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Research Report

Reduced Dimension Space-Time Processing for Multi-Antenna Wireless Systems

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Abstract

The need for wireless communication systems has grown rapidly during the last few years. Moreover, there is a steady growth in the required data rates due to the fact that more and more users request high bit rate services. To meet those requirements, current and next generation wireless systems and networks such as the Universal Mobile Telecommunications System (UMTS) and Wireless LANs (e.g. IEEE 802.11a) will support much higher data rates compared with established standards. This is basically done by applying advanced transmission schemes and usage of bandwidth resources. However, another very promising approach is the introduction of multiple antennas at one or both ends of a link to exploit the spatial dimension of signal transmission for improved link quality and enhanced system capacity. Smart antenna concepts are extensively discussed in this context. The application of concepts with multiple antennas necessitates the introduction of more advanced and computational expensive transmitter and receiver structures, where space-time (ST) processing techniques are required to carry out spatial and temporal information processing jointly. This paper introduces a new ST processing concept to enable reduced dimension ST receiver signal processing. The signal dimension can be considerably reduced compared to the number of antennas by exploiting spatial correlation properties of the received antenna signals. The associated signal transformation applies the concept of the Karhunen-Loève-Transformation (KLT).

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Key words

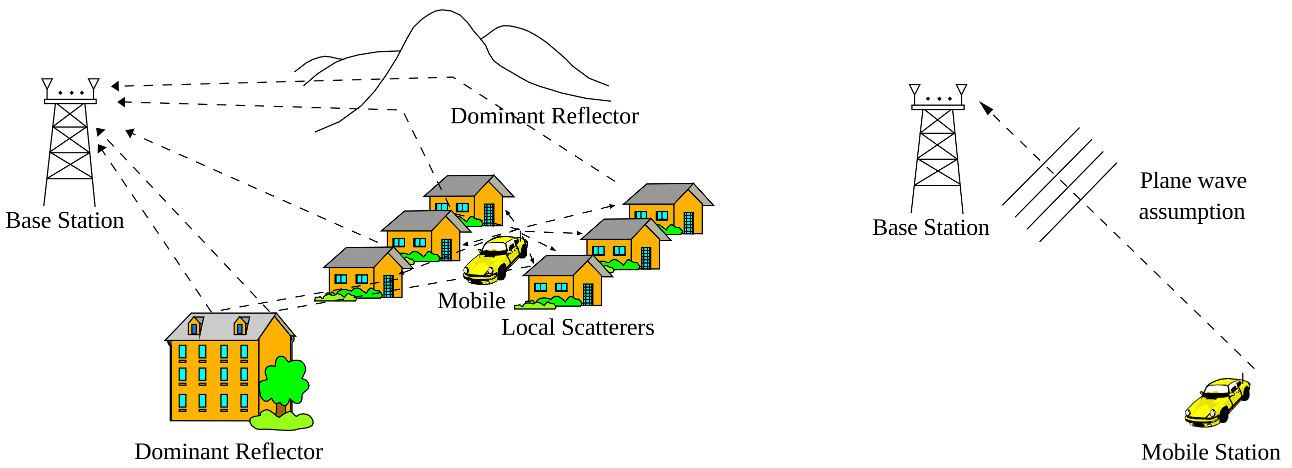
Wireless LAN's, Space-Time-Processing, Low-rank modeling, Beamforming, Diversity Combining, Karhunen-Loève-Transformation

1 Introduction

One of the ultimate goals for the design of new indoor and outdoor communication systems is the increase of the system capacity. This includes the support of a growing number of users and at the same time the provision of high and variable data rates for every single link. The aim to enable high data rates for a single user could be achieved by allocating more bandwidth. However, this approach will reduce the number of possible users, which can be active within a system at a given available bandwidth. Another possibility is the application of spectrally more efficient modulation schemes, which enable the transmission of a greater overall amount of user data within a given time for a given bandwidth. This approach provides the means to support high data rate links without decreasing the number of active users. The drawback of such advanced modulation schemes is their lack of robustness against channel distortion and noise, which will result in an increased amount of transmission errors.

Therefore, the question arises of how those channel imperfections can be compensated to reduce the number of transmission errors. In this context the introduction of multiple antennas for data transmission and/or reception can be of great advantage. If an antenna array is introduced at one end of a wireless link, the given data stream will be transmitted over multiple, statistically more or less independent wireless channels. The application of multiple antennas at the transmitter and receiver results in the possibility to transmit multiple independent data streams simultaneously, where the number of independent streams is limited by the minimum of the number of antennas at the transmitter and receiver.

In this article, we will limit our attention to the case where multiple antennas are applied at the receiver. One problem that arises with the introduction of antenna arrays is the increasing complexity of the Radio-Front-End as well as in the digital signal processing unit. Spatial and temporal processing of the received antenna signals is now required instead of a pure temporal equalization of the received signals from only one antenna. The spatial and temporal processing stages can be combined into a joint space-time processing unit or can be treated separately. In the latter approach the antenna signals are commonly combined within a spatial processing stage, which is often implemented as a beamformer, smart antenna processor [1, 2] or spatial diversity combiner [3, 4]. This can often be viewed as a spatial preprocessing stage in front of a classical receiver. The first approach of joint ST processing is the more general approach, which can be adapted to varying scenarios to yield the expected performance improvements. These improvements heavily depend on the



(a) (b)

Figure 1: (a) Typical mobile communication scenario, (b) Adaptive beamforming scenario

wireless channel characteristics, especially on the degree of spatial correlation, which determines the ability of the receiver to compensate for channel distortions such as fast fading effects. The most important improvements which can be achieved by applying antenna array concepts are stated below:

- The signal-to-noise ratio (SNR) of the desired signal can be improved proportionally to the number of antenna elements through coherent superposition of the antenna signals.
- Since the weighted combination of the antenna signals can be viewed as a spatial filtering operation, undesired signals can be suppressed spatially. This yields an improved signal-to-noise-and-interference ratio (SINR).
- Several users can be active simultaneously in the same frequency band, if they are separable otherwise. This can be done by the assignment of different codes for every user (Code Division Multiple Access = CDMA) or, in the case of multiple antennas, by spatial user separation. This concept of Space Division Multiple Access (SDMA) enables the improvement of user and system capacity.

Besides these potential benefits multi-antenna systems can efficiently be used to minimize fading effects by exploiting spatial diversity. The basic principle of this concept can be described as follows: if the channel distortions associated with the different antennas are uncorrelated, there is a high probability that if the signal strength heavily drops at one antenna element the same is not true for other antenna elements. This effect will in turn lead to a smaller error rate in case of suitable antenna signal combination. The exploitation of the spatial correlation properties, which heavily influence the possible spatial diversity gain, leads us to a new approach for the integration of spatial and temporal processing units into a reduced dimension ST processor. The concept includes two stages, which will be discussed in this article. In the first stage the received signal components are decorrelated using a linear transformation. Thereafter, a second stage removes transformed signal components that are not relevant for subsequent signal processing units. The properties and performance issues of the resulting spatial dimension reduction, which uses the Karhunen-Loève-Transformation (KLT) [5] as a key component, will also be analyzed in this article.

2 Receiver Architectures

Typical outdoor mobile communication as well as indoor propagation scenarios are commonly characterized by multipath propagation of the transmitted signal on its way to the receiver antennas. These multipaths are caused by reflections and scattering effects at objects in the propagation environment, which is exemplified in Fig. 1(a) for a typical outdoor scenario. Those propagation effects will result in a temporal spread of the received signal due to the different propagation delays and in angular signal spread depending on the location of the reflectors and scatterers. The most general approach for a receiver equipped with multiple antennas to compensate for those propagation effects is the application of an fully armed joint space-time equalizer [6] as depicted in Fig. 2(a), where M determines the number of antennas and N the number of temporal equalizer taps. The main advantage of such ST processors is a joint spatial and temporal parameter (channel) estimation and equalization in contrast to an independent treatment of spatial and temporal equalizer stages. At the same time, joint ST approaches face the problem of a high number of free parameters to be estimated. The full dimension ST processor with M antenna elements and N temporal equalizer taps requires the estimation of $M \times N$ param-

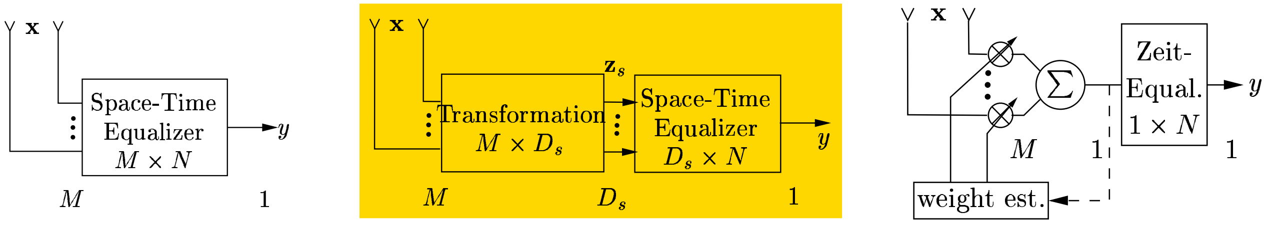


Figure 2: Space-Time processing concepts: (a) full dimension ST processing (b) reduced dimension ST processing, (c) spatial combining followed by temporal equalization

eters. Besides the computational load of this estimation process, numerical problems may arise for certain channel conditions. Assuming for example the case where only one wavefront is propagating across the M receive antennas as depicted in Fig. 1(b), the resulting received signals and their respective channels are almost identical up to a phase shift, which corresponds to the incidence angle of the wavefront and the array geometry, and some decorrelation caused by additive noise. The associated channel impulse responses for the M receiver chains are in this case linearly dependent. If we introduce a channel matrix $\mathbf{H}(t)$, which contains the M channel impulse responses as rows, than this channel matrix will be close to singular [7, 8].

Therefore, in environments with only one strong propagation path or with small angular spread the application of a separate spatial processor (beamformer, spatial diversity combiner) and a temporal equalizer as indicated in Fig. 2(c) might be more feasible. For this beamforming approach the optimization of M beamforming weights and the estimation of N temporal equalizer coefficients is required. However, this approach will limit the applicability of the receiver, since it is adapted to certain propagation conditions.

Looking at the previously discussed equalizer structures it becomes obvious that there are several degrees of freedom for the implementation of a structure which can be placed (in terms of complexity and flexibility) in between the spatial combining approach and the fully armed ST processor. An important reason for this is that even in multipath scenarios with considerable angular and temporal spreads there exists partial correlation between the received signals at the M antenna elements. This correlation can be removed in a preprocessing or transformation stage. Additionally, this effect enables the reduction of the signal space and a reduced dimension ST processor, as shown in Fig. 2(b) with $D_s \leq M$ as reduced spatial dimension.

3 Reduced Dimension Space-Time Receiver Concept

Let us consider the basic principles and the structure of the proposed ST receiver. The main challenges in the receiver design are twofold: first we need to find an appropriate algorithm to decorrelate the antenna signals, and second we have to determine a selection criterion to remove components which do not significantly contribute to the receiver performance. The first step shall be referred to as transformation stage and the second as selection stage. The selection stage is the means to reduce the signal dimension and is therefore the key to enable reduced dimension ST equalization. The principle is depicted in Fig. 3. Clearly, the design of the transformation and selection stages should be done jointly. The transformation stage should move the desired information into as few transformed signal components as possible to allow the selection stage to efficiently reduce the dimensionality.

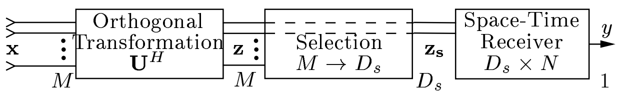


Figure 3: Reduced dimension ST receiver concept

Spatial Correlation Properties As mentioned earlier, the spatial correlation properties of the received antenna signals determine the possible degree of the dimension reduction. Therefore, we will introduce the spatial correlation matrix $\mathbf{R}_\mathbf{x}^S$ of the received signal vector $\mathbf{x}(t)$. To simplify the interpretation, we assume zero mean and identically distributed data symbols as well as spatially and temporally white noise, which is uncorrelated with the data symbols. Than we can write the spatial correlation matrix as

$$\mathbf{R}_\mathbf{x}^S = \mathcal{E}\{\mathbf{x}(t)\mathbf{x}(t)^H\} = \mathcal{E}\{\mathbf{H}\mathbf{H}^H\} + \mathbf{R}_\mathbf{n}^S \qquad (1)$$

with $\mathbf{R}_\mathbf{n}^S = \sigma_n^2\mathbf{I}$ as diagonal matrix containing identical noise variance σ_n^2 for all antenna elements. The matrix $\mathbf{H} = \mathbf{H}(t)$ of dimension $M \times N$ describes the transmission channel for M receive antennas and a temporal channel response with a duration limited to N symbol periods. The properties of the transmission channel are influenced by the propagation scenario, namely the temporal and angular signal spread introduced by obstacles in the environment, the number of significant propagation paths and their respective propagation loss, but also by filters in the transmission chain and antenna characteristics such as the geometry of the antenna array. These parameters determine the spatial correlation properties. Recalling the beamforming scenario depicted in Fig. 1(b) and assuming, that the antenna elements are spaced sufficiently close and that no noise is present, the signals at the receive antennas are basically phase shifted copies of each other due to the signal propagation across the antenna array. This results in M almost perfectly correlated channels and hence in a channel matrix $\mathbf{H}$ with linearly dependent rows. Therefore, the $\mathbf{H}$ and $\mathbf{R}_{\mathbf{x}}^{S}$ matrices will have a rank of 1 in this special case. More generally, scenarios with less multipath components than antennas M will result in spatial correlation matrices $\mathbf{R}_{\mathbf{x}}^{S}$ that are rank deficient or close to rank deficient in noisy environments. Although this is not true for rich scattering scenarios, which typically occur in wireless indoor and outdoor communication scenarios as was depicted in Fig. 1(a), even in these cases the received signals and the associated channels are partially correlated [9].

To further investigate these spatial correlation properties in conjunction with the dimension reduction approach, the Singular Value Decomposition (SVD) is introduced for hermitian matrices as

$$\mathbf{R}_{\mathbf{x}}^{S} = \mathbf{U}\Lambda\mathbf{U}^{H}, \tag{2}$$

with $\mathbf{U}$ as the left-hand side eigenvector matrix of $\mathbf{R}_{\mathbf{x}}^{S}$ and Λ as a diagonal matrix containing the eigenvalues sorted in descending order, $\Lambda = \operatorname{diag}\left[\lambda_0^2 \quad \lambda_1^2 \ldots \lambda_{M-1}^2\right]$. Note that the eigenvalues are determined by the received signal properties and the noise variance, $\lambda_i^2 = \sigma_i^2 + \sigma_n^2$, as can be seen from Eqn. (1).

In order to clarify the dependency of the eigenvalue distribution on the propagation scenario, the cumulative distribution functions of the normalized eigenvalues $\tilde{\lambda}_i^2 = \lambda_i^2 / \sum_{m=0}^{M-1} \lambda_m^2$ are shown in Fig. 4 for two different scenarios. It is assumed that no noise is present, which results in $\lambda_i^2 = \sigma_i^2$. The path delays and angles are drawn from random processes, where for the angular distribution two different spreads were assumed. In the first case all multipath components are impinging on the antenna array from almost identical directions. The resulting small angular spread yields a eigenvalue distribution as depicted in Fig. 4(a). There is one strong eigenvalue $\tilde{\lambda}_0^2$ corresponding to the main direction, the second eigenvalue is already much smaller. For large angular spread values the situation turns out to be quite different as indicated by Fig. 4(b). There exist several relatively strong eigenvalues. The next paragraphs will show, how this eigenvalue properties can efficiently be used for spatial dimension reduction.

Transformation Stage In order to be able to efficiently reduce the spatial signal dimension, we need to find an orthogonal transformation, which decorrelates the received antenna signals and at the same time concentrates the signal energy within as few transformed signal components as possible. It can be shown that the KLT [5] in this context plays a key role among the orthogonal transformations, since it is problem adapted by directly using the signal correlation properties. If the M-dimensional data vector $\mathbf{x}(t)$ results from a wide sense stationary vector process with zero mean and correlation $\mathbf{R}_{\mathbf{x}}^{S}$, then the signal vector can be expanded as linear combination of the eigenvectors $\mathbf{u}_i$ of $\mathbf{R}_{\mathbf{x}}^{S}$,

$$\mathbf{x}(t) = \sum_{i=0}^{M-1} z_i(t)\mathbf{u}_i = \mathbf{U}\mathbf{z}(t). \tag{3}$$

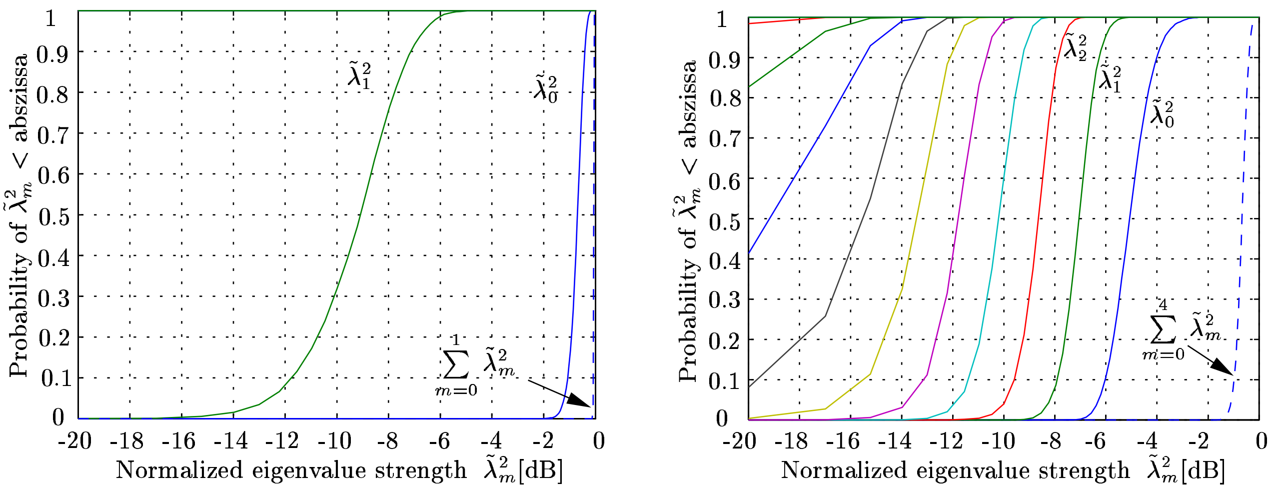
The associated coefficients $z_i(t)$ are zero mean and uncorrelated random variables, which can be represented in vector notation as

$$\mathbf{z}(t) = \mathbf{U}^{H}\mathbf{x}(t). \tag{4}$$

Eqn. (4) exactly describes the desired transformation stage as was shown in Fig. 3. The transformation matrix $\mathbf{U}$ contains the eigenvectors of the spatial correlation matrix $\mathbf{R}_{\mathbf{x}}^{S}$ which makes the KLT a signal-adapted transformation. The resulting components in the transformed signal vector $\mathbf{z}(t)$ are uncorrelated to each other. Furthermore, it can be shown that the variance or signal energy of the vector components $z_i(t)$ is equal to the respective eigenvalues $\lambda_i^2 = \mathcal{E}\{|z_i(t)|^2\}$ of the spatial correlation matrix [5]. This property results in transformed components $z_i(t)$ with unequal variance or mean signal energy determined by the eigenvalues λ_i^2 with maximum variance in the first component. This fact, that the signal energy is concentrated in the first transformed components $z_i(t)$ is the key to the dimension reduction with minimum signal energy loss.

Using this fact, it turns out that there exists a great potential to reduce the spatial signal dimension for scenarios with eigenvalue distributions as depicted in Fig. 4(a). On the other hand, the dimension reduction potential is limited for eigenvalue distributions as shown in Fig. 4(b) corresponding to scenarios with large temporal and angular spread. However, the dashed line shows that in this example the selection of 5 out of 16 components belonging to the 5 strongest eigenvalues will result in a loss of signal energy, which is less than or about 1 dB. Consequently, also this scenario provides a considerable dimension reduction potential.

Dimension Selection Stage Having transformed the received signals we need to smartly select only those transformed signal components $z_i(t)$, which are essential for the subsequent ST processing stage. As discussed earlier in this section, in some cases the spatial correlation matrix will be rank deficient or close to rank deficient. This is especially true if there exist less multipath components then antenna elements. In such situations the space spanned by the eigenvectors $\mathbf{u}_i$ is larger than the actual signal space. Stated differently, there exist eigenvectors, that exclusively correspond to noise components, the respective eigenvalues are equal to the noise variance σ_n^2. Removing those components, which belong to the so called noise subspace,



(a) (b)

Figure 4: Cumulative distribution function of the normalized eigenvalue strength for $M = 16$ antennas, delay spread $\sigma_\tau = 4T_{sym}$, (a) small angular spread $\sigma_\theta = 2°$, (b) large angular spread $\sigma_\theta = 40°$

will reduce the overall noise variance of the received signal and therefore enable improved receiver performance. There exist several powerful algorithms to efficiently estimate the dimension of the signal and noise subspaces, which are known as information theoretic criteria [10].

However, in many wireless communications scenarios with rich multipath scattering and a rather limited number of receive antennas, the method described above will not be appropriate. Therefore, a different approach is suggested here, which is known as low-rank modeling [11]. The basic idea is to trade the modeling error introduced by removing signal components with weak eigenvalues λ_i^2 for the noise variance saved when removing noisy components.

It was shown in Eqn. (3) that the received signal vector can be expanded as a linear combination of the eigenvectors $\mathbf{u}_i$. If components are removed from this sum, an approximation error $\varepsilon_{\hat{\mathbf{r}}}$ is introduced which is also referred to as bias. This bias heavily depends on the eigenvalue distribution. It can be shown [11, 7], that the mean squared error (MSE) introduced by removing a signal component $z_i(t)$ is equal to the corresponding eigenvalue λ_i^2. Consequently, the strength of the bias introduced by removing components with small eigenvalues will depend on the ratio between strong and weak eigenvalues. A large ratio between strong and weak eigenvalues will result in a small bias and vice versa.

On the other hand, with the assumption of equal noise variance for all received antenna signals this noise variance will remain unchanged after the transformation stage. Therefore, removing transformed signal components will also reduce the overall noise variance and the respective MSE $\varepsilon_{\hat{\mathbf{n}}}$. This effect will in turn decrease the MSE of the approximated receive signal, which results from the truncated linear combination. Hence, the removal of transformed signal components can be viewed as a bias-variance-tradeoff.

Comparing the two effects it can be shown that the low rank model [11] as well as the transformed received signal will be improved in the MSE sense, when the signal energy neglected is less than the noise variance saved,

$$\sum_{i=D_s}^{M-1} \sigma_i^2 = \sum_{i=D_s}^{M-1} (\lambda_i^2 - \sigma_n^2) \leq (M - D_s)\sigma_n^2, \qquad (5)$$

where D_s is the truncated spatial signal dimension. The middle term of Eqn. (5) indicates that the "measured" eigenvalues λ_i^2 are also influenced by the noise variance. An example of the bias-variance-tradeoff is shown in Fig. 5 for $M = 8$ antennas, a mean input SNR of 3 dB, and assuming rapidly decaying eigenvalues as indicated by the dashed line. This curve shows the MSE $\varepsilon_{\hat{\mathbf{r}}}$ introduced when approximating the received signal by D_s instead of M components (cf. Eqn. (3)). The dashed-dotted line visualizes the error $\varepsilon_{\hat{\mathbf{n}}}$ caused by the overall noise variance associated with the number of components D_s. Finally, the solid curve shows the resulting MSE $\varepsilon_{\hat{\mathbf{x}}}$ introduced by the dimension reduction, which in this example reaches its minimum value for $D_s = 2$ transformed components. It can be observed from Fig. 5 that the ratios between the eigenvalues σ_i^2 strongly influence the optimum dimension D_s. However, it can be shown, that for most scenarios the number of strong eigenvalues is very limited. For antenna configurations of 8 and 16 antennas the spatial dimension can frequently be reduced to $D_s = 1 \ldots 3$ [7, 9].

If we compare these results with the rank deficiency approach discussed earlier, the advantages become clear. In the example discussed in Fig. 5 no rank deficiency exists. This means, that with traditional methods to determine the

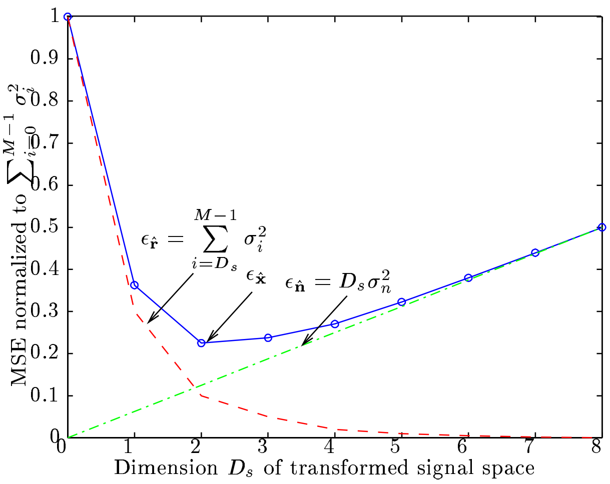


Figure 5: Bias-Variance tradeoff for $M = 8$ received signals, mean input SNR of 3 dB, and normalized eigenvalue distribution $\text{diag}(\Sigma) = [0.7, 0.2, 0.05, 0.03, 0.01, 0.005, 0.003, 0.002]^T$

signal subspace dimension no reduction of the spatial dimension would result. In contrast, the application of the bias-variance-tradeoff provides a considerable dimension reduction potential. Moreover, at the same time the MSE of the transformed vector signal is minimized. This effect will be further discussed in the following paragraph.

The selection process discussed here does not depend on additional a-priori information. However, depending on the actual system it might be essential to introduce additional user specific information, either in front of the transformation stage or for the selection stage.

Reduced Dimension Space-Time Equalizer Stage Finally, we need to investigate the implications of the spatial dimension reduction for the successive ST equalizer. There exist various space-time extensions for conventional equalizer structures. These include ST versions of the minimum-mean-squared error (MMSE) equalizer, the decision feedback equalizer (DFE) as well as the maximum-likelihood sequence estimation (MLSE) equalizer [12, 13, 14]. We will here focus our attention to the ST-MLSE equalizer, which can efficiently be implemented as an extension of the well known Viterbi equalizer [14]. One key element of the Viterbi equalizer is the branch metric (BM) computation, which is performed for every symbol. We will show here how the reduced dimension approach influences this BM computation process and the receiver performance.

The ST extension of the Viterbi equalizer is as follows: the BM's are independently computed for all M received signal branches, the results are than summed to the overall BM accordingly. Reducing the dimension of the received signals to D_s results in a linear decrease of the computational load.

Moreover, the BM computation requires estimates of the channel parameters as input. An improved channel estimation therefore directly influences the performance of the equalizer. Using the reduced dimension signal stream as input, the channel estimation problem is simplified. Instead of $M \times N$ parameters now only the estimation of $D_s \times N$ channel coefficients needs to be performed. Furthermore, as we recognized in the previous paragraph, the dimension reduction to the optimum dimension D_s also reduces the MSE and the overall noise variance of the transformed signal. Hence, the channel estimation will become more reliable. The underlying reason for this effect is, that instead of using only a short training sequence for the channel estimation, additional knowledge about the received signal contained in the spatial correlation matrix is exploited.

4 Results

Following the performance of the proposed reduced dimension ST receiver will be analyzed. In the discussed example BPSK modulated data were transmitted from a transmitter with one antenna to a receiver with $M = 8$ antenna elements. The channel characteristics were modeled using a tapped delay line model with 12 taps, which is characterized by Rayleigh-fading components and rather high temporal spread. Additionally, an angular value was assigned as spatial information to every multipath tap. The angles were drawn from a uniform distribution with an angular beamwidth of $\pm 70°$. The spatial correlation matrix was estimated for every data block of length 2093 including a training sequence of length 93. The SVD was performed for the spatial correlation matrix estimate. The receiver performance was investigated for various ST receiver dimensions D_s. To limit the complexity of the Viterbi equalizer, the number of temporal channel taps was limited to $N = 6$. The results for the achievable BER are shown in Fig. 6 and plotted over the average input SNR.

The solid rightmost curve shows a reference simulation for one antenna element. When this curve is compared with the other curves, which present simulation results for 8 antenna elements, considerable gains of $\geq$ 9dB can be identified for the multi-antenna approach. This gain is determined by two effects. First, the usage of M antenna elements results in a SNR gain of $10 \log(M) = 9$dB. This is a well known result from beamforming approaches [1], which also holds for the proposed dimension reduction technique. Second, a spatial diversity gain is achieved by combining multiple antenna signals. This means, that the probability of deep fades in the transformed signal components is considerably reduced resulting in a reduced variance of the SNR at the output of the dimension reduction stage. The achievable diversity gain strongly depends on the degree of correlation between the different received signals. If we recall the scenario shown in Fig. 1(b), we can draw an important conclusion. For cases, where only one strong path and no scattering is present, the proposed pro-

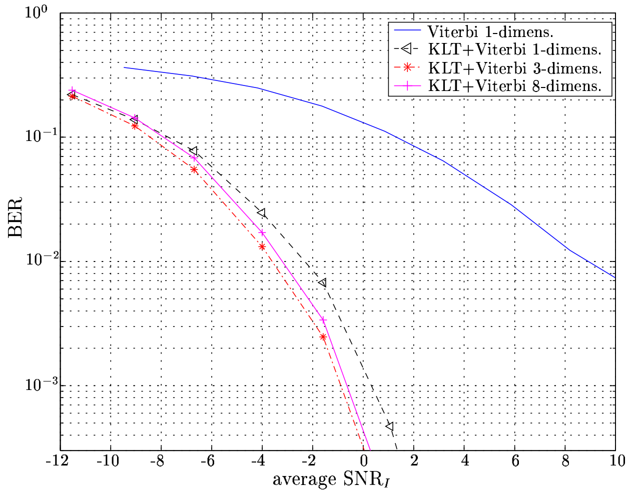


Figure 6: Bit Error Rate performance for reduced dimension ST-Viterbi equalizer

cedure yields the same results as a classical beamformer. The dimension can be reduced to $D_s = 1$, since one strong path corresponds to one strong signal eigenvalue. Due to the total signal correlation no spatial diversity can be achieved. If, on the other hand, we assume scattering around the receiver, but with very limited temporal spread, which results in a frequency flat channel, we also end up with only one strong eigenvalue. However, in this case the antenna signals are more or less decorrelated, which results in an additional spatial diversity gain. For statistically independent spatial channels the proposed dimension reduction approach therefore also includes the maximal ratio (diversity) combining (MRC) scheme. Hence, we can conclude that the discussed approach brings together the two concepts of beamforming and MRC as special cases, which are usually considered as independent concepts. Another important statement is, that using the reduced dimension ST receiver concept, the geometry does not play an important role as it does for beamforming concepts, since the antennas are basically only considered as "independent" information sources.

Comparing the three left curves in Fig. 6 in more detail, it turns out that the dependency of the achievable gain and the number of selected components for the given channel conditions is limited. The gain difference between the dimension reduction to one $(- - \triangleleft - -)$ and the optimum dimension is less than 2dB for the considered SNR range. For very low SNR values the channel estimation is very noisy. In this case the dimension reduction to $D_s = 1$ yields the best results. For increasing SNR's the loss caused by neglecting information bearing components becomes dominant compared to the noise variance reduction. When comparing the curves for dimension reduction to $D_s = 3$ $(- \cdot * \cdot -)$ and to 8 (—+—) components, the full dimension case performs worse in the entire SNR range. This indicates that for the given channel model the signal energy will be concentrated in the first transformed components, the components corresponding to low eigenvalues basically contain only noise. For the optimum dimension selection case applying the bias-variance-tradeoff the respective BER curve is determined by the minimum of the array of curves for all possible dimensions D_s.

5 Conclusion

Emerging wireless services with high and variable data rate demands and the increasing numbers of mobile users require the efficient usage of available resources. The exploitation of the spatial dimension by applying multiple transmit/receive antennas is a promising approach to increase the required system performance. In this article a new reduced dimension space-time processor concept has been introduced. The KLT is applied to decorrelate the received signals. Using the eigenvalue properties of the spatial correlation matrix of the received signals, the optimum reduced receiver dimension can be determined by applying a bias-variance tradeoff. In contrast to many subspace approaches, this concept also works in rich multipath scenarios. Furthermore, the antenna configuration is not of major concern for the approach discussed here as compared to beamforming algorithms, whose performance is highly dependent on antenna characteristics, especially when direction-of-arrival estimation techniques are involved. Antenna configurations which result in spatial decorrelation will improve the achievable diversity gain.

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