REALISTIC MIMO SIMULATIONS BASED ON MULTIDIMENSIONAL CHANNEL-SOUNDING MEASUREMENTS

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ABSTRACT

MIMO systems (with multiple antennas at the base station and at the mobile) are frequently modeled with optimistic scattering assumptions, which do not necessarily hold in real environments that have time-varying spatial and temporal correlations. Real-time multidimensional measurements, taken from a channel sounding campaign at Ilmenau University of Technology, are analyzed in this contribution and an improved method for adaptive channel estimation that exploits long-term channel characteristics is proposed. We use the angle between the signal subspaces of two consecutive spatio-temporal snapshots to adapt the forgetting factor of the long-term signal subspace tracking algorithm.

INTRODUCTION

MIMO sytems promise huge capacity gains in wireless communications [1]. Especially, spatial and temporal correlated scenarios have achieved growing attention recently [2]. Novel space-time processing methods which benefit from those correlations have been proposed recently, e.g., in [3]. In this contribution, we analyze the time-varying subspaces of spatial covariance matrices to benefit from long-term channel statistics. The stability of this subspace structure depends on the time variance of the scenario and can be improved by averaging over a certain time window. Moreover, we show how the channel estimation can be improved by projecting the short-term channel estimate onto the signal subspace of the long-term spatial covariance matrices, representing the dominant paths of the channel [4].

MEASUREMENTS

The multidimensional MIMO channel sounder uses multiple antennas at the transmitter as well as at the receiver position [5]. By measuring the channel impulse response between any pair of the antennas on both sides, the 4-dimensional spatial channel response array $\boldsymbol{H} \in \mathbb{C}^{M_R \times M_T \times W \times N}$ can be constructed, where M_R denotes the number of receiving antennas, M_T is the number of transmit antennas, W is the number of samples in delay time, and N denotes the number of temporal snapshots. The high measurement repetition rate of the sounder hardware and its long-term recording capability enables the resolution of fast fading and the assessment of the long-term variations of the channel impulse response (CIR) sequence as well.

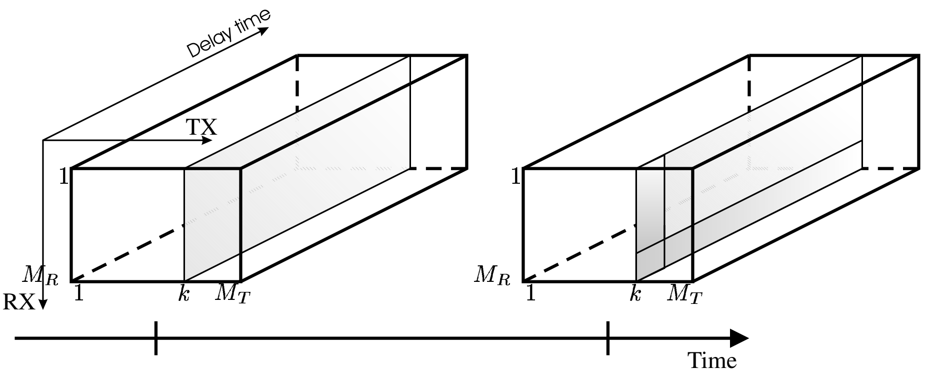

Figure 1: Structure of the measured / estimated channel impulse responses

SUBSPACE ANALYSIS

The spatial correlation can be assessed via an eigenanalysis of the spatial covariance matrices. In MIMO scenarios, this can be calculated separately both for the transmitter and the receiver.
Let us consider a SIMO (single input multiple output) scenario ($M_T = 1$) first. Then the spatial covariance matrix for a particular time snapshot n is

$$\boldsymbol{R}_R^{(n)} = \frac{1}{W}\boldsymbol{H}(:,1,:,n) \cdot \boldsymbol{H}(:,1,:,n)^H = \frac{1}{W}\sum_{w=1}^{W}\boldsymbol{H}(:,1,w,n) \cdot \boldsymbol{H}(:,1,w,n)^H \ . \tag{1}$$

For the MIMO subspace analysis we calculate the time dependent spatial covariance matrices at the transmitter and the receiver and average over several time snapshots

$$\boldsymbol{R}_R^{(n)} = \rho\,\boldsymbol{R}_R^{(n-1)} + \frac{1-\rho}{W}\sum_{w=1}^{W}\boldsymbol{H}(:,:,w,n) \cdot \boldsymbol{H}(:,:,w,n)^H \tag{2}$$

$$\boldsymbol{R}_T^{(n)} = \rho\,\boldsymbol{R}_T^{(n-1)} + \frac{1-\rho}{W}\sum_{w=1}^{W}\boldsymbol{H}(:,:,w,n)^H \cdot \boldsymbol{H}(:,:,w,n)\ , \tag{3}$$

with a forgetting factor ρ. This was proposed for the SIMO case in [4] and is now extended to MIMO systems. Following Matlab notation, indexing with the colon operator $(:)$ returns all elements of the corresponding dimension. Furthermore, let any singleton dimension be squeezed out, forming a new array of smaller dimensionality.
Let $\boldsymbol{V}_R^{(n)} \cdot \boldsymbol{\Lambda}_R^{(n)} \cdot \boldsymbol{V}_R^{(n)H} = \boldsymbol{R}_R^{(n)}$ and $\boldsymbol{V}_T^{(n)} \cdot \boldsymbol{\Lambda}_T^{(n)} \cdot \boldsymbol{V}_T^{(n)H} = \boldsymbol{R}_T^{(n)}$ be an eigenvalue decomposition of the Hermitian spatial covariance matrices of the receiver and the transmitter, respectively, and let the eigenvalues in the diagonal matrix $\boldsymbol{\Lambda}_R^{(n)}$ and $\boldsymbol{\Lambda}_T^{(n)}$ be arranged in descending order.
To build the projection matrices that project the current noise-corrupted channel estimate into the dominant subspaces of the receive and transmit arrays, respectively, let $\boldsymbol{U}_R^{(n)} \in \mathbb{C}^{M_T \times L}$ and $\boldsymbol{U}_T^{(n)} \in \mathbb{C}^{M_R \times L}$ contain the eigenvectors corresponding to the L dominant eigenvalues of $\boldsymbol{R}_R^{(n)}$ and $\boldsymbol{R}_T^{(n)}$, respectively. Then the projection matrices are

$$\boldsymbol{P}_R^{(n)} = \boldsymbol{U}_R^{(n)} \cdot \boldsymbol{U}_R^{(n)H} \tag{4}$$

$$\boldsymbol{P}_T^{(n)} = \boldsymbol{U}_T^{(n)} \cdot \boldsymbol{U}_T^{(n)H}\ . \tag{5}$$

The operation

$$\hat{\boldsymbol{H}}(:,:,w,n) = \boldsymbol{P}_R^{(n)} \cdot \boldsymbol{H}(:,:,w,n) \cdot \boldsymbol{P}_T^{(n)} \tag{6}$$

projects the current channel estimate into the long-term subspace at the transmitter and the receiver and thereby decreases the noise significantly.
It is also possible to build a joint spatial covariance matrix of the dimension $(M_T \cdot M_R) \times (M_T \cdot M_R)$, containing all possible combinations between transmit and receive antennas. But the subspace analysis of separate spatial covariance matrices at the transmitter and receiver as proposed here has a significantly lower computational complexity.
Figure 2 shows the eigenvalues of the spatial covariance matrices taken from a MIMO-channel sounding campaign in a court yard scenario, measured at the campus of Ilmenau University of Technology. It can be seen that over the whole measurement time only $L = 1$ dominant eigenvalue occurs.

IMPROVED CHANNEL ESTIMATION

In this section, we describe how the channel estimate can be improved by projecting it into the dominant subspace of the receive antenna array. To show this, we use measured channel impulse responses [5] in our simulations. Let us now consider a multi-user SIMO scenario, containing K mobiles each equipped with one antenna and a base station with an antenna array of M_R elements.
Let $\boldsymbol{H}(:,k,:,n)$ be the short-term estimate of the channel impulse response matrix for the k-th user at the n-th temporal snapshot, where W is the length of the channel impulse response. This short-term estimate can be computed sequentially, using a joint recursive least squares (RLS) estimation or by batch processing, using the least squares (LS) solution for example. To resolve the different paths of the channel, different training sequences with optimized cross-correlation properties are used for each transmit antenna.

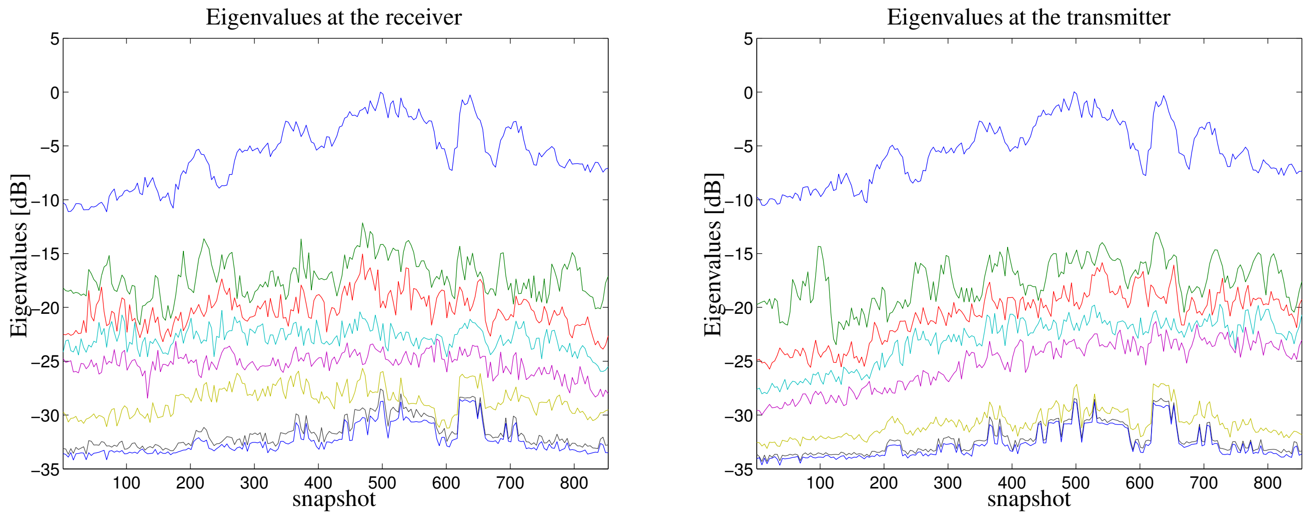

Figure 2: Eigenvalues at the receiver and the transmitter for the MIMO scenario

To benefit from the slow time variance of the channel, the spatial covariance matrix $\boldsymbol{R}_R^{(n)}(k)$ is averaged over several time slots. The forgetting factor ρ $(0 \leq \rho \leq 1)$ allows to adapt for different speeds of time variance.

$$\boldsymbol{R}_R^{(n)}(k) = \rho\, \boldsymbol{R}_R^{(n-1)}(k) + \frac{1-\rho}{W} \boldsymbol{H}(:,k,:,n)\; \boldsymbol{H}(:,k,:,n)^H, \quad \text{with} \quad \boldsymbol{R}_R^{(1)}(k) = \frac{1}{W} \boldsymbol{H}(:,k,:,1)\; \boldsymbol{H}(:,k,:,1)^H \tag{7}$$

The new short-term channel estimate can now be improved by projecting it on the subspace that is spanned by the L dominant eigenvectors of $\boldsymbol{R}_R^{(n)}(k)$,which form the columns of the matrix $\boldsymbol{U}_R^{(n)}(k) \in \mathbb{C}^{M_R \times L}$.

$$\hat{\boldsymbol{H}}(:,k,:,n) = \boldsymbol{P}_R^{(n)}(k)\; \boldsymbol{H}(:,k,:,n), \quad \text{with} \quad \boldsymbol{P}_R^{(n)}(k) = \boldsymbol{U}_R^{(n)}(k)\; \boldsymbol{U}_R^{(n)H}(k) \tag{8}$$

To compare the estimation errors we use the following performance measure:

$$e(n) = \frac{\sum_{m_R=1}^{M_R} \sum_{w=1}^{W} \left| \boldsymbol{H}_{\text{measured}}(m_R,k,w,n) - \boldsymbol{H}(m_R,k,w,n) \right|^2}{\sum_{m_R=1}^{M_R} \sum_{w=1}^{W} \left| \boldsymbol{H}_{\text{measured}}(m_R,k,w,n) \right|^2} \tag{9}$$

Figure 3 shows the errors for a 120 seconds SIMO measurement with $M_R = 8$, $W = 15$, and $N = 500$ temporal snapshots. It can be seen that the projection improved version outperforms the short-term estimate at almost every temporal snapshot. After 55 seconds the channel changes rapidly so that the projection into the long-term subspace leads to a bigger error.

To handle also rapid changes, the forgetting factor has to be chosen adaptively. For this purpose we need a criterion that tells us if the channel has changed significantly compared to the last temporal snapshot. Therefore, we calculate the angle between the current and the last signal subspace estimate $\boldsymbol{U}_R^{(n)}(k)$ and $\boldsymbol{U}_R^{(n-1)}(k)$. By simple thresholding on the angle (here 0.08 rad), we switch between two values for the forgetting factor $\rho = 0.4$ and $\rho = 0.8$, respectively. The better performance of this approach with variable forgetting factor is shown in figure 5. Figure 6 plots the angle between the current and the last signal subspace estimate and the adapted forgetting factor ρ.

CONCLUSIONS

In this contribution, we show how to benefit from spatial and temporal correlations via a projection technique into the dominant subspaces of the spatial covariance matrices of a MIMO communication system. Based on simulations with measured channel impulse responses, we show that a projection of the current channel impulse response estimate into the averaged dominant subspaces of the long-term CIR estimates improves the channel estimation procedure in a noisy environment. An adaptation of the averaging algorithm via simple thresholding on the angle between two consecutive signal subspaces improves the performance even further, because it allows to react on rapid changes in the channel characteristics.

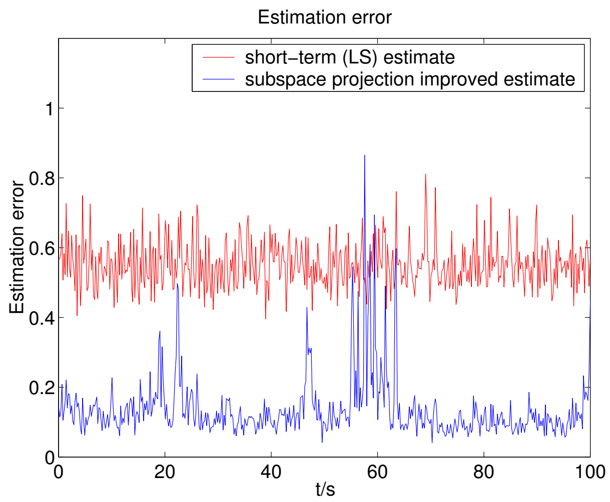

Figure 3: Estimation error with $\rho = 0.8$

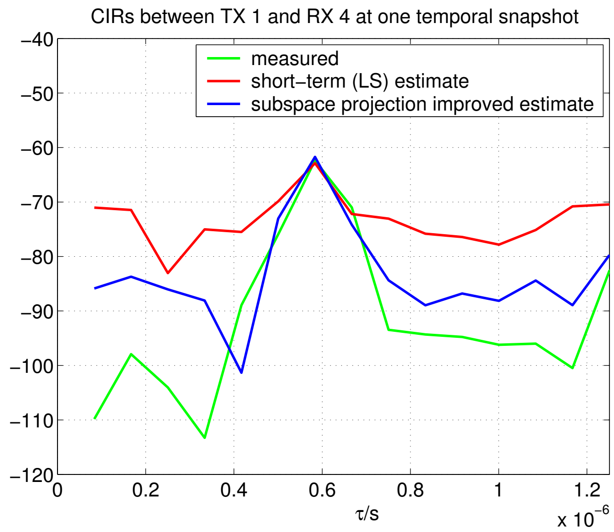

Figure 4: Sample CIR

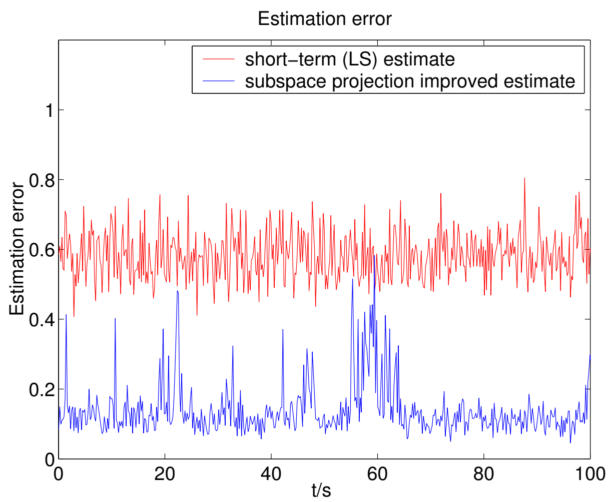

Figure 5: Estimation error with adaptively chosen forgetting factor $\rho = \{0.4, 0.8\}$

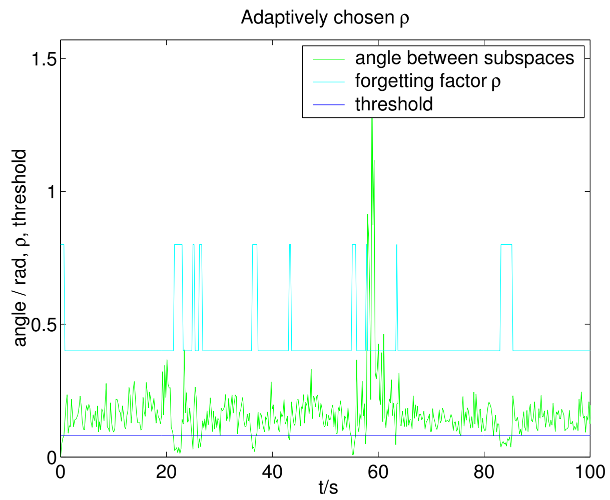

Figure 6: Angle between two consecutive signal subspaces and the forgetting factor

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