Statistical Prefiltering for MMSE and ML Receivers with Correlated MIMO Channels

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***Abstract*-The performance of wireless MIMO systems is known to suffer significantly from fading correlation between the antenna elements in a poor scattering environment if the transmitter is non-adaptive. However, acquiring accurate short-term channel state information to control TX adaptivity can be a serious problem, in particular in FDD systems. Thus, we are proposing statistical linear transmit prefiltering schemes for MMSE and ML detection in the receiver that are solely based on long-term channel state information. It is demonstrated that long-term adaptive prefiltering can achieve a significant gain over non-adaptive (blind) transmission. Prefiltering for ML detection in a strongly correlated channel is shown to yield almost the same performance as the blind scheme in an uncorrelated channel. Moreover, exploiting long-term properties of the channel is especially appealing in terms of computational complexity and channel estimation, as the long-term channel estimation process can be carried out in a wide time window.**

I. Introduction

In this paper, we study long-term channel state information (CSI) based linear transmit prefiltering with correlated MIMO channels for minimum mean squared error (MMSE) and maximum likelihood (ML) receivers. This work is motivated by results on correlated multiple input multiple output (MIMO) channel capacity with long-term CSI based waterfilling at the transmitter (cf. [1][2][15]). It has been shown that the performance penalty due to long-term processing in terms of ergodic channel capacity compared to the short-term case is only minor if adequate statistical waterfilling algorithms are employed at the transmitter.

Several system proposals, including e.g. antenna subset selection ([3]) and linear prefiltering based on a mean squared error (MSE) criterion (cf. [4][5][6]), have demonstrated that the performance in terms of bit error rate (BER) of MIMO wireless systems can significantly be improved by exploiting CSI at the transmitter. The focus so far has been mainly on MIMO channels with uncorrelated fading between the antenna elements and short-term (ST) CSI at the transmitter, where by short-term CSI we mean information on the fast fading channel state. However, especially in outdoor scenarios the assumption of independent fading can certainly not be fulfilled. In particular at the base station there is normally a low angular spread (AS) causing high fading correlation, while the mobile station experiences a richer scattering scenario with vanishing correlation.

Furthermore, the requirement of accurate ST CSI at the transmitter is hard to fulfill in a real system. One example would be a low mobility TDD system, where the channel state estimated in receive direction may be assumed to be stable enough to be still valid for the following transmit cycle. Given a FDD system, however, the short-term fading states of uplink and downlink are not interrelated. In this case, the TX CSI is restricted to statistical long-term (LT) CSI that is determined by the large scale scattering environment, which shall be assumed to be changing only on a long-term time-scale. Statistical TX CSI can be accurately determined e.g. via low rate feedback from the receiver or via frequency transformation of the TX antenna array correlation matrix.

After recapitulating two underlying performance measures for MMSE and ML detection, namely the MSE and the pairwise error probability (PEP), respectively, we give two simple bounds on these quantities in a correlated Rayleigh fading environment. Based on these bounds, we derive the optimum statistical linear matrix prefilters. The potential of statistical prefiltering with correlated MIMO channels is then demonstrated in simulations. There is a noticeable performance improvement due to the prefiltering operation. Especially the gain in case of prefiltering with ML detection is significant. In a strongly correlated channel, the proposed scheme can achieve a performance similar to that of an equivalent non-adaptive MIMO system with vanishing fading correlation.

In section II, we are introducing the signal and channel model that is the basis of our work. Section III presents performance results without transmit prefiltering in semi-correlated channels for MMSE and ML MIMO receivers. Statistical linear prefiltering is derived and simulation results are presented in sections IV and V.

II. Signal And Channel Model

We consider a flat fading MIMO link modeled by

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$$\mathbf{y} = \mathbf{HFs} + \mathbf{n} \,, \qquad (1)$$

where $\mathbf{s}$ is the L×1 TX symbol vector, $\mathbf{F}$ is a M_{TX}×L TX linear matrix filter that maps L TX symbols on M_{TX} transmit antennas, $\mathbf{H}$ is the M_{RX}×M_{TX} MIMO channel matrix, $\mathbf{n}$ is the M_{RX}×1 noise vector, $\mathbf{y}$ is the M_{RX}×1 receive vector (see Fig. 1). L is the number of independent subchannels (L symbols are transmitted in parallel), M_{RX} is the number of RX antennas, and M_{TX} is the number of TX antennas.

A linear or nonlinear receiver can detect (ML) or estimate (MMSE), respectively, the symbol vector $\hat{\mathbf{s}}$ from the received signal vector $\mathbf{y}$. In the following we denote the noise covariance matrix by $\mathbf{R}_{nn}$ and the TX signal covariance is generally given by $\mathbf{R}_{ss}$.

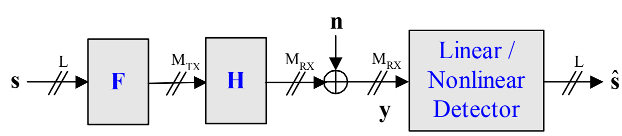

Fig. 1: System model with linear precoding

With common assumptions on the MIMO propagation model given e.g. in [2][7], the correlated channel can mathematically be described by the matrix product

$$\mathbf{H} = \mathbf{A}^H \mathbf{H}_w \mathbf{B} \,, \qquad (2)$$

where $\mathbf{H}_w$ is a M_{RX}× M_{TX} matrix of complex i. i. d. Gaussian variables of unity variance and

$$\mathbf{AA}^H = \mathbf{R}_{RX} \qquad \mathbf{BB}^H = \mathbf{R}_{TX} \,, \qquad (3)$$

where $\mathbf{R}_{RX}$ and $\mathbf{R}_{TX}$ is the long-term stable (normalized) receive and transmit correlation matrix, respectively.

III. Blind Transmission

The performance of MIMO systems employing MMSE and ML receivers with transmitters devoid of any CSI shall be studied in this section. In this case, the best the transmitter can do is transmitting independent data streams, each via a different transmit antenna. We will refer to this scenario as blind transmission. Note that in this case we have $\mathbf{F} = \mathbf{I}_{M_{TX}}$ if we transmit a different symbol on each TX antenna, i.e. L=M_{TX}, where $\mathbf{I}_{M_{TX}}$ is an identity matrix of size M_{TX}× M_{TX}.

Assuming full instantaneous channel knowledge at the receiver, the optimum receive matrix filter $\mathbf{G}_{opt}$ that minimizes the mean squared error between RX and TX signal is given by the well known MMSE solution (cf. [8])

$$\mathbf{G}_{opt} = \left(\mathbf{R}_{ss}^{-1} + \mathbf{F}^H \mathbf{H}^H \mathbf{R}_{nn}^{-1} \mathbf{HF}\right)^{-1} \mathbf{F}^H \mathbf{H}^H \mathbf{R}_{nn}^{-1} \qquad (4)$$

and the vector $\hat{\mathbf{s}}$ that is used for subsequent detection reads

$$\hat{\mathbf{s}} = \mathbf{G}_{opt} \mathbf{y} \,. \qquad (5)$$

On the other hand, the nonlinear ML receiver directly detects the symbol vector (assuming Gaussian noise) via

$$\hat{\mathbf{s}} = \arg \min_{\mathbf{s}_k} \left(\mathbf{y} - \mathbf{HFs}_k\right)^H \mathbf{R}_{nn}^{-1} \left(\mathbf{y} - \mathbf{HFs}_k\right), \qquad (6)$$

where $\mathbf{s}_k$ is the hypothesized TX symbol vector. The search for the minimum is over all Q^L possible TX vectors with the constellation size Q and the number of independent subchannels L.

All correlated fading simulations presented in this paper are based on the following assumptions, if not explicitly stated otherwise. We are considering uncoded QPSK transmission on the subchannels. The noise at the RX is additive white Gaussian (AWGN) and we assume unity power symbols, i.e. $\mathbf{R}_{nn}$ and $\mathbf{R}_{ss}$ are (scaled) identity matrices. For each channel use, a new random channel matrix is determined via (2), while the correlation matrices $\mathbf{R}_{RX}$ and $\mathbf{R}_{TX}$ are constant, i.e. the large-scale scattering environment does not change. Both RX and TX arrays are uniform linear (ULA) and have an antenna element spacing of 0.5 wavelengths.

The receiver is assumed to be surrounded by a huge number of scatterers, resulting in an angular spread (AS) of 360 degrees with equally distributed power. We note that under this assumption the fading between the RX antenna elements is approximately uncorrelated. On the transmit side we assume a mean direction of departure (DOD) of 20 degrees with respect to the array perpendicular with the AS having a Laplacian power distribution, as it was proposed for the macrocellular vehicular environment in [9]. The correlation matrices $\mathbf{R}_{RX}$ and $\mathbf{R}_{TX}$ are determined by these parameters.

We define the signal-to-noise ratio (SNR)

$$SNR = 10 \log_{10} \frac{M_{TX} E_b}{N_0} \quad [dB] \,, \qquad (7)$$

where N_0 is the variance of the complex Gaussian noise on each RX antenna and E_b is the energy per information bit.

The performance degradation due to fading correlation with blind transmission becomes obvious in Fig. 2.

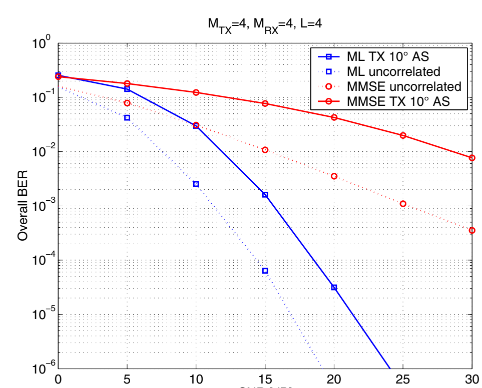

Fig. 2: Blind transmission in a SCC

We have plotted BER curves for a 4×4 system with MMSE and ML receivers for an uncorrelated as well as a semi-correlated channel (SCC) with a root mean square AS of 10 degrees at the TX side. Especially the performance of the linear MMSE receiver deteriorates noticeably in the presence of fading correlation. It is also obvious that the ML receiver provides the full diversity of 4 (which is equal to the number of RX antennas), while the MMSE receiver exhibits only a diversity of 1.

IV. MMSE Design Recapitulated

A. Generalized MMSE Prefiltering

The generalized MMSE design aims on minimizing the mean square of the error vector

$$\mathbf{e} = \mathbf{s} - \mathbf{G}\mathbf{y} = \mathbf{s} - \left(\mathbf{GHFs} + \mathbf{Gn}\right) \quad (8)$$

by jointly optimizing the matrix filters $\mathbf{F}$ and $\mathbf{G}$ subject to a power constraint on the TX vector

$$\min_{\mathbf{G},\mathbf{F}} \; c\left(\mathbf{G},\mathbf{F}\right) = E\left[\left\|\mathbf{e}\right\|^2\right] \quad s.t.: tr\left(\mathbf{F}\mathbf{R}_{ss}\mathbf{F}^H\right) \le \rho \quad (9)$$

The objective function c is the MSE and the total transmit power is given by ρ. It turns out that the optimum receiver matrix $\mathbf{G}_{opt}$ in the sense of (9) is given by the standard solution in (4). With this RX filter choice, the MSE reads (cf. [8])

$$\bar{c}\left(\mathbf{F}\right) = c\left(\mathbf{F},\mathbf{G}_{opt}\right) = tr\left(\mathbf{R}_{ss}^{-1} + \mathbf{F}^H\mathbf{H}^H\mathbf{R}_{nn}^{-1}\mathbf{H}\mathbf{F}\right)^{-1}. \quad (10)$$

We introduce the eigenvalue decompositions (EVD)

$$\mathbf{R}_{ss} = \mathbf{\Psi}\mathbf{\Delta}\mathbf{\Psi}^H \quad (11)$$

and

$$\mathbf{H}^H\mathbf{R}_{nn}^{-1}\mathbf{H} = \mathbf{V}\mathbf{\Lambda}\mathbf{V}^H, \quad (12)$$

whereas we will refer to an eigenvector with its corresponding eigenvalue in (12) as short-term eigenmode, as it is directly derived from the instantaneous MIMO channel matrix. Furthermore, we decompose $\mathbf{F}$ as

$$\mathbf{F} = \mathbf{V}\cdot\mathbf{\Phi}_f\cdot\mathbf{\Psi}^H. \quad (13)$$

From (10)-(13) we then get

$$\bar{c}\left(\mathbf{F}\right) = tr\left(\mathbf{\Delta}^{-1} + \mathbf{\Phi}_f^H\mathbf{\Lambda}\mathbf{\Phi}_f\right)^{-1}. \quad (14)$$

It was shown in [4] that without loss of generality $\mathbf{\Phi}_f$ can be assumed to be real diagonal. Via Lagrange optimization, the optimum power allocation (PA) policy can be found to be

$$\mathbf{\Phi}_f = \left(\mu^{-1/2}\mathbf{\Lambda}^{-1/2} - \mathbf{\Lambda}^{-1}\mathbf{\Delta}^{-1}\right)_+^{1/2}, \quad (15)$$

with the constant μ chosen according to the power constraint in (9), resulting in

$$\mu^{1/2} = \frac{tr\left(\mathbf{\Lambda}^{-1/2}\right)}{tr\left(\mathbf{\Lambda}^{-1}\mathbf{\Delta}^{-1}\right) + \rho}. \quad (16)$$

Note that one has to assure $\phi_{f,l}>0$ for all l, which is indicated by the plus sign in (15). To this end, one can iteratively assign zero power to the weakest eigenmodes (i.e. they are not used for transmission of information) until all subchannels get a positive power assignment via (15) and (16).

B. Minimizing BER With MMSE Power Allocation

Minimizing the MSE does not simultaneously minimize the overall BER averaged over all subchannels. It is clear that the subchannel with the worst BER dominates the overall BER. Thus, forcing the BER to be the same on all subchannels while keeping the MSE constant minimizes overall BER. In the following we will assume uncorrelated unity power data symbols $\mathbf{R}_{ss}=\mathbf{I}_L$ (implying $\mathbf{\Psi}=\mathbf{\Delta}=\mathbf{I}_L$), where $\mathbf{I}_L$ denotes an identity matrix of size L×L.

Equal BER on the subchannels can be achieved by distributing the transmit symbol vector via a discrete Fourier transform (DFT) matrix on the eigenmodes [see (12)] of the MIMO channel (cf. [6]). Let $\mathbf{D}_L$ be a normalized DFT matrix of size L×L with $\mathbf{D}_L\mathbf{D}_L^H=\mathbf{I}$, then we can modify (13) according to

$$\mathbf{F} = \mathbf{V}\cdot\mathbf{\Phi}_f\cdot\mathbf{D}_L, \quad (17)$$

while the power allocation and the receive matrix filter $\mathbf{G}$ remain unaffected except for an inverse DFT. In the simulations of this paper, we will use a matrix prefilter $\mathbf{F}$ designed via (13), (15), (16), and (17).

We mention that the transmitter has to know the covariance matrix of the receiver noise, namely $\mathbf{R}_{nn}$, in order to be able to carry out the EVD in (12) and find the optimum prefilter in (17). However, one can assume that $\mathbf{R}_{nn}$ is sufficiently stable and can thus be fed back by the RX on a low rate link to the TX.

C. Long-Term MMSE Processing

Having only long-term CSI available, the transmitter is clearly not capable of determining the instantaneous EVD of the channel and a prefilter design via (17) is not possible. However, it can adjust the matrix prefilter $\mathbf{F}$ in a long-term sense by averaging the MSE criterion over fast fading. From (10) the optimization problem can now be written as

$$\begin{aligned}\mathbf{F}_{opt} &= \arg\min_{\mathbf{F}} \; E\left[\bar{c}\left(\mathbf{F}\right)\right] \\ &= \arg\min_{\mathbf{F}} tr\; E\left[\left(\mathbf{R}_{ss}^{-1} + \mathbf{F}^H\mathbf{H}^H\mathbf{R}_{nn}^{-1}\mathbf{H}\mathbf{F}\right)^{-1}\right]\end{aligned} \quad (18)$$

subject to the power constraint in (9). The expectation is now with respect to the channel Rayleigh fading statistics. Explicit calculation of the expected value of the MSE in (18) is at least very challenging. Similar problems have occurred in literature in the context of optimum combining with uncorrelated fading (e.g. [10][11]). The theory of complex Wishart matrices was used in [12] to analyze a related problem, namely the performance of MIMO zero-forcing receivers in semi-correlated channels. Application of random matrix theory for the design of statistical prefilters for MIMO systems with linear receivers is investigated in [15].

In this paper, we consider a simple lower bound of the MSE, namely

$$E\left[\bar{c}(\mathbf{F})\right] \geq tr\left(\mathbf{R}_{ss}^{-1} + \mathbf{F}^{H} E\left[\mathbf{H}^{H}\mathbf{R}_{nn}^{-1}\mathbf{H}\right]\mathbf{F}\right)^{-1}, \qquad (19)$$

which can be optimized more easily. In order to derive (19), we have applied Jensen's inequality for a convex function (cf. [13], where it is shown that the inverse is a convex function of a positive definite matrix argument). Simulation results below show that although we are actually optimizing a loose lower bound on the expected MSE, the true expected MSE is also noticeably reduced by the linear prefilter **F**, thus resulting in a lower overall BER.

For an arbitrary deterministic m×m matrix **A** and an m×n matrix **X** with i. i. d. unity variance complex Gaussian distributed entries one can derive by straightforward algebraic evaluation

$$E\left[\mathbf{X}^{H}\mathbf{A}\mathbf{X}\right] = tr(\mathbf{A}) \cdot \mathbf{I}_{n \times n}. \qquad (20)$$

Applying (20) to (19), we get

$$E\left[\mathbf{H}^{H}\mathbf{R}_{nn}^{-1}\mathbf{H}\right] = tr\left(\mathbf{R}_{nn}^{-1}\mathbf{R}_{RX}\right) \cdot \mathbf{R}_{TX}. \qquad (21)$$

Now we introduce an EVD

$$E\left[\mathbf{H}^{H}\mathbf{R}_{nn}^{-1}\mathbf{H}\right] = \mathbf{V}_{LT}\mathbf{\Lambda}_{LT}\mathbf{V}_{LT}^{H}, \qquad (22)$$

where the eigenvectors and corresponding eigenvalues are now referred to (compare to the short-term case) as long-term eigenmodes. We emphasize that the long-term eigenmodes are only functions of the scaled transmit correlation matrix $\mathbf{R}_{TX}$. Based on this EVD the same optimization as in the short-term case may be carried out, i.e. we can use equations (13), (15), (16), and (17) for the design of the matrix filter **F**, with the ST matrices **V** and $\mathbf{\Lambda}$ replaced by their long-term equivalents $\mathbf{V}_{LT}$ and $\mathbf{\Lambda}_{LT}$. To this end, we only need to provide $\mathbf{R}_{TX}$ to the transmitter, e.g. via feedback from the receiver or direct frequency transformation of the correlation matrix in receive direction.

D. MMSE Simulation Results

Simulation results for the overall BER of a $M_{TX}=M_{RX}=4$ system with L=4 subchannels are depicted in Fig. 3, again with an AS of 10° at the TX. As expected, there is a noticeable performance improvement when ST transmit processing is applied compared to the blind case. The proposed LT CSI based curve also clearly achieves a significant gain.

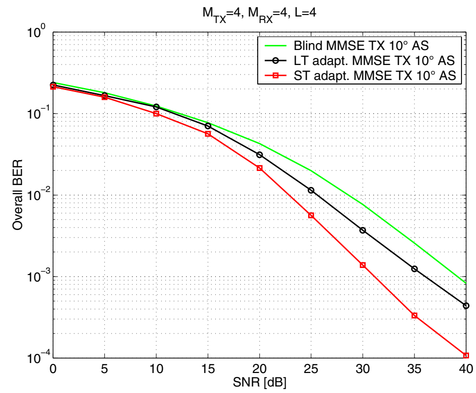

Fig. 3: Full usage of eigenmodes with a SCC

However, in the system at hand the requirement of 4 independent subchannels forces the transmitter to use all 4 available MIMO channel eigenmodes, therefore leaving it no degrees of freedom to avoid transmission on the weakest eigenmodes. We emphasize that in a strongly correlated channel zero transmit power could be assigned via (15) to some of the subchannels. Hence, those subchannels carry no information and lead only to an increased overall BER. This is clearly sub-optimum.

The potential of adaptive TX processing may thus be better exploited by keeping the number of independent subchannels lower than the number of channel eigenmodes (Fig. 4), given by min(M_{TX}, M_{RX}).

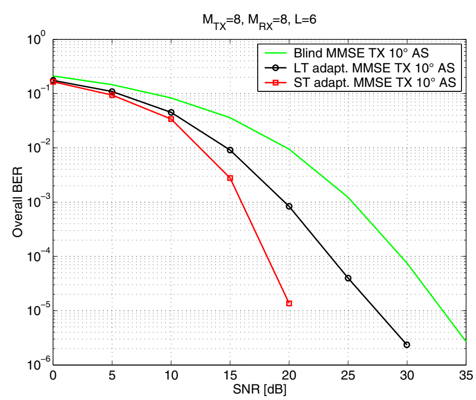

Fig. 4: Partial usage of eigenmodes with a SCC

In Fig. 4 BER curves for a $M_{TX}=M_{RX}=8$ system with L=6 independent data streams are depicted. Now the improvement of ST as well as LT prefiltering becomes more significant.

We note that for a fair comparison, the blind system in Fig. 4 transmits each of the independent streams on one of the outer 6 antennas, i.e. the two antennas in the middle of the array are not used. It is clear that the outer antenna elements are subject to the least fading correlation.

V. LINEAR PREFILTERING FOR ML DETECTION

A. Derivation of the Matrix Prefilter

Using the standard approximation of the Gaussian tail function, the pairwise error probability (the probability that the receiver erroneously decides for symbol vector $\mathbf{s}_j$, when $\mathbf{s}_k$ was actually transmitted) for ML detection is well bounded by (see e. g. [14])

$$P_e \le e^{\frac{-d_{min}^2}{2}}, \quad (23)$$

where d_{min} is the minimum distance between two hypothesized TX vectors after matched filtering and noise whitening at the receiver

$$d_{\min}^2 = \min_{\mathbf{s}_j, \mathbf{s}_k} \left[\left(\mathbf{s}_j - \mathbf{s}_k\right)^H \mathbf{F}^H \mathbf{H}^H \mathbf{R}_{nn}^{-1} \mathbf{H} \mathbf{F} \left(\mathbf{s}_j - \mathbf{s}_k\right) \right]. \quad (24)$$

Analog to the derivation of the MMSE prefilter, we average the pairwise error probability over fast Rayleigh fading, namely

$$E\left[P_e\right] \le E\left[e^{\frac{-d_{\min}^2}{2}}\right]. \quad (25)$$

Instead of explicitly calculating the expectation in (25), which also appears in a similar form in the context of space-time code design, in this paper we consider a simple bound that results from application of Jensen's inequality

$$E\left[e^{\frac{-d_{\min}^2}{2}}\right] \le e^{\frac{-E\left[d_{\min}^2\right]}{2}}. \quad (26)$$

After introducing the long-term expectation of the minimum distance

$$d_{\min,LT}^2 = \min_{\mathbf{s}_j, \mathbf{s}_k} \left[\left(\mathbf{s}_j - \mathbf{s}_k\right)^H \mathbf{F}^H E\left[\mathbf{H}^H \mathbf{R}_{nn}^{-1} \mathbf{H}\right] \mathbf{F} \left(\mathbf{s}_j - \mathbf{s}_k\right) \right], \quad (27)$$

the transmit matrix filter can now be chosen to maximize the expected squared minimum distance according to

$$\mathbf{F}_{opt} = \arg \max_{\mathbf{F}} \min_{\mathbf{s}_j, \mathbf{s}_k} \left[\left(\mathbf{s}_j - \mathbf{s}_k\right)^H \mathbf{F}^H E\left[\mathbf{H}^H \mathbf{R}_{nn}^{-1} \mathbf{H}\right] \mathbf{F} \left(\mathbf{s}_j - \mathbf{s}_k\right) \right]. \quad (28)$$

The minimax problem in (28) with the inner expectation given by (21) comprises a huge number of terms. Its complexity grows exponentially with the number of transmit antennas and the constellation. However, symmetries of the symbol constellation can be exploited to simplify the problem. Moreover, we note that the transmit prefilter has to be updated only on a long-term time scale, reducing the computational requirements at the transmitter.

B. ML Simulation Results

We have used a random optimization technique to design the optimum matrix prefilter $\mathbf{F}$ according to (28) for a M_{TX}=M_{RX}=2 MIMO system with QPSK modulation. The simulation results with optimum matrix prefiltering are given in Fig. 5 with 10° AS at the TX.

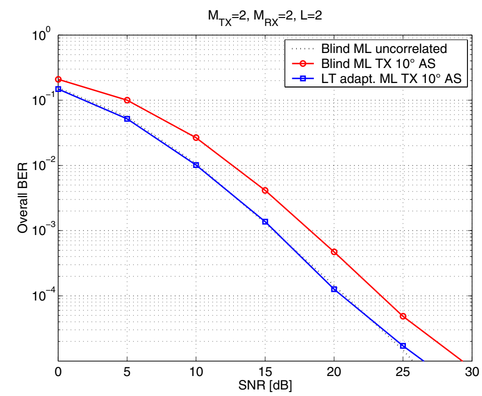

Fig. 5: Prefiltering for ML detection

We have plotted the curves for blind ML processing with correlated and uncorrelated fading for comparison. Obviously, statistical prefiltering in the correlated channel allows us to yield a similar performance as in the blind case with uncorrelated fading. In the given SNR range, the SNR gain is about 2.5 dB in this particular scenario.

If one considers the minimum distance in (27) for the uncorrelated blind case and the case with fading correlation (10° AS) and prefiltering according to (28), one finds with $\mathbf{R}_{ss}$=$\mathbf{I}$ that $d_{min,unc}$=2 and $d_{min,LT,corr}\approx 1.59$, i.e. the expected minimum distance between two MIMO constellation points is actually reduced due to TX fading correlation. However, we emphasize that the symbol error rate in the low/medium SNR range of the ML detector is a function of the distance spectrum of the total signal constellation, not only of the minimum distance. A more detailed analysis of the ML detector performance (taking into account all pairwise error probabilities) is necessary to better explain the behavior in this SNR region [17]. On the other hand, in the high SNR range the minimum distance is the dominant factor, which can readily be observed in the ML system simulations of this paper. Systems with the greatest minimum distance according to (27) yield the best performance in terms of BER at high SNR.

The improvements that may be achieved by linear prefiltering are even more significant in a strongly correlated channel with a root mean square AS of 2 degrees at the transmitter (Fig. 6). It can again be observed that with prefiltering we can achieve and even exceed the performance of the blind uncorrelated reference case in the presence of TX correlation (about 4.6 dB gain compared to blind transmission) in the low/medium SNR range. In this particular case, we find with correlation and prefiltering $d_{min,LT,corr}\approx 1.68$. The prefilter can obviously again improve the distance spectrum properties of the MIMO signal constellation.

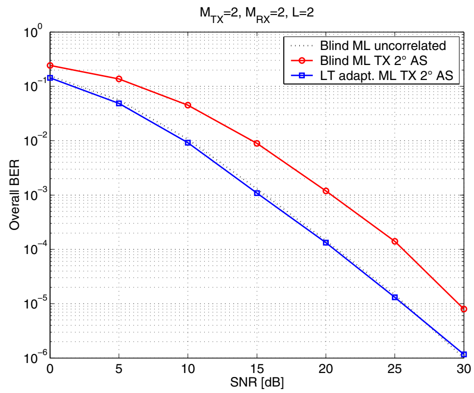

Fig. 6: Prefiltering for ML detection – strong correlation

A descriptive insight in the prefilter operation for ML detection can be given by looking at the effective symbol constellation. We have plotted the first element of the resulting symbol constellations with TX channel correlation and prefiltering (left), given by the superposition of all vectors $\tilde{\mathbf{s}}_k = \mathbf{BFs}_k$ for all k, and without prefiltering (right), given by the superposition of the first element of all vectors $\hat{\mathbf{s}}_k = \mathbf{Bs}_k$ in Fig. 7. In this example, **B** [cf. (2)(3)] is chosen again according to the scenario with 2 degrees AS at the transmitter.

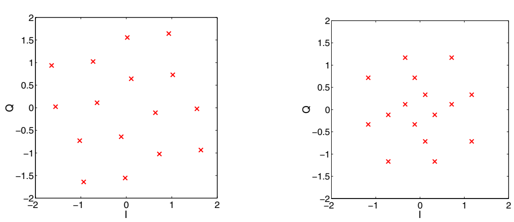

Fig. 7: Symbol constellation with/without prefiltering

Obviously, the optimum matrix prefilter **F** arranges the constellation points more regularly, thus simultaneously increasing both the effective minimum distance and the effective distance spectrum.

VI. Summary And Conclusion

We have derived statistical matrix prefilters based on long-term channel state information at the transmitter for MMSE and ML wireless MIMO receivers. The simulation results presented in this paper have demonstrated that exploiting long-term information to adapt the MIMO transmitter to the prevailing scattering scenario can significantly improve performance in terms of BER. Interestingly, the ML prefilter is capable of achieving the performance of a system with an uncorrelated channel even with high fading correlation. Due to the complexity of the ML prefilter design, simpler algorithms have to be found that allow for a real-time implementation in the transmitter. Nevertheless, the design presented in this paper can be used as a benchmark for other, low complexity schemes.

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