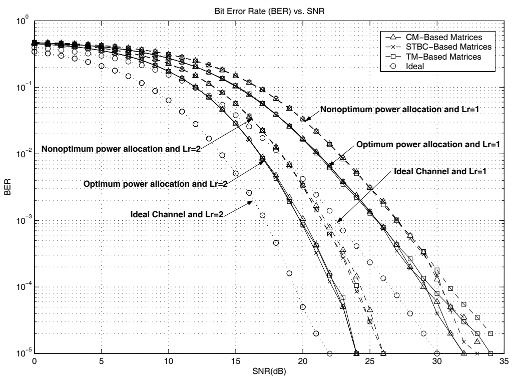

Fig. 1. The graph of BERs in the quasi-static flat Rayleigh fading channel.

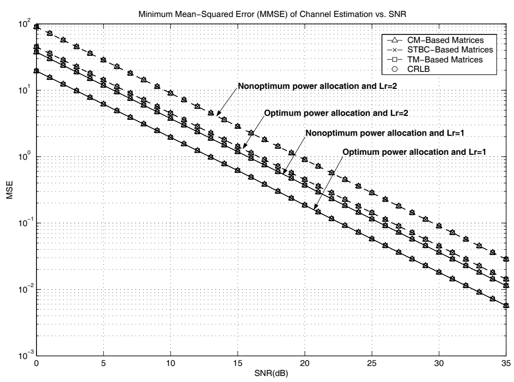

Fig. 2. The graph of MMSEs of the channel estimation in the quasi-static flat Rayleigh fading channel.

5.2. The Nonquasi-Static Flat Rayleigh Fading Channel

In this situation, we consider the situation where the channel coefficient matrix is not constant over the ST symbol block. Without loss of generality, we give an example where the channel coefficient matrix changes twice within one ST symbol block, i.e. there exists $\mathbf{H}_1(t)$ and $\mathbf{H}_2(t)$ in the t^{th}-block ST symbol matrix. In addition, the normalized time-varying channel is modelled as Jakes' model [5], where the Doppler's shifts are changing, i.e. 30, 90, 270, 810, 2430 H_z.

In Fig.3, we plot BERs of the pilot-embedded optimum-power-allocated MIMO system with different Doppler's shifts, where the Doppler's shifts of the normalized time-varying channel are 10, 30, 90, 270, 810, and 2430 H_z. Notice that, when Doppler's shifts are small, e.g. 10, 30 H_z, the probability of detection error of the three types of data bearer and pilot matrices are quite similar; however, when Doppler's shifts are getting larger, e.g. 90, 270, 810, 2430 H_z, the CM-based structure is better than the TM-based and the STBC-based structures, as we anticipated earlier. Since the nonquasi-static flat Rayleigh fading channel is a severe situation, there exist error floors that increase significantly as the Doppler's shift increases, which is resulted from a faster time-varying channel.

6. CONCLUSION

In this paper, we have briefly explained and analyzed the performance of our data-bearing approach for pilot-embedding for joint data detection and channel estimation in ST coded MIMO systems. For quasi-static flat Rayleigh fading channels, the performances of three data bearer and pilot matrices, i.e. the TM-based, STBC-based, CM-based one, are quite similar, where the optimum-power-allocated scheme

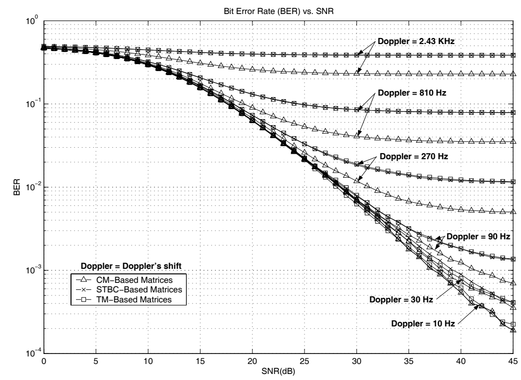

Fig. 3. The graph of BERs of the pilot-embedded optimum-power-allocated MIMO system in the nonquasi-static flat Rayleigh fading channel.

yields better performance than that of the nonoptimum-power-allocated schemes in which the SNR differences are about 2 dB, at BER = 10^{-3}. Furthermore, for nonquasi-static flat Rayleigh fading channels, the CM-based data bearer and pilot matrices show superior performances over the TM-based and STBC-based structures especially under the scenarios with high Doppler's shifts, where the error floors of the former are smaller than the other two. Clearly, from the simulation results, for our specific problem, the optimum power allocation obtained from optimizing the PEUB mismatched factor is better than optimizing solely the MMSE of the channel estimation or the open-loop ergodic capacity, as stated in [9].

7. REFERENCES

[1] C. Budianu and L. Tong, "Channel estimation for space-time orthogonal block codes," *IEEE Trans. Signal Processing*, Vol. 50, pp. 2515-2528, Oct. 2002.

[2] J.K. Cavers, "An analysis of pilot symbol assisted modulation for Rayleigh fading channels," *IEEE Trans. Veh. Technol.*, Vol. 40, pp. 686-693, Nov. 1991.

[3] H. Cheon and D. Hong, "Performance analysis of space-time block codes in time-varying Rayleigh fading channels," in *Proc. IEEE ICASSP*, Vol. 3, pp. 2357-2360, May, 2002.

[4] A.V. Geramita and J. Seberry, *Orthogonal Designs*, Marcel Dekker, INC., NY, 1979.

[5] W.C. Jakes, Jr., "Multipath Interference", in *Microwave Mobile Communication* W.C. Jakes, Jr., Ed., Wiley, NY, pp. 67-68, 1974.

[6] C. Pirak, Z.J. Wang, K.J.R. Liu, and S. Jitapunkul, "A Data-Bearing Approach for Pilot-Embedding in Space-Time Coded MIMO Systems," submitted to *IEEE Trans. Wireless Communications* 2004.

[7] J.G. Proakis, *Digital Communications, 3rd ed.*, McGraw-Hill, INC., NY, 1995.

[8] A.P. Sage and J.L. Melsa, *Estimation Theory with Applications to Cimmunications and Control*, McGraw-Hill, INC., NY, 1971.

[9] D. Samardzija and N. Mandayam, "Pilot-assisted estimation of MIMO fading channel response and achievable data rates," *IEEE Trans. Signal Processing*, Vol. 51, pp. 2882-2890, Nov. 2003.

[10] V. Tarokh, N. Seshadri, and A.R. Calderbank, "Space-time codes for high data rate wireless communication: performance criterion and code construction," *IEEE Trans. Infor. Theory*, Vol. 44, pp. 744-765, Mar. 1998.

[11] V. Tarokh, N. Seshadri, and A.R. Calderbank, "Space-time block codes from orthogonal designs," *IEEE Trans. Infor. Theory*, Vol. 45, pp. 1456-1467, Jul. 1999.