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Channel Prediction in MIMO-OFDM Wireless Systems by Exploiting Spatio-Temporal Correlations

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Abstract: ***Channel prediction is an appealing technique to mitigate the performance degradation due to the inevitable feedback delay of the channel state information (CSI) in modern wireless systems. In the existing method, the 2-step algorithm fixes the prediction order, which first exploits temporal correlation temporal correlation and then follows spatial correlation. Our proposed method is selected flexibly from both spatial and temporal domains. We first propose a general MIMO-OFDM channel prediction framework, so that both the spatial and temporal correlation among antennas is exploited. Then our proposed predictor, reduced complexity FSS algorithm selects data for auto regressive (AR) predictor according to the proposed framework and chooses the data in heuristic way, which aims to reduce the computational complexity. An application to our algorithm is discussed to improve the precoding performance in multi-user MIMO-OFDM systems. Simulation results show that the proposed reduced complexity fss method can perform better even in the presence of feedback delay.***

Keywords: MIMO-OFDM, channel prediction, spatial temporal correlation, AR model

1. Introduction

Multiple input multiple output orthogonal frequency division multiplexing (MIMO-OFDM) is considered to be a most important technique for wireless systems, which can provide high spectral efficiency and also high data rate transmission over frequency selective channels [1]. Recently, adaptive multi-user resource allocation [2] and precoding [3] techniques are introduced to modern MIMO-OFDM systems to further improve the spectral efficiency and the system performance. However, the benefit of these techniques significantly depends up on the exact (to some level) channel state information (CSI) at the transmitter [4]. In frequency division duplex (FDD) systems, CSI can only be estimated at the receiver and then be fed back to the transmitter. While in mobile environments with the time varying channel, the CSI fed back to the transmitter would be outdated due to the feedback delay, which results in significant performance degradation. An effective mean to overcome the feedback delay is the channel prediction technique discussed in this paper, which predicts future channel coefficients based on the history data.

2. Existing System

Existing system is a lower complexity 2-step prediction algorithm, which first exploits temporal correlations using a classical single-input single-output (SISO) MMSE time domain prediction filter for each entry in the MIMO channel, followed by an MMSE spatial smoothing step to exploit the spatial correlations. Compared to the SISO and specular prediction approaches, this approach either achieves lower MSE with a slight increase in complexity, or comparable MSE with lower complexity, in a wide range of wireless channel conditions.

Disadvantages of Existing System:
The existing method, the 2-step algorithm fixes the prediction order, which first exploits temporal correlation by a SISO MMSE time-domain predictor, and then follows by an MMSE spatial predictor to exploit the spatial correlation.

The proposed algorithms are an extension work from [29]. We give more detailed analysis and simulation results in this paper. Furthermore, we present an appealing application of the proposed prediction algorithms, which can improve the precoding performance in MU-MIMO systems.

The rest of this paper is organized as follows. Section. In section III, describes the MIMO-OFDM system used in this paper. In section IV, we develop a general framework for spatial-temporal MIMO-OFDM channel prediction. In section V, prediction algorithms are presented. Their applications in multi-user precoding methods are presented in Section VI. Performance analysis and simulation results are provided in Section VII. Finally, we conclude the paper with some remarks in section VIII.

3. MIMO-OFDM System Model

OFDM System Model
Consider a MIMO-OFDM system with M transmit antennas, N receive antennas, and K subcarriers. At the transmitter, the transmitted symbol $Xm(i, k)$ is transformed into the time domain signal at the m-th transmit antenna, i-th symbol time and the k-th subcarrier using IFFT [29], [30]. Then, a cyclic prefix (CP) is inserted to avoid inter-symbol interference. At the receiver, the CP is removed before the FFT process. We assume that the CP is greater than the maximum delay spread of channel, and the time and frequency synchronization is perfect, such that the received symbol at the n-th receive antenna can be represented as

$$Y_n(i,k) = \sum_{m=1}^{M} H_{n,m}(i,k)X_m(i,k) + Z_n(i,k), \qquad (1)$$

where $Hn,m(i, k)$ is the frequency response of the channel impulse response (CIR) at the k-th subcarrier and the i-th symbol time for the (m, n)-th antenna pair. $Zn(i, k)$ is the background noise plus interference term of the n-th receive antenna, which can be approximated as a zero mean additivewhite Gaussian noise (AWGN) with variance $\sigma 2Z$

4. Spatial-Temporal Channel Prediction Framework

As indicated in [12], the time-domain predictor in OFDM systems has better MSE performance than the frequency domain predictor while maintaining a low complexity. Thus, we adopt the time-domain prediction approach (cf. Fig. 1) in this paper, which is an extension for MIMO-OFDM channel from the SISO model in [13].Firstly, the time-domain channel coefficient of every channel pair (m, n) can be estimated by conventional methods ,e.g. IFFT with interpolation, reduced LS and LMMSE [34],[35]. For instance, a K-points IFFT can be used to do the frequency-time transformation job in Fig. 1,

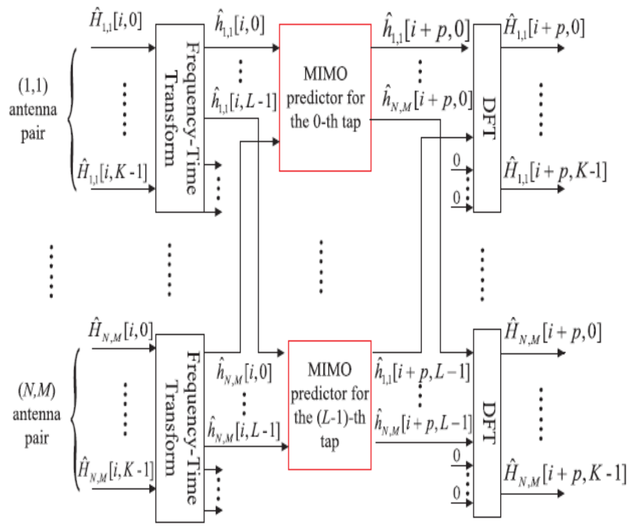

Figure 1: System model of the spatial-temporal MIMO-OFDM channel prediction.

Firstly, the time-domain channel coefficient of every channel pair (m, n) can be estimated by conventional methods, e.g. IFFT with interpolation, reduced LS and LMMSE [34] ,[35]. For instance, a K-points IFFTcan be used to do the frequency-time transformation job in Fig.1,

$$\hat{h}_{n,m}(i,l) = \frac{1}{K}\sum_{k=0}^{K-1} \hat{H}_{n,m}(i,k)e^{j2\pi lk/K}$$
$$= \begin{cases} h_{n,m}(i,l) + z_{n,m}(i,l) & l = 0,\ldots,L-1 \\ z_{n,m}(i,l) & l = L,\ldots,K-1. \end{cases}$$

Here, we suppose the channel delay $\tau n,m(l)$ of every tapis an integer multiple of sampling interval. Then, all of the energy from the path will be mapped to the zero to L –1taps. In that case, it can be easily proved that $zn,m(i, l)$ is also a zero mean AWGN with variance $\beta^2 = \sigma_z'^2/K$

Subsequently, a MIMO predictor is performed to predict the time domain channel impulse response $hn,m(i+p, l)$ for each delay $l = 0, \ldots, L-1$, where $L-1$ represents the channel's maximum delay, and p denotes the prediction length. Due to the WSSUS property, as mentioned earlier, $hn,m(i + \Delta i, l)$and $h_{n',m'}(i,l')$ are uncorrelated for $l \neq l'$. Therefore, the MIMO predictor for the l-th tap only needs to consider the corresponding tap of every channel pair (m, n) (as other taps are uncorrelated with the predicted tap, they are useless for prediction). Thus the multi-carrier MIMO prediction problem is transformed to the single-carrier MIMO prediction problem in this step.

5. Prediction Algorithms

The MIMO predictor showed in the red box of Fig.1 is discussed in detail in this section. We begin with the AR model, which can capture most of the fading dynamics [13].In fact, a thorough comparison of different channel prediction algorithms is performed in [12]. Their conclusion is that the AR approach outperforms other prediction modeling for measured channels. Define p as the prediction length. For every tap of the channel, Q current and previous estimated coefficients of the channel are considered. Denote

$$\hat{\mathbf{h}}_{n,m}(i,l) = [\hat{h}_{n,m}(i,l), \hat{h}_{n,m}(i-1,l), \ldots, \hat{h}_{n,m}(i-Q+1,l)]^T.$$

To predict $\hat{h}^{pre}_{n,m}(i+p,l)$ the data set ˆ**h** is utilized, where

$$\hat{\mathbf{h}} = [\hat{\mathbf{h}}_{1,1}(i,l)^T, \hat{\mathbf{h}}_{1,2}(i,l)^T, \ldots, \hat{\mathbf{h}}_{1,M}(i,l)^T, \hat{\mathbf{h}}_{2,1}(i,l)^T, \ldots, \hat{\mathbf{h}}_{N,1}(i,l)^T, \ldots, \hat{\mathbf{h}}_{N,M}(i,l)^T]^T.$$

A. Extreme predictors

We first introduce two extreme prediction methods, which will be helpful to introduce our algorithms.

1) SISO predictor: A traditional prediction algorithm is called the SISO predictor [26], which ignores the spatial correlation and only considers the temporal correlation. To predict $\hat{h}^{pre}_{n,m}(i+p,l)$ the data set $\hat{\mathbf{h}}_{n,m}(i,l)$ is used with a Q-order MMSE filter **w**s as

$$\hat{h}^{pre}_{n,m}(i+p,l) = \mathbf{w}_s^H \hat{\mathbf{h}}_{n,m}(i,l)$$

Where

$$\mathbf{w}_s = \arg\min_{\mathbf{w}_s} E\{\|h_{n,m}(i+p,l) - \mathbf{w}_s^H \hat{\mathbf{h}}_{n,m}(i,l)\|^2\}$$

$$\mathbf{w}_s = (\mathbf{R}_s + \beta^2\mathbf{I})^{-1}\mathbf{r}_s$$

Where **R**$s$is the Hermitian-symmetric and Toeplitz $Q \times Q$ temporal autocorrelation matrix with entries

$$[\mathbf{R}_s]_{i,j} = r_t((i-j)T_s),$$
$$\mathbf{r}_s = [r_t(pT_s), \ldots, r_t((P+Q-1)T_s)]^T$$

The MSE is given by

$$\varepsilon_s = r_t(0) - \mathbf{r}_s^T(\mathbf{R}_s + \beta^2\mathbf{I})^{-1}\mathbf{r}_s$$

2) All-correlation predictor: Then, we introduce the prediction algorithm at the other extreme: all-correlation predictor, which exploits all the possible spatial-temporal correlations [18]. This method is also a general case of JST filtering method [28]. The JST filtering in [28] assumes that

different transmit antennas are uncorrelated and only considers the spatial correlation of receive antennas, while the all-correlation predictor considers both the temporal and spatial correlations. The data set h is used to predict ˆhpren,m(i+p,l), where a $M \times N \times Q$-order MMSE filter $\mathbf{w}_{2D}$ is applied as

$$\hat{h}^{pre}_{n,m}(i+p,l) = \mathbf{w}^H_{2D}\hat{\mathbf{h}}.$$

Similarly, we can get w2D in the SISO predictor's way. Using the orthogonal principle, the all-correlation predictor should satisfy $E\{(h_{n,m}(i+p,l) - \mathbf{w}^H_{2D}\hat{\mathbf{h}})^*\hat{\mathbf{h}}\} = \mathbf{0}.$

After some simplifications, we have

$$\mathbf{w}_{2D} = (\mathbf{R}_s \otimes \mathbf{R}_{MIMO} + \beta^2\mathbf{I})^{-1}(\mathbf{r}_s \otimes \mathbf{R}^{(N*(m-1)+n)}_{MIMO})$$

where $\mathbf{R}^{(N*(m-1)+n)}_{MIMO}$ denotes the $(N*(m-1)+n)$-th column of $\mathbf{R}_{MIMO}$. And the MSE is

$$\varepsilon_{2D} = r_t(0) - (\mathbf{r}_s \otimes \mathbf{R}^{(N*(m-1)+n)}_{MIMO})^T(\mathbf{R}_s \otimes \mathbf{R}_{MIMO} + \beta^2\mathbf{I})^{-1}(\mathbf{r}_s \otimes \mathbf{R}^{(N*(m-1)+n)}_{MIMO}).$$

Since the all-correlation predictor exploits all the possible spatial and temporal correlations, we can expect that it outperforms the SISO predictor when the spatial correlation is present. However, the $M \times N \times Q$-order AR model requires a huge computation compared with the Q-order AR model. So we need a tradeoff between the prediction precision and the computational complexity, which is the motivation of the proposed algorithms in the following.

B. Forward-stepwise subset (FSS) predictor

A reduced order AR predictor is proposed in this subsection, which aims to reduce the computational burden of the all correlation predictor. In this algorithm, the observations are not considered to be equally important for prediction. Some observations just offer little information for the AR model. Particularly, if a datum is independent with the predicted datum, then the datum has no help for prediction. Therefore we come up with the idea that the most helpful data can be chosen to create the AR prediction model, considering both the spatial and temporal correlations. The key problem remained is how to measure the helpfulness of each datum. Suppose we have already chosen Q' data from ˆ**h**, where Q' is a tradeoff between the prediction precision and complexity, to form a $Q' \times 1$ vector ˜**h**. The prediction AR model is

$$\hat{h}^{pre}_{n,m}(i+p,l) = \mathbf{w}^H_B\tilde{\mathbf{h}}$$

According to the MMSE criterion, we get

$$\mathbf{w}_B = \arg\min_{\mathbf{w}} E\{\|h_{n,m}(i+p,l) - \mathbf{w}^H_B\tilde{\mathbf{h}}\|^2\}$$

Similarly, using the orthogonal principle, (23) can be written as

$$\mathbf{w}_B = E[\tilde{\mathbf{h}}\tilde{\mathbf{h}}^H]^{-1}E[h_{n,m}(i+p,l)^*\tilde{\mathbf{h}}],$$

where the MSE is

$$\varepsilon_B = r_t(0) - E[h_{n,m}(i+p,l)\tilde{\mathbf{h}}^*]^T E[\tilde{\mathbf{h}}\tilde{\mathbf{h}}^H]^{-1}E[h_{n,m}(i+p,l)\tilde{\mathbf{h}}^*]$$

Since the proposed prediction algorithm exploits the most useful observations, it outperforms the SISO prediction algorithm even using the same order of AR model. However, the process of data choosing is a huge computational burden. An inversion of $k \times k$ matrix is needed to measure the MSE in the k-th step. In total, $(2MNQ - Q')Q'/2$ computations are needed to find the optimal model.

C. Reduced-complexity FSS predictor In this subsection, a prediction algorithm is introduced which aims to further reduce the computational complexity of FSS method. The key idea is to select the data incrementally for prediction from the correlation's view. If the new observation has a high correlation with the selected data in previous steps, then the new observation cannot provide more new information and may help little. Therefore, the considering value $\tilde{h}_k$ in the k-th step can be chosen by the analysis of the selected data $[\tilde{h}_1, \ldots, \tilde{h}_{k-1}]$. Based on this idea, the k-th element is chosen as follows.

First-step: according to MMSE criterion and AR model $\hat{h}^{pre}_{n,m}(i+p,l) = \mathbf{w}^H_R\tilde{\mathbf{h}}$ we get $\mathbf{w}_R$, where $\tilde{\mathbf{h}} = [\tilde{h}_1, \ldots, \tilde{h}_{k-1}]^T$

Second-step: define *residual* $= h_{n,m}(i+p,l) - \mathbf{w}_R^H\tilde{\mathbf{h}}$, the $\tilde{h}_k$ is the selected data which is most correlated with the *residual*. The complete prediction algorithm which aims to create the Q'-order desired AR model The proposed reduced-complexity FSS predictor reduces the times of computing MSE to Q', and only needs one timeinversion of a $Q' \times Q'$ matrix in each selection.

6. The Application of Proposed Prediction Methods

To further investigate the application of the proposed prediction methods, the multi-user MIMO-OFDM (MU-MIMOOFDM) system with precoding is considered in this section. In this section, we will apply the proposed reduced-complexity FSS predictor to overcome the outdated problem (cf. Fig. 2).Suppose there are P users communicating with the BS simultaneously. User $p(p = 1, \ldots, P)$ has N_p receive antennas. The predicted channel matrix of BS to the p-th user at the k-th subcarrier and the i-th symbol time can be represented

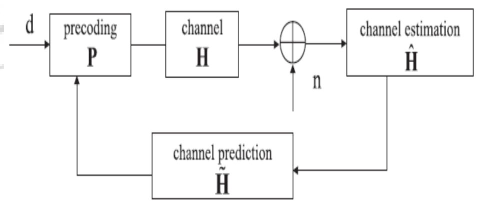

Figure 2: A MU-MIMO-OFDM system with predicted precoding

by the $N_p \times M$ channel matrix

$$\tilde{\mathbf{H}}_p(i,k) = \begin{pmatrix} \tilde{H}^1_{p,1}(i,k) & \ldots & \tilde{H}^1_{p,M}(i,k) \\ \vdots & \ddots & \vdots \\ \tilde{H}^{N_p}_{p,1}(i,k) & \ldots & \tilde{H}^{N_p}_{p,M}(i,k) \end{pmatrix}$$

where $\tilde{H}^j_{p,m}(i,k)$ denotes the predicted frequency response of the channel impulse response (CIR) at the k-th subcarrier, the *i*-th symbol time and the (*j*,*m*)-th antenna pair of user *p*. Define the whole predicted channel as

$$\tilde{\mathbf{H}}(i,k) = [\tilde{\mathbf{H}}_1^T(i,k), \ldots, \tilde{\mathbf{H}}_P^T(i,k)]^T$$

And **P**(*i*, *k*) is the precoding matrix at the *k*-th subcarrier and the *i*-th symbol.

In order to validate the performance improvement of the proposed prediction method, three classic MU-MIMO precoding schemes [36] are used as follows based on the predicted channel coefficients.

A. Zero Forcing

In the ZF scheme, **P**(*i*, *k*) is chosen such that each user receives no interference from other users,

B. MMSE

The MMSE precoding scheme can be considered as an improvement of ZF

C. Block Diagonalization

The block diagonalization (BD) scheme can be considered as a generalization of channel inversion for situations with multiple antennas per user.

7. Performance Analysis And Simulations

A. Prediction Performance of Different Spatial Correlation Cases

We investigate the effect of spatial correlation on predictors in this subsection. A 2 × 2 MIMO-OFDM system is considered in Fig. 3-6. In order to show the effect of the spatial correlation, we consider the high, medium and low correlation cases one by one. As the velocity increases, the time correlation decreases and the spatial correlation is more significant for the prediction method. The performance difference of SISO method and the proposed methods in Fig. 3 where Doppler frequency is 70 Hz is bigger compared with Fig. 5 whose Doppler frequency is 5 Hz. To show the benefit of spatial correlation brings, we choose a middle velocity scenario whose Doppler is frequency 70 Hz. In Fig. 3, Fig. 4, and Fig. 5, the all-correlation approach has the lowest NMSE among all the algorithms for all parameter configurations.

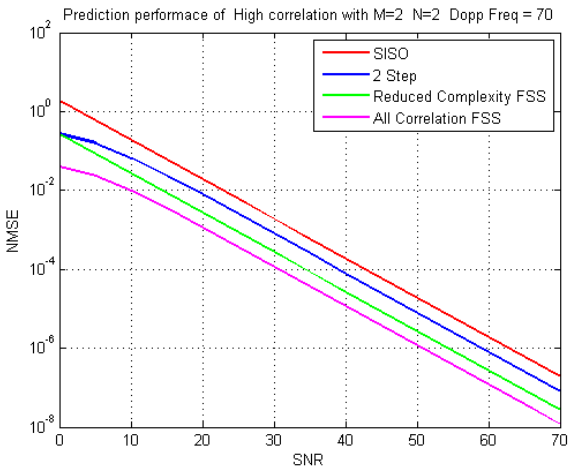

Figure 3: Prediction performance of a high correlation scenario ,M = 2,N = 2, doppler frequency is 70 Hz.

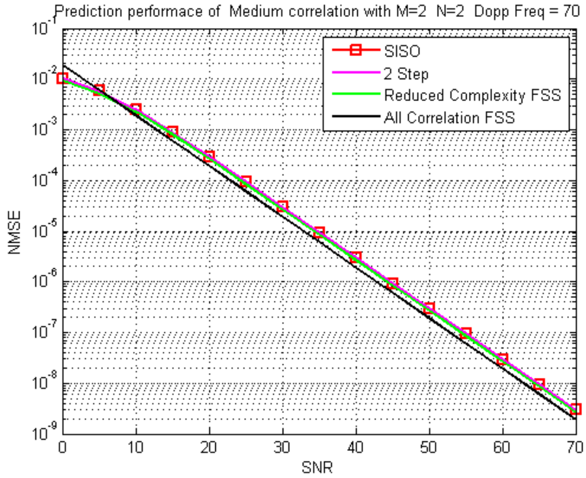

Figure 4: Prediction performance of a medium correlation scenario ,M = 2,N = 2, doppler frequency is 70 Hz.

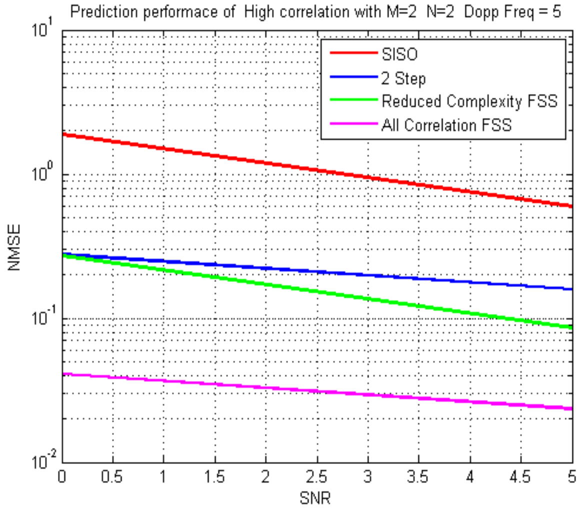

Figure 5: Prediction performance of a high correlation scenario ,M = 2,N = 2, doppler frequency is 5 Hz.

Our proposed prediction methods and 2-step method outperform the SISO approach, which proves that the spatial correlation is really helpful. It is also observed that the proposed method perform better than 2-step algorithm, particularly when the SNR is low. Medium correlation scenario is considered in Fig. 4. It can be seen that proposed algorithm and the 2-step method outperform the SISO method slightly, and the performances of the proposed algorithms lie between the 2-step and all-correlation methods. It is observed that exploiting the spatial correlation has a little help to improve the prediction performance, when the spatial correlation is low.

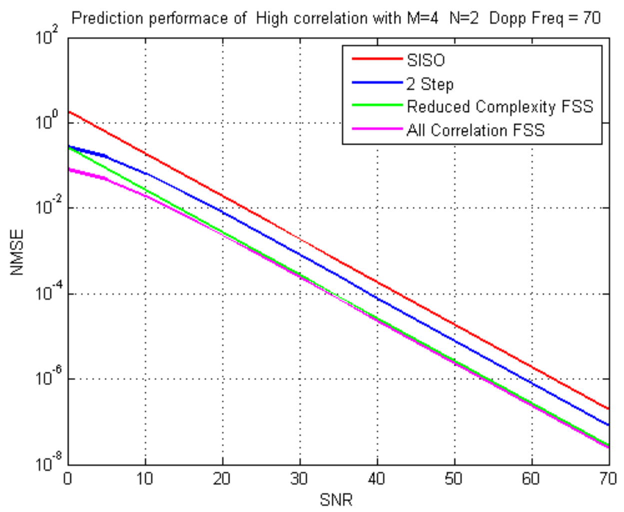

Figure 6: Prediction performance of a medium correlation scenario ,$M = 4, N = 2$, doppler frequency is 70 Hz.

Furthermore, when the spatial correlation is zero and only the temporal correlation exists, the all correlation, 2-step and proposed method degrade to the SISO method.

B. Uncoded BER Performance of Precoding with the Reduced-complexity FSS Predictor

We finally investigate the uncoded bit error rate (BER) performance of the overall MU-MIMO-OFDM system with precoding using predicted channel coefficients of the proposed reduced complexity FSS predictor, the results are showed in Fig.7 and Fig.8. The outdated error caused by the feedback delay is acceptable, when the channel changes slowly. However, when the channel changes rapidly, the outdated error results in significant performance degradation, So, we expect to improve the precoding utilizing the predicted channel information. Three classic precoding methods (ZF, BD, and MMSE) with the reduced-complexity FSS predictor are tested to evaluate the performance improvement In the simulations, two users are considered to form a MU-MIMO group, and each user has two receive antennas.

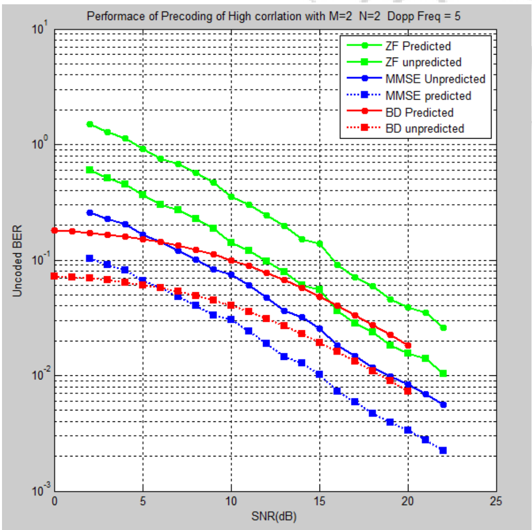

Figure 7: Performance of precoding with predicted channel coefficient of a high correlation scenario, $P = 2, M = 4, Np = 2$, doppler frequency is 5 Hz.

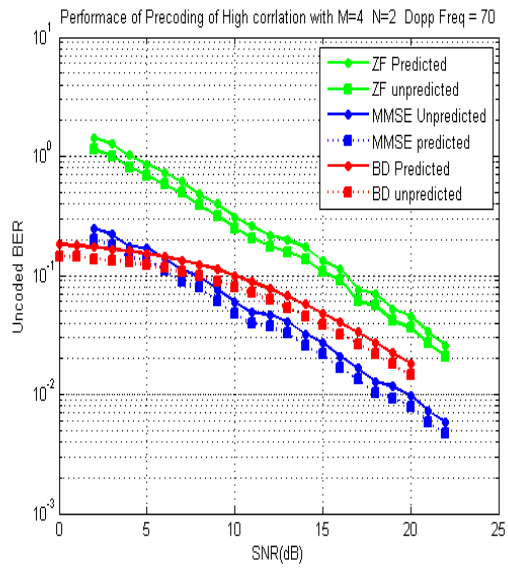

Figure 8: Performance of precoding with predicted channel coefficient of a high correlation scenario , $P = 2, M = 4, Np = 2(p = 1, 2)$, doppler frequency is 70 Hz. The base station is equipped with eight transmitted antennas. Slow velocity scenario with Doppler frequency 5 Hz is used in Fig. 7. It is showed that the performance of all the considered precoding methods (ZF, BD, and MMSE) which exploit the predicted channel coefficient are only slightly better than those corresponding unpredicted precoding methods'. However, in Fig. 8 with the Doppler frequency 70 Hz, it is illustrated that the precoding schemes which using the predicted channel coefficient outperform than those corresponding unpredicted precoding methods.

8. Conclusion

There are two main contributions in our work. First, we derive a novel channel prediction framework for MIMO OFDM systems which takes both spatial and temporal correlations into account. Second, we propose MIMO prediction algorithm which select the useful data for AR modeling.

Simulation results show that the prediction performance can be effectively improved by exploiting the spatial correlation, especially when the spatial correlation is relatively high.

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