

Enhanced Eigenbeamforming for the 3GPP WCDMA FDD Downlink

Ralf Seeger, Karl-Dirk Kammeyer¹, Thomas Hindelang, and Wen Xu²

Abstract:

In this paper, the 3GPP downlink eigenbeamformer scheme is investigated. The eigenbeamformer scheme performs an eigendecomposition (EVD) of the spatial long-term covariance matrix to obtain beamforming weights. Diversity gains are obtained due to switching between so-called eigenbeams. Since the EVD is carried out by the mobile station, computationally efficient algorithms are required. We show that the computational efforts can be drastically reduced by exploiting the quasi-stationarity of the long-term spatial covariance. For a given feedback rate, the performance of closed-loop schemes drop at high velocities due to delay introduced by feedback of side information. To cope with this problem, an efficient spatio-temporal prediction scheme is proposed. Our simulations, in which realistic coding, feedback delay, channel estimation and quantization of eigenbeams are considered, show that for a given target block error rate, the operational range, i.e. the maximally allowed speed of the mobile station, can then be significantly increased.

1. Introduction

Future mobile and wireless applications such as multimedia services will require significantly higher data rates, better QoS and lower costs as compared to current systems. With conventional single antenna systems, it is usually difficult to meet these high requirements on data rate, link quality, spectral efficiency, and mobility. Therefore, antenna arrays will be employed at least at the base station (BS). Due to the asymmetric nature of most data services (internet downloads, broadcast services) there is a demand on increased downlink capacity. Several multiple-input multiple-output (MIMO) and transmit diversity concepts are currently proposed to 3GPP for standardization. While MIMO schemes imply multiple antennas at both ends of a transmission link to increase the throughput, transmit diversity schemes and/or beamforming schemes which intend to raise the signal-to-noise-and-interference ratio (SINR) at the mobile station (MS) generally require only one receive antenna, thus being attractive to build low cost mobile stations. In this paper we focus on the downlink eigenbeamformer scheme [1] which is based on [6]. The beamforming weights are obtained by an eigendecomposition (EVD) of the spatial long-term covariance matrix. Since the EVD is performed by the MS, highly efficient algorithms are necessary. We will show in Sec. 3.1. that the computational complexity can be drastically reduced by exploiting the quasi-stationarity of the long-term spatial covariance [19].

Fading, especially flat fading, is one of the main reasons to affect the downlink capacity. In order to improve

this, spatial diversity can be exploited by switching between weight vectors (eigenbeams) [1]. For a given feedback rate, the performance of closed-loop schemes drops at higher velocities due to limited uplink bandwidth in connection with a delay involved in the feedback of side information [4]. To cope with loop delays, an efficient spatio-temporal prediction scheme is proposed in Sec. 3.2.. We will show by simulation including channel estimation and quantization of eigenbeams that the operational range, i.e. the maximal allowed speed of the MS for a given target block error rate (BLER), can then be significantly increased.

2. Spatial Channel Model

In [11][15], stochastic multiple-input-multiple-output (MIMO) radio channel models are derived from the classical tap delay line model that is based on the wide-sense stationary uncorrelated scattering (WSSUS) assumption where L independent time-varying taps model the signal dispersion in a multipath environment. Let the BS have M transmit antennas. The tap fading process is extended by incorporating long-term spatial correlations ρ_{m_1, m_2} between the signals from different transmit antennas m_1 and m_2 . The matrix capturing all spatial correlation coefficients for tap l is denoted by $\mathbf{R}_l \in \mathbb{C}^{M \times M}$. It is assumed that the M signals from the antennas associated with tap delay l arrive simultaneously at the MS. The channel coefficients of different antennas m at delay l , $h_{l,m}$, can be modeled by a linear combination of M independent normalized complex Gaussian processes $\mathbf{g}_l(t) = [g_{l,1}(t), g_{l,2}(t), \dots, g_{l,M}(t)]^T$ with required power density spectrum, leading to

$$\mathbf{h}_l(t) = \mathbf{R}_l^{1/2} \mathbf{g}_l(t). \quad (1)$$

The projection matrix $\mathbf{R}_l^{1/2} \in \mathbb{C}^{M \times M}$ is obtained using a standard matrix square root decomposition method $\mathbf{R}_l = \mathbf{R}_l^{1/2} \mathbf{R}_l^{1/2H}$ [8, p.149].

Assume that at the BS the antenna weights $\mathbf{w}^* = [w_1^*(t), w_2^*(t), \dots, w_M^*(t)]^T$ are applied [18], then the signal received at the MS (after descrambling and despreading), which is equipped with one receive antenna, can be written as

$$r(t) = \sum_{l=1}^L [\mathbf{w}^H s(t - \tau_l)] \mathbf{h}_l(t) + n(t), \quad (2)$$

where $s(t)$ is the dedicated user signal prior to spreading and scrambling, and $n(t)$ denotes the additive white Gaussian noise (AWGN).

Using the channel model described in [11], the normalized long-term spatial correlation matrix is given by the superposition of time discrete micro paths components which cannot be resolved by the receiver

¹e-mail: {seeger, kammeyer}@ant.uni-bremen.de, University of Bremen, Communications Engineering, Bremen, Germany.

²e-mail: {Thomas.Hindelang, Wen.Xu}@siemens.com, Siemens AG - Mobile Phones, Grillparzer Str. 10-18, 81675 Munich, Germany

$$\mathbf{R}_l = \frac{1}{\sigma_l} \sum_{\mu \in \mathcal{L}_l} \sigma_\mu \mathbf{a}(\phi_\mu, \theta_\mu) \mathbf{a}^H(\phi_\mu, \theta_\mu), \quad (3)$$

where \mathcal{L}_l , $\mathbf{a}(\phi_\mu, \theta_\mu)$ denote a class of non-resolvable micro paths associated with the temporal tap l , the steering vector as a function of direction of departure (DOD) in azimuth ϕ and elevation θ , respectively. The power per micro path is denoted by σ_μ , and total power of superposed paths is denoted by σ_l . It is assumed that the long-term properties behave quasi-stationary (magnitudes, angles-of-departure changes very slowly over several 100 ms).

3. 3GPP Eigenbeamforming Scheme

The main idea behind the eigenbeamformer method is the decomposition of the directional fading channel (2) into its fundamental processes in order to provide a decorrelation of spatial diversity branches (see [1][6]). Using orthogonal common pilot sequences (CPICHs) transmitted from the BS, the MS estimates the short-term spatial covariance matrix averaged over the temporal taps of the channel. In the sequel we will restrict to the flat fading case to simplify the signal model. Therefore, omitting the temporal tap index l from (1) the short-term spatial covariance can be calculated as follows:

$$\mathbf{R}_{ST}(k) = \mathbf{h}(k) \mathbf{h}^H(k), \quad (4)$$

where k is the time slot index. The long-term spatial covariance matrix is obtained by averaging over the short-term covariance matrices applying the forgetting factor ρ

$$\mathbf{R}(k) = \rho \mathbf{R}(k-1) + (1-\rho) \mathbf{R}_{ST}(k). \quad (5)$$

In general it is reasonable to assume a spatially quasi-stationary environment (the long-term covariance is nearly constant over several 100 time slots [16]), consequently the forgetting factor ρ is set close to unity. Decorrelation in space is achieved by an eigenanalysis of the Hermitian matrix \mathbf{R}

$$\mathbf{R}\mathbf{W} = \mathbf{W}\mathbf{D}, \quad (6)$$

where the orthonormal column vectors \mathbf{w}_m of \mathbf{W} are eigenvectors (in the sequel termed *eigenbeams*) of \mathbf{R} and $\mathbf{D} = \text{diag}[d_1, d_2, \dots, d_M]$ is a diagonal matrix with the corresponding eigenvalues. Without loss of generality we assume $d_1 > d_2 > \dots > d_r > \dots > d_M$.

A subset of the strongest r eigenbeams out of M eigenbeams is fed back to the BS. Exploiting the quasi stationarity of the long-term parameter (3) the feedback bits are distributed over a large number of slots. In addition, a slot-by-slot selection of the strongest eigenbeam out of the strongest r eigenbeams is performed by the MS according to

$$\mathbf{w}_{\max}(k) = \arg \max_{\mathbf{w}_m} (\mathbf{w}_m^H(k) \mathbf{R}_{ST}(k) \mathbf{w}_m(k)), \quad (7)$$

i.e., the eigenbeam \mathbf{w}_m that maximizes the receive signal power is selected and the index m is sent to the BS

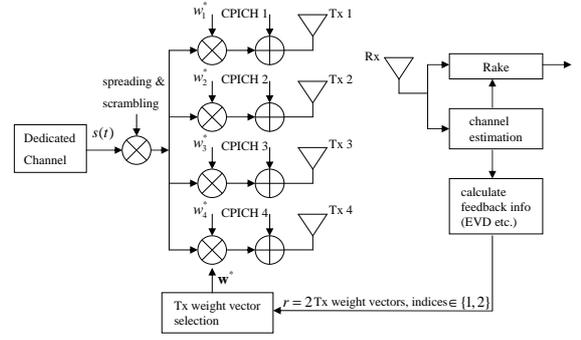


Figure 1: 3GPP eigenbeamforming scheme according to [1]

which applies the corresponding eigenbeam after some delay (see Fig. 1).

3.1. Tracking the Eigenbeams

The benefit of the 3GPP downlink eigenbeamforming scheme is that, since the eigenbeams are calculated by the MS, diversity can be gained by beam-switching. On the other hand the eigendecomposition must be performed at the MS which has normally tight energy constraints (small battery supply) in connection with reduced computational capabilities. In this section we propose computationally efficient EVD algorithms, which exploit the quasi-stationary property of spatial long-term covariance matrix to *track* the eigenspace.

In contrast to batch EVD methods like the symmetric QR-algorithm the following algorithms can make use of the eigenvectors calculated from past time slots as an approximation of the current one, based on the assumption that the spatial covariance changes very slowly with time. Note, although we will use the time slot index k in the sequel, the eigendecomposition is practically performed only once every several 100 ms up to one second [4]. Concrete update rates will be discussed in Section 4..

3.1.1. Jacobi algorithm

The Jacobi algorithm is one possible method to solve the symmetric eigenvalue problem (6). The idea behind the Jacobi algorithm is to systematically reduce the energy stored in off-diagonal elements and shift it to the main diagonal elements [8]. This iterative diagonalization is done by Jacobi rotations (unitary transforms) $\mathbf{J}_i(k) \in \mathbb{C}^{M \times M}$

$$\mathbf{W}(k) = \prod_i \mathbf{J}_i(k),$$

$$\mathbf{D}(k) = \mathbf{W}^H(k) \mathbf{R}(k) \mathbf{W}(k), \quad (8)$$

where the approximated eigenspace $\mathbf{W}(k)$ of $\mathbf{R}(k)$ is the product of all previously applied rotations, and i the iteration index. The Jacobi rotation is defined by:

functions required to implement Jacobi rotations is neglected. However, some special implementation techniques, e.g. approximated Jacobi rotation, exist [10]. Table 2 summarizes the results from above discussion.

Beside its low computational complexity, the favored orthogonal iteration method based on elementary Householder reflections offers excellent numerical properties, i.e. it is numerical stable (see references in [13][8]).

3.2. Predictive Beam-Switching

According to [1] the downlink eigenbeamformer scheme selects the eigenbeam which maximizes the *expected* instantaneous signal-to-noise ratio (7). To do so, the MS transmits the corresponding beam-index to the BS, which applies the desired transmit weight vector after some processing delay. In addition to the measurement delay, i.e. the MS calculates the short-term feedback information based on the already received slot, up to two delay slots must be considered due to uplink transmission and some processing delay at the BS. Consequently, for high MS velocities the applied transmit weights are outdated due to fast channel fluctuations. In the following, the total amount of delay (in slots) is denoted as *loop delay* κ .

We can conclude from the underlying channel model that the temporal short-term processing for the eigenbeam selection can be analyzed independently from the spatial long-term processing. To cope with the loop delay the channel coefficients in (7) can be replaced by *predicted* channel coefficients obtained from a bank of M mutually independent linear complex-valued predictors (i.i.d. temporal fading processes are assumed in (1)). Let $\mathbf{h}(k + \kappa|k)$ denote the predicted channel coefficient vector in the current slot k for the future slot $k + \kappa$, we obtain from (7):

$$\mathbf{w}_{\max} = \arg \max_{\mathbf{w}_m} (\mathbf{w}_m^H \mathbf{h}(k + \kappa|k) \mathbf{h}^H(k + \kappa|k) \mathbf{w}_m), \quad (11)$$

with

$$m = 1, 2, \dots, M.$$

However, in the multiple-input-single-output (MISO) case, channel estimation has to be performed for all M spatial paths in order to calculate the spatial covariance. Nevertheless, the MS can exploit the set of calculated eigenvectors *after* channel estimation to reduce the complexity of consecutive short-term processing. We are enabled to apply matrix multiplication with \mathbf{W} prior to the temporal prediction scheme

$$\tilde{\mathbf{h}}(k) = \mathbf{W}_r^H \mathbf{h}(k), \quad (12)$$

where the dimensionally reduced channel coefficient vector is denoted by $\tilde{\mathbf{h}} = [\tilde{h}_1, \tilde{h}_2, \dots, \tilde{h}_r]^T$.

By constraining the r predictors to be linear FIR filters of order $N_p - 1$, the output of the r predictors at time slot

k can be described as follows

$$\begin{bmatrix} \tilde{h}_1(k + \kappa|k) \\ \tilde{h}_2(k + \kappa|k) \\ \vdots \\ \tilde{h}_r(k + \kappa|k) \end{bmatrix} = \begin{bmatrix} \mathbf{p}_1 & & & \\ & \mathbf{p}_2 & & \\ & & \ddots & \\ & & & \mathbf{p}_r \end{bmatrix}^H \begin{bmatrix} \tilde{h}_1(k) \\ \tilde{h}_1(k-1) \\ \vdots \\ \tilde{h}_1(k-N_p-1) \\ \tilde{h}_2(k) \\ \tilde{h}_2(k-1) \\ \vdots \\ \tilde{h}_2(k-N_p-1) \\ \tilde{h}_r(k) \\ \tilde{h}_r(k-1) \\ \vdots \\ \tilde{h}_r(k-N_p-1) \end{bmatrix}, \quad (13)$$

where $\mathbf{p} \in \mathbb{C}^{N_p \times 1}$ are the coefficient vectors associated with the r predictors. Therefore, (11) simplifies to

$$m_{r,\max} = \arg \max_{m_r} (\tilde{h}_{m_r}^*(k + \kappa|k) \tilde{h}_{m_r}(k + \kappa|k)), \quad (14)$$

with

$$m_r = 1, 2, \dots, r.$$

As mentioned above, spatially uncorrelated coefficients \tilde{h}_{m_r} can be obtained with (12), if (6) holds. Then, we are able to determine the prediction filter coefficients for each of the r predictors separately. According to the minimum mean-square-error (MMSE) criterion, the optimal weight vector is obtained from the solution of the Wiener-Hopf equation :

$$\mathbf{R}_{m_r} \mathbf{p}_{m_r} = \mathbf{r}_{m_r}, \quad (15)$$

where $\mathbf{R}_{m_r} \in \mathbb{C}^{N_p \times N_p}$ and $\mathbf{r}_{m_r} \in \mathbb{C}^{N_p \times 1}$ are the *temporal* autocorrelation matrix and vector, respectively [12]. To determine \mathbf{R}_{m_r} and \mathbf{r}_{m_r} the vector $\tilde{\mathbf{h}}'_{m_r} = [\tilde{h}_{m_r}(k-\kappa), \tilde{h}_{m_r}(k-\kappa-1), \dots, \tilde{h}_{m_r}(k-\kappa-N_p+1)]^T$ is defined. It follows

$$\mathbf{R}_{m_r} = E\{\tilde{\mathbf{h}}'_{m_r} \tilde{\mathbf{h}}_{m_r}^H\}, \quad (16)$$

$$\mathbf{r}_{m_r} = E\{\tilde{h}_{m_r}^*(k) \tilde{\mathbf{h}}'_{m_r}\}, \quad (17)$$

where $E\{\cdot\}$ denotes the expectation, which can be practically calculated analogical to (5) assuming quasi-stationary temporal fading processes. Thus exploiting the Toeplitz structure of \mathbf{R}_{m_r} the Levinson-Durbin algorithm can be used to solve (15), or alternatively, the Trench algorithm can be applied to directly compute the matrix inversion. Both algorithms exhibit $\mathcal{O}(N_p^2)$ computational complexity [8]. Note that the explicit estimation of autocorrelation \mathbf{R}_{m_r} matrix is required. This takes additional $\mathcal{O}(N_p^2)$ operations. In order to avoid explicit calculation of (inverse) autocorrelation matrix, the RLS algorithm with $\mathcal{O}(N_p^2)$ complexity can be employed [12]. Eq. (14) implies an absolute square operation after linear prediction, thus the *power* predictor is nonlinear. The authors of [7] pointed out that the employed kind of power predictor is optimal in the MMSE sense if the bias is removed according to [7, Eq.(11)]. However, we found out by simulation (not shown in this paper) that the bias removal does not observably improve the results presented in Sec. 4..

EVD algorithm	flops	$M = 4, r = 2$
Batch EVD (Symmetric QR)	$9M^3$	576
Jacobi (1 sweep)	$2M^3 + 2(M^3 + (M - 1)M^2)$	352
orthogonal iteration (1 iteration)	$4(M^2r - Mr^2 + r^3/3) + rM^2 + (M - 1)Mr$	131

Table 2: Number of complex-valued operations. For the Jacobi method the two-sided pre-multiplication (10) is included. Since an EVD takes place e.g. only once per second (1500 slots), the number of operations per slot is very low.

4. Simulation Results

In order to evaluate the discussed algorithms, some simulations were conducted. Since we are interested in an overall performance of the communication system, the bit error rates (BERs) instead of mean-square-error results are used to evaluate the subspace tracking algorithms. The transmit power is normalized to the number of transmit antennas and $E\{\sum_l |h_{l,m}(t)|^2\} = 1$ holds.

According to [1] $M = 4$ Tx antennas and switching between two, $r = 2$, eigenbeams are assumed. The array geometry is set to uniform linear array (ULA), which is also the reference topology in [2], with half-wavelength spacing. One user with a bit rate of 240 kbit/s (spreading factor 32) is considered. The total power of the common pilot channels equals to the power of the dedicated channel. All downlink intracell interferer are mutually orthogonal since flat fading is assumed.

The prediction scheme consists of two predictors of order 10, and the RLS algorithm is used to adapt the filter coefficients.

The batch EVD and Jacobi algorithm were initialized with the unity matrix, whereas for the orthogonal iteration method the first $r = 2$ columns were used to initialize \mathbf{W} . The number of iterations (resp. sweeps) is set to 1 for the orthogonal iteration and Jacobi algorithm. Since the feedback rate in a UMTS Rel. 99 system is fixed to one bit per uplink slot, there is a trade-off between the eigenspace update rate and the number of bits per eigenvector, which affects the spatial resolution. A detailed analysis is, however, out of the scope of this paper.

The eigenvectors are quantized by using 3 bits for the phase argument and 2 bits for the magnitude part of a complex number. According to [1], one long-term bit and 14 short-term bits are fed back every frame (15 slots). It has to be mentioned that errors during uplink transmission of feedback bits may occur. Consequently, additional redundancy for the long-term bits and antenna weight verification is indispensable for practical systems [18]. Here error-free uplink transmission is assumed. A code rate of $r_c = 1/2$ for the long-term bits and one antenna as phase reference are used. The EVD update rate is 680 ms (i.e. (3.3bit phase+4.2bit amplitude)·2beams· $1/r_c$ · 10 ms).

In the spatially quasi-stationary scenario, where the MS moves on a trajectory as depicted by Fig. 2, no difference between tracking and batch EVD is noticed. However, the computational complexity can be drastically reduced compared to the standard batch EVD method. The orthogonal iteration yields nearly the same performance at the lowest computational cost. Note that ideally known channel state information is assumed.

Next, we compare the conventional eigenbeamformer

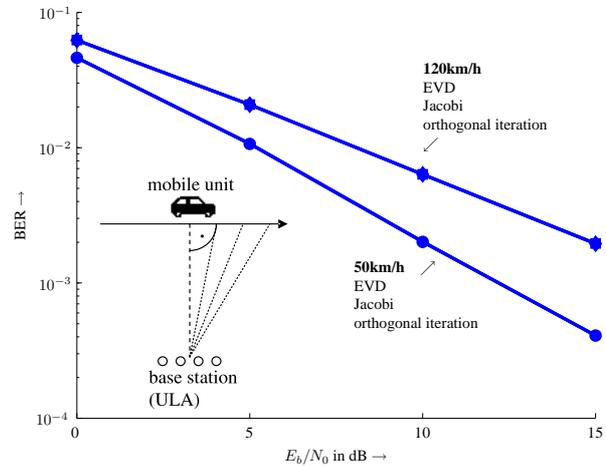


Figure 2: Spatially quasi-stationary environment: the MS moves parallel w.r.t. the BS antenna array axis. The angle spread is fixed to 30° , therefore, this corresponds to a spatially highly correlated case with one dominant eigenvalue. The distance between the MS and the BS is set to 500 m (perpendicular to the array axis).

scheme proposed to 3GPP [1] to the enhanced version incorporating subspace tracking and predictive beam-selection. The spatially stationary *Microcell* scenario defined in [17] is used. Channel estimation based on the mutually orthogonal common pilot channels is performed. We simply average the pilot symbols over one slot, since a Wiener smoothing filter spanning over multiple slots would contribute an additional processing delay. It can be seen that the reduced dimensional prediction scheme (14) exhibits slightly better performance compared to the conventional prediction scheme, and much less computational complexity, i.e. 2 instead of 4 predictors are required (see Fig. 3).

In realistic communication systems coded transmission is employed. Therefore, one important figure of merit for link level simulations is the BLER. The applied convolutional encoder (with rate $r_c = 1/2$) and the intra and inter frame interleavers were implemented according to [3]. The transmission time interval (TTI) is set to 20 ms (i.e. two frames per block). At the receiver a Max-Log-MAP-Decoder is applied for decoding [5]. All other parameters are left unchanged regarding to the uncoded system described above. In Fig. 4 BLERs for a system with one Tx antenna, the conventional and the proposed enhanced predictive eigenbeamforming scheme are depicted. The subspace tracking scheme based on orthogonal iteration from Sec. 3.1. is used. The predictive eigenbeamforming scheme yields the lowest BLERs over the

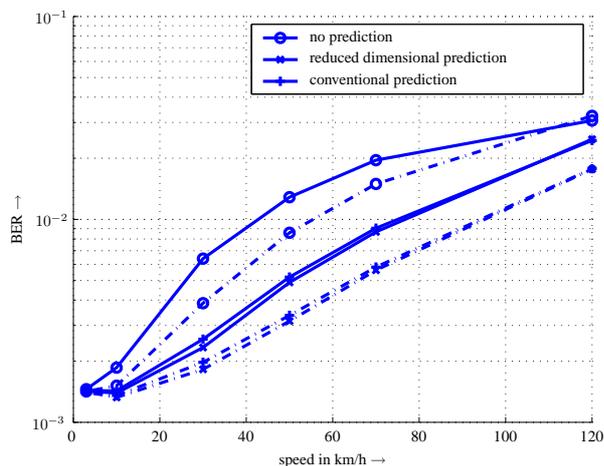


Figure 3: Microcell environment with fixed $E_b/N_0 = 10$ dB. The eigenbeamformer uses eigenbeam tracking based on orthogonal iteration and predictive beam-switching. The loop delay is set to 2 (dash-dot lines) and 3 (solid lines).

whole range of considered speeds. For a fixed speed of the MS an significant signal-to-noise gain can be obtained as it can be seen from Fig. 5.

5. Conclusions

We studied the 3GPP eigenbeamforming scheme with realistic feedback delay, quantization of eigenbeams and channel estimation in spatially stationary and quasi-stationary environments. The conventional scheme exhibits a strong degradation for relatively high mobile station velocities. It was shown that due to the predictive short-term processing based on the efficient spatio-temporal prediction scheme, a velocity of 70 km/h and a fixed signal-to-noise ratio of $E_b/N_0 = 4$ dB, the BLER is lowered from $1.3 \cdot 10^{-2}$ ($4.7 \cdot 10^{-2}$) to $1.4 \cdot 10^{-3}$ ($5.1 \cdot 10^{-3}$) for a loop delay of 2 (3) slots. It can be concluded that for a given BER/BLER the operational range, i.e. the maximally allowed speed of the mobile station, can be significantly increased. Furthermore, we have shown, by exploiting the quasi-stationarity of the spatial covariance matrix, that the proposed eigenbeam tracking scheme can lower the computational costs considerable.

REFERENCES

- [1] 3GPP. Tx diversity solutions for multiple antennas. In *3GPP technical report, 3G TR25.869 V1.0.0*, 2002.
- [2] 3GPP. Spatial channel model for Multiple Input Multiple Output (MIMO) simulations. In *3GPP technical report, 3G TR25.996 V6.1.0*, 2003.
- [3] 3GPP. Multiplexing and channel coding (FDD). In *3GPP technical specification, 3G TR25.212 V6.2.0*, 2004.
- [4] A.Seeger, A.Lobinger, R.Wiedmann, and B.Raaf. Performance of Downlink Eigenbeamformer with Realistic Feedback Transmission. In *Proc. IEEE VTC Fall*, 2001.

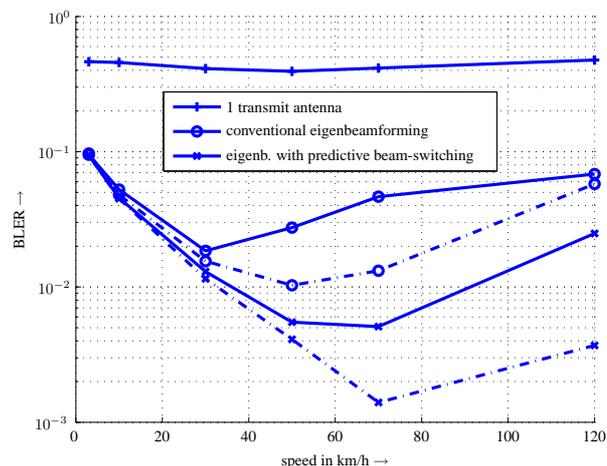


Figure 4: Coded system performance: BLER vs. speed, $E_b/N_0 = 4$ dB, Microcell environment. Both eigenbeamforming schemes employ eigenbeam tracking based on orthogonal iteration, whereas the proposed enhanced scheme benefits from predictive beam-switching. The loop delay is set to 2 (dash-dot lines) and 3 (solid lines).

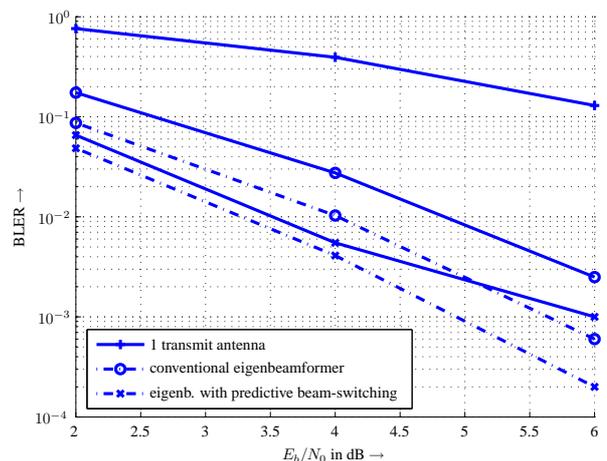


Figure 5: Coded system performance: BLER vs. E_b/N_0 , 50 km/h. The loop delay is set to 2 (dash-dot lines) and 3 (solid lines).

- [5] S. Benedetto, G. Montorsi, D. Divsalar, and F.Pollara. Soft-Output Decoding Algorithms in Iterative Decoding of Turbo Codes. *The TDA Progress Report. Pasadena, CA: Jet Propulsion Lab.*, 42-124:63–87, 1996.
- [6] C. Brunner. *Efficient Space-Time Processing Schemes for WCDMA*. PhD thesis, TU München, 2000.
- [7] T. Ekman, M. Sternad, and A. Ahlén. Unbiased Power Prediction of Rayleigh Fading Channels. In *Proc. IEEE VTC Fall*, 2002.
- [8] G.H. Golub and C.F. van Loan. *Matrix Computation*. The John Hopkins University Press, Baltimore, 3rd edition, 1996.

- [9] J. Götze. Monitoring the Stage of Diagonalization in Jacobi Type Methods. In *Proc. IEEE ICASSP*, volume 3, pages 441–444, 1994.
- [10] J. Götze. On the Parallel Implementation of Jacobi and Kogbetliantz Algorithms. *SIAM J. Scientific Computing*, 15(6):1331–1348, 1994.
- [11] J.S. Hammerschmidt and A.A. Hutter. Spatio-Temporal Channel Models for the Mobile Station: Concept, Parameters, and Canonical Implementation. In *Proc. IEEE VTC Spring, Tokyo*, May 2000.
- [12] S. Haykin. *Adaptive Filter Theory*. Prentice Hall, 4th edition, 2001.
- [13] R.B. Lehoucq. The Computation of Elementary Unitary Matrices (LAPACK Working Note 72). <http://www.netlib.org/lapack/lawns>, October 1995.
- [14] C. Michalke, M. Stege, F. Schäfer, and G. Fettweis. Efficient Tracking of Eigenspaces and its Application to Eigenbeamforming. In *Proc. IEEE PIMRC*, volume 3, pages 2847–2851, 2003.
- [15] K.I. Pedersen, J.B. Andersen, J.P. Kermoal, and P.E. Mogensen. A Stochastic Multiple-Input-Multiple-Output Radio Channel Model for Evaluation of Space-Time Coding Algorithms. In *Proc. IEEE VTC Fall*, volume 2, pages 893–897, 2000.
- [16] 3GPP TSG RAN1. Description of the eigenbeamformer concept (update) and performance evaluation. In *TSGR1#19 R1-01-0203*, Las Vegas, USA, February 27- March 2, 2001.
- [17] 3GPP TSG RAN1. Simulation parameters for Tx diversity simulations using correlated antennas. In *TSGR1#16 R1-00-1180*, October 10-13, 2000, Pusan, Korea.
- [18] A. Seeger, M. Sikora, and W. Utschick. Antenna Weight Verification for Closed-Loop Downlink Eigenbeamforming. In *Proc. IEEE Global Telecommunications Conference, Taipei, Taiwan*, 2002.
- [19] I.J. Viering. *Analysis of Second Order Statistics for Improved Channel Estimation in Wireless Communications*. PhD thesis, University of Ulm, Germany, 2003.
- [20] B. Yang. Projection Approximation Subspace Tracking. *IEEE Trans. Signal Processing*, 43(1):95–107, Jan. 1995.