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1 INTRODUCTION

This document summarises the research activities carried out in the framework of the project "Smart Antennas for Mobile Communication System". The project is based on the contract P-12147 MAT between Austrian Science Fund (Fonds zur Förderung der wissenschaftlichen Forschung, FWF) and Institut für Nachrichtentechnik und Hochfrequenztechnik, TU Wien (INTHF). The project started in May 1997 and this deliverable considers the achievements during the first two project years.

The aim of the project is to contribute to the utilisation of adaptive antennas with the existing and forthcoming mobile communication systems. The focus of the research is to develop new signal processing schemes for adaptive antennas in mobile radio application. However, we have also carefully considered application specific issues like influences and restrictions caused by physical propagation phenomena and imperfect receiver hardware.

This deliverable omits technical details, but gives an overview and acts as a guide to find more information in the other project related publications with more technical nature. The section is divided further into subsections, each describing one of the following main activities:

- Channel Modeling
- Downlink Algorithms
- Receiver Imperfections and Calibration
- Robust Algorithms (Blind and Semi-Blind Estimation)
2 PROJECT DOCUMENTATION

2.1 Channel Modeling

2.1.1 Introduction

Realistic spatial channel modeling is vital for the simulations of adaptive antenna systems. Only a channel model which reflects the radiowave propagation in typical environments, in the time as well as in the angular domain, can be used for simulations. Violation of this basic legitimacy may lead to wrong conclusions about the analysed algorithms and the system itself.

The theoretical basis of the Geometry-based Stochastic Channel Model (GSCM) [FMB_98] was already existing before the current project. The model consists of scatterers in the vicinity of the mobile station and the received signal is calculated by simple ray-tracing. The location of the scatterers is selected according to the appropriate PDF (probability density function). In addition, it is possible to include far scatterers which correspond to reflections from far obstacles, like mountains in rural environments or high-rise buildings in suburban and urban environments.

In the framework of the current project we extended and parametrised the model to enable realistic simulations with different purposes and environments. For example, we have included the MS movement to be able to consider the time variation of the channel. Further, we had to fit the parameters of the model in a way that the characteristics like power delay profile (PDP) and azimuthal power spectrum (APS) agree with recent channel sounder measurements [Ped_97]. In addition to the modifications of the uplink channel model we created a corresponding downlink implementation with the same requirements.

2.1.2 Parameter fitting of the GSCM

The fundamental requirement for the spatial channel models is that the PDP and APS correspond to the distributions observed in the channel measurements. As discussed above, the distribution defining the location of the scatterers forms the basis of the GSCM and determines also the responses at the receiving antennas in a straightforward way. In our model we have considered three different PDFs for the distance between the MS and the scatterers; Gaussian, Rayleigh and uniform distributions [LSB_98]. Figure 1 shows the simulated azimuthal power spectra with these PDFs when only local scatterers were present. Comparison to the recent measurements results [Ped_97] shows that Gaussian distribution fits well to the measured Laplacian APS and it approximates properly also the exponential PDP of the well known stochastic COST 207 models. Corresponding considerations have been carried out also for the scenario with far scatterers. Our results show that parameter selection modeling urban environment with base stations above the rooftop level gives perfect fit with the COST 207 TU (typical urban) model (Fig. 3.)

The investigations shown above are also possible by employing analytical bijective mathematical transformation between scatterer locations and resulting delays and DOAs (direction of arrival) at the receiver. Accordingly the measured joint ADPS (azimuthal delay power spectrum) can be transformed to the scatterer constellation under the single scattering assumption [MLK_98], [Egg_98]. This enables direct parametrisation of the GSCM by utilising measured data.

1 Following the established notation in the literature we use word "scatterer" even if strictly speaking specular reflections are assumed.
2.1.3 **Time variation of the spatial channel model**

In normal propagation environments buildings, hills and mountains act as the dominant reflectors. Therefore the scattering points do not change their position when the MS moves through the scattering scenario. Further, in link level simulations we are typically interested in the short term variations of the mobile radio channel. For downlink beamforming we have to carry out the parameter estimation by means of averaging, because the instantaneous downlink channel is not known due to the uncorrelated fading in different transmission directions. However, averaging over small-scale fading is adequate which corresponds to the mobile movement over 10-20λ. Notation λ denotes the wavelengh of the signal, being about 16 cm for GSM1800 frequencies.

However, for some special simulation purposes it might be also relevant to consider longer term channel variations, which correspond to the movement of the MS over the hundreds of wavelengths. For these situations we have proposed the special implementation of the GSCM, in which we locate scatterers uniformly over the whole area under consideration beforehand and we weight the scattering cross sections according to the MS movement during the simulation. We call this implementation NSCS, nonuniform scatterer cross section [MKLH_98]. Additionally, we have also proposed to include other long-term effects, like shadowing, if needed.

![Power Amplitude Spectra](image1)

![Power Delay Profile](image2)

Fig. 1. APS for the GSCM  
Fig. 2. PDP for the GSCM

2.1.4 **Downlink channel model**

Our downlink channel model has identical principle than the corresponding uplink implementation described above. Naturally, also the scattering points have same locations. The only required modifications for the downlink model were the time displacement between uplink and downlink transmission (e.g. three timeslots in GSM system) and different carrier and Doppler frequencies. The frequency shift between uplink and downlink, however, leads to fully uncorrelated channel responses.

This modified uplink channel model and the corresponding downlink part were used in all the simulations described in this document.
2.2 Downlink Algorithms

2.2.1 Introduction

Uplink array processing is different to that of the downlink in an adaptive antenna system. In uplink reception we can react on the actual channel situation and several algorithms are proposed in literature (see overview in [Fuhl_97]) which promise large capacity gains. But in the downlink the channel is unknown. We have to extract the important parameters of the uplink channel to get an estimate of the downlink propagation situation if we want to prevent mobile station feedback [GP_96]. But the fading in up- and downlink is totally uncorrelated due to the different carrier frequencies in an FDD (Frequency Division Duplex) system. In downlink transmission the fading is unknown and therefore the unique possibility is to utilise the mean channel characteristics. Only the directions and the mean powers of the signal paths are the same in up- and downlink. As a consequence the gain of an adaptive antenna system is smaller by about 3-4dB in the downlink.

The goal of a mobile communication system applying adaptive antennas is to get the same capacity increase in the downlink as in the uplink. Therefore it is essential to develop signal processing methods which can cope with the problems of the downlink. Moreover the importance of the downlink part has increased dramatically in the last few years. Data transmission applications of cellular mobile communication systems, e.g. the Internet, require a higher downlink capacity compared to the uplink.

In the downlink our goal is to select the weight vectors in a way that most of the power is transmitted to the desired user and the produced interference for the other users is kept as low as possible. We divide the weight calculation in four consecutive steps which are explained in the sequel. Our downlink beamforming approach is illustrated in Fig. 1.2.1.

![Fig. 3. Consecutive steps of the downlink beamforming process.](image_url)

2.2.2 Estimation of the spatial covariance matrix

We used the spatial covariance matrix of the downlink channel for weight calculation purpose. The spatial covariance matrix contains all important information of the mobile radio channel. Further it is the most flexible way because a lot of different beamforming features like angular diversity or null broadening can be included in this system matrix with no need to change the used weight calculation approaches. We investigated two different methods to estimate the spatial covariance matrix at the downlink frequency.

2.2.2.1 Direction based Approach

Herein we first estimate the dominating DOAs (directions-of-arrival) and the corresponding powers coming from that specific directions. For high-resolution DOA estimation we applied a spatial reference algorithms called Unitary ESPRIT [HN_95]. Afterwards the estimated DOAs are assigned to the specific users by utilising user identification algorithms. We allocated the DOAs ideally, because this was not part of our investigations. With these estimates on the hand you can create the spatial covariance matrices of the downlink.
where \( a(\Theta_l, f_d) \) denotes the array steering vector of the direction \( \Theta_l \) at the downlink frequency \( f_d \). The power values \( P(\Theta_l) \) were estimated using a simple beamformer.

### 2.2.2.2 Transformation based Approach

In an FDD system the frequency dependent array response vector and thus also the spatial covariance matrix changes significantly from up- to downlink. The idea of this approach was to estimate the spatial covariance matrix at the uplink and apply a frequency transformation. We investigated two already proposed algorithms, which should perform this necessary conversion.

The first approach uses a Compensation Matrix [Zet_97] utilising averaging over the angular domain. This compensation matrix decreases the error for small frequency shifts and inter-element distances of the antenna array. But this method changes also the mathematical structure of the spatial covariance matrix, as shown in [Hug_98].

The Duplex Array Approach [RDJP_95] assumes dominant angles of arrival and small duplex frequencies. This restricts the application to narrowband systems and scenarios with negligible angular spread.

Both methods did not lead us to satisfactory results. But especially this transformation will be important for 3\textsuperscript{rd} generation systems, where the number of users will exceed the number of available antenna elements by far and therefore makes the application of DOA based methods impossible.

### 2.2.3 Null Broadening

Null broadening should provide wide enough nulls in the antenna pattern to reduce the produced interference as far as possible. Array imperfections, calibration errors and a limited channel estimation accuracy (spatial covariance matrix or DOA) lead us to the urgency of null broadening. Especially in suburban and urban environments with large spreading of the user signals over the angular domain (angular spread AS), the performance loss without null broadening is considerable. As a consequence null broadening in such propagation environments is necessary. If we use exclusively discrete DOAs for covariance matrix approximation, the beamforming algorithms produce sharp nulls in the directions of the interferers, illustrated in Fig. 1.2.2. We demonstrate the effect of null broadening on the antenna pattern in Fig. 1.2.3.

![Antenna pattern without null broadening](image1.png) ![Antenna pattern with null broadening](image2.png)
We studied methods to modify the covariance matrix in a way that the used beamforming algorithms automatically produce broad nulls in the direction of the co-channel users. The analysed null broadening approaches are called Higher-Order Null Broadening [GNB_97], Angular Spread based Approach [RGV_97] and Multiple Nulling [Stey_86]. The null broadening related part of our downlink work is subject of one of our papers [HLB_99], where we show a gain of up to 5dB in SNIR (Signal-to-Noise-plus-Interference Ratio). The three null broadening schemes have comparable performance but the angular spread based approach is most flexible.

2.2.4 Beamforming Algorithms

We considered beamforming algorithms based on the spatial covariance matrix. Four methods were taken from literature and one new beamformer was created.

These algorithms can be divided in two subgroups:
• algorithms with interference suppression
  - Summed Inverse Carrier-to-Interference Ratio Minimiser (SICR) [Zet_97]
  - Interference Minimisation [FN_95]
  - Linearised Power Minimiser (LPM) [Far_97]
  - Interference Rejection Method (IRM) [Hu_98] - our beamforming algorithm
• algorithms without interference suppression
  - Maximum Desired Power (MDP) [Zet_97].

Our simulations indicated that interference suppression is essential in an SDMA (Space Division Multiple Access) system. The produced interference with no nulling of the co-channel users is too large to provide a satisfactory link quality.

Our new algorithm, the IRM (Interference Rejection Method), showed similar results with a computational complexity smaller by a factor of 3 compared with the best of the other considered algorithms [Hu_98]. Nevertheless the standard algorithm in the literature, the SICR (Summed Inverse Carrier-to-Interference Ratio Minimiser), was used in most of the performed simulations because most of the scientists use this algorithm for weight calculation purpose. Therefore it was possible for us to compare our downlink performance with already published results.

2.2.5 Downlink Transmit Power

The calculated antenna weights, using beamforming algorithms, define only the shape of the produced antenna pattern. But it is also essential to balance the transmitter power of the co-channel users to maximise the SNIR of all users.

We analysed three different transmitter power calculation methods. Transmitting the signals with equal power from the BS to each user lead to better results than the two other, more sophisticated approaches (Carrier Balancing and Carrier-to-Interference Balancing [SB_97]). The reason the impossible prediction of the actual path loss even if the mean power values are already known. Further the mean path loss of MSs served on the same physical channel varies only slightly, if ambitious channel allocation schemes are used. This channel allocation provides the spatial separability of the MSs (the mobiles do no lie in the same direction seen from the base) and the mobiles are arranged in power classes (mobiles in the same power class have similar transmitter powers and path losses) [Tan_95]. Thus it is absolutely not necessary to apply sophisticated transmitter power calculation methods in the downlink beamforming process.
2.2.6 Simulations and Results

The downlink beamforming methods described above were used for comparative simulations between different combinations of the interchangeable blocks of the complete downlink beamforming process illustrated in Fig. 1.2.1. The performed simulations lead us to the following conclusions:

- DOA estimation is necessary for downlink beamforming in an SDMA-FDD system if it is not possible to transform the spatial covariance matrix from uplink to downlink frequency.
- Null broadening is vital in real operating SDMA systems because of the angular spreading, transceiver imbalances and the limited estimation accuracy.
- The SICR showed the best performance of the investigated beamforming algorithms, slightly better than our IRM algorithm. Nevertheless the IRM performs also very good but has an extremely reduced computational complexity.
- Transmitting with the same power to each user gives the best link level performance with sophisticated channel allocation.
- Angular diversity slightly improves the link quality. The simulated diversity gain would have been larger, if both scattering clusters had equal mean power values. But this is not the case in our local/far scattering model due to the higher path loss of the far scattering cluster.

A detailed description of all algorithms and simulation results concerning the downlink can be found in [Hu_98].

2.3 Receiver Imperfections and Calibration

2.3.1 Introduction

Typically in signal processing simulations the hardware parts of the receiver are assumed to operate ideally. Especially in array processing applications, in which the whole operation is based on several independent transceiver trains, the non-idealities of the hardware parts reduce the performance of the whole adaptive antenna system drastically. In practice the antenna pattern with imperfections differs essentially from the ideal one, shifting the main beams and nulls from their correct directions. Other recent research projects, demonstrating the adaptive antenna operation with field trials, have also reported significance of these issues [SB_98]. The differences in independent hardware components or drifting because of variations in environmental conditions cause nonlinearities in different receiver trains. In this work we included an extensive error model into our simulation environment and analysed the performance impairment with two different receiver structures.

In operating mobile systems the effect of these nonlinearities must be eliminated by using some kind of calibration method. A widely used method is the so-called switched calibration which means that a pure oscillator signal is regularly coupled to all input antenna ports and the differences between the receiver train outputs are used to update the calibration coefficients. This well-known method has been successfully used in different testbed implementations [TB_97]. However, this technique adds to the complexity of the expensive hardware part, which naturally is not desirable. In addition to that, the stability of the calibration sub-system can be problematic in practical operation environments e.g. with very large temperature variations. Normally the stability does not cause problems in testbed implementations, because operation times and conditions do not necessarily fully correspond to situation in real networks.

We considered alternative calibration techniques based on the so-called auto-calibration concept. With these techniques the desired parameters, like DOAs (direction of arrival), and the error factors corrupting the antenna signals are estimated in a joint way in the signal processing part of the receiver.
Auto-calibration schemes have been successfully used in other array processing applications, like radar and military systems and we tested their applicability on the mobile radio.

This work is described in details in [Sch_98] and results are partially shown also in [LSB_98], [LKSB_99a] and [LKSB_99b].

2.3.2 Model of Imperfections

In the error model of our simulation environment we included the following error sources:

- **Mutual coupling:**
  The elements of an antenna array interact with each other, i.e. the current of one element induces voltages also for neighbouring antennas. We modelled this phenomena by means of mutual impedances leading to an error matrix, where the non-diagonal elements defined the coupling between the different antenna elements. Defining these coupling coefficients for arbitrary array geometries is a non-trivial task leading to numerical procedures, but values for practically interesting array topologies are available in the literature [Kui_97], [ST_81].

- **Phase noise of oscillators:**
  In the receiver one or more oscillators are needed to downconvert the signal from RF (radio frequency) to baseband. Ideally, the oscillator output would consist only of one single frequency, but in reality the energy spreads onto the nearby frequency band as well. This effect, mainly caused by phase noise, perturbs the downconverted signal causing some undesired random phase modulation. In our error model we describe the phase noise of the local oscillators (LO) by their spectral power density. This is a commonly used method to model oscillator noise, because it allows simple spectrum analyser measurements. The parameter selection of our model was based on the measurements of the commercial receiver chips [Ben_98].

- **Imbalances between receiver trains:**
  The independent transceiver trains connected to the practical adaptive antenna system can never be exactly equal, because of component spread. Thus, magnitude and phase imbalances destroy the array manifold which is the underlying structure for the many signal processing schemes (spatial reference algorithms). We selected these error factors from the Gaussian distribution using different variances.

- **Imbalances between I/Q branches of one transceiver train**
  Especially when analog downconversion from IF (intermediate frequency) to the complex baseband is used, imbalances will be present also between I/Q (in-phase/quadrature-phase) channels of one receiver chain. In case of digital downconversion the imbalance between different branches is less significant.

- **Quantisation noise**
  The number of quantisation steps of the ADC (analog to digital converter) is an important design parameter affecting the whole subsequent digital part of the transceiver. Naturally, it is desirable to minimise the number of quantisation steps still allowing the appropriate operation of the receiver. We included the effect of the quantisation noise in our simulation chain and defined the lower limit for A/D conversion levels for both considered receivers.

- **Cable length differences:**
  In practice the antenna elements are coupled to the receiver hardware with some kind of cable. Small differences of the electrical length of the transmission lines cause signal phase shifts, which were also taken into account in the error model.
2.3.3 Simulations and Results

The error model described above was used for comparative simulations between two different receiver structures. Chapter 2.4 describes more exactly the first considered receiver utilising semi-blind estimation technique. This algorithm is not based on the information about the array manifold, but utilises the known signal properties and initialises the estimates by known bit fields (e.g. training sequences of GSM system). As a reference for performance comparisons we considered also a more traditional array processing scheme consisting of DOA estimation, followed by a beamformer and a standard baseband receiver. For DOA estimation we used Unitary-ESPRIT [HN_95], which is a numerically advanced subspace based approach. The weight vectors for the beamformer were calculated using generalised Moore-Penrose pseudo-inverse [Gol_89]. Note, that more advanced beamforming methods could provide some gain in sense of output SNIR, but for this work more interesting was to consider the relative performance impairment with different imperfections. Finally the decision feedback equaliser (DFE) combined with differential detector performed signal detection.

The first receiver structure based on semi-blind estimation combines space-time equalisation, signal separation and detection. Because of its joint estimation principle, it is reasonable to consider the simulation results in the form of raw BER (without forward error correction). On the other hand, with another receiver the processing can be divided into separate parts and thus in addition to the final detected sequences also the DOA estimator and beamformer outputs can be considered separately. We used three different performance measures for our spatial reference receiver; in addition to the BER also distributions of the DOA estimation error and SNIR after beamforming were considered.

In our simulation campaign we found out that the semi-blind estimation was much more robust when different imperfections were taken into account. It is reasonable that spatial reference algorithms relying on the known array geometry suffer more from imperfections disturbing array manifold structure. Correspondingly the semi-blind estimator was insensitive against all errors affecting the phase of the received signals. This is due to the fact, that phase imperfections can be hidden in the channel impulse responses during the blind estimation process. The only considered imperfection somehow affecting the semi-blind receiver was magnitude imbalances between different receiver trains. However, this effect was also observed only with strong imbalance values exceeding 5dB (Fig.6). The reason for this behaviour is that singular values needed in subspace estimation part of the algorithm were disturbed by multiplicative magnitude factors.

![Fig. 6. Semi-blind technique: BER with magnitude imbalances](image1.png)

![Fig. 7. Spatial reference technique: DOA estimation errors with magnitude imbalances, SNR=20dB](image2.png)

The most significant imperfection affecting the performance of the spatial reference receiver was the phase- and magnitude imbalances between different receiver trains. Both of these effects increased the
number of non-correct DOA estimates. Fig. 7. shows the effect of the magnitude imbalances on the number of the failed DOA estimates. In this simulation the DOA estimate is considered to have failed when the error exceeds 7.5°. Correspondingly, performance deterioration can also be seen at the output of the beamformer. Fig. 8. shows the cumulative distribution function (CDF) of the output SNIR values for the different magnitude imbalance values with input SNR 20dB.

![Graph](image1.png)

![Graph](image2.png)

**Fig. 8.** Spatial reference technique: Output SNIR with magnitude imbalances, SNR=20dB

**Fig. 9.** Calibration performance using method [BCH_91], magnitude imbalances

### 2.3.4 Calibration Considerations

As already shortly discussed above the imperfections present in the real operating systems require calibration of these disturbing effects. Auto-calibration techniques estimate jointly the needed parameters and hardware distortions from the baseband signals. Each of these methods minimises some kind of cost function using appropriate constraints. In our work we considered the applicability of the following algorithms, mainly developed for other array processing applications, for the mobile radio systems:

- Method exploiting the orthogonality of the noise subspace and the Hermitian array steering matrix [ASO_97].
- Calibration technique utilising the Toeplitz structure of the spatial covariance matrix in case that sources are uncorrelated and uniform linear array is used [PK_85].
- Technique that makes use of the fact that each perturbed array steering matrix can be constructed as a linear combination of the eigenvectors spanning the signal subspace [BCH_91]
- Calibration scheme using the properties of the eigenvalue decomposition of the spatial covariance matrix [WF_96]
- A method based on the MAP (Maximum A Posteriori) estimator of the array perturbations [Swi_96]

In simulations we created a relative performance measure describing the gain obtained by different calibration schemes. In addition to the Rayleigh fading signals with different angular spread (AS) values we considered also single waves arriving at the receiver.

All of the investigated algorithms reduced the imperfection levels. As an example Fig. 9. shows the relative performance measure for the calibration method [BCH_91] with magnitude imbalances in non-AS conditions. However, many algorithms might have problems to meet the strict requirements of the mobile radio systems in practical operation conditions. Reference [SB_98] gives the following
requirements for the accuracy of the calibration; for magnitudes variation less than 0.5 dB and for phases less than 3°. In [She_97] even more stringent values are given. The problems of auto-calibration techniques are related to the fading nature of the propagation channel and the angular spread destroying the plane wave assumption. Sometimes deep fades lead to totally failed imperfection estimates, which can even worsen the situation after calibration. However, the performance degradation because of totally failed estimated can be prevented by employing some kind of tracking techniques.

2.4 Robust Algorithms (Blind and Semi-Blind Estimation)

2.4.1 Introduction

As discussed above, the robustness of the algorithms against different hardware imperfections is important feature in the mobile radio application. Thus, one of the aims of the current project has been to consider and create new robust signal estimation and detection techniques. We have focussed the research onto the blind techniques which utilise the known signal properties during the estimation process. Traditional array signal processing techniques are based mainly either on known array manifold (spatial reference algorithms, MUSIC [Sch_86], ESPRIT [RPK_86] or its more recent extensions [HN_95]) or utilisation of the training sequences included in the slot structure of the systems (temporal reference algorithms, e.g. employing well known recursive least-squares techniques [Fuhl_97]).

The signals used in mobile communication systems include typically several such rich structural properties which enable their blind estimation. In our work we have mainly employed the following known features:

- **fixed symbol rate**: allows the factorisation of the received data onto the channel response and signal matrices by means of the special structure of the data matrix.
- **finite alphabet property** (i.e. the limited number of the modulation symbols): enables together with the first property solving the FIR-MIMO (Finite Impulse Response, Multiple Input, Multiple Output) problem.

Other useful properties are: *cyclostationarity* [TXK_94], *constant modulus* [VP_96a], *spectral self-coherence* [Agee_90] and *higher order statistical properties* [Car_91].

Utilising these signal characteristics the channel response matrix which maps the simultaneously transmitted signals to the received array data samples can be identified without the aid of the known bit sequences.

In addition to the robustness we see also several other benefits which motivate the use of blind estimation methods [LSB_98]:

- We are not relying on the known array manifold, therefore neither discrete DOAs (direction-of-arrival) with limited angular spread nor angular separability are required.
- In our blind estimation case there are no requirements on the synchronisation of the incoming signals.
- The utilisation of the known signal properties leads to reduced need of overhead information, which means additional capacity increase.

We have shown that purely blind signal separation and detection is possible in SDMA (space division multiple access) system where several users are served in the same traffic channel [LB_97]. However, in all current digital mobile radio standards some known bit fields (training sequences) are available. Utilising this included information together with the known signal properties leads to the semi-blind estimation concept. The main idea is to exploit all available information (hidden in the training sequences and signal properties) and thus improve the estimation accuracy and robustness.
Nevertheless we omit the spatial information because it is often disturbed by transceiver imperfections and angular spread present in mobile radio application. Additionally, we need some kind of known bit fields to allow user identification when several users are present in the same traffic channel (SDMA application). Naturally, it is reasonable to use this information already in the signal estimation phase, not only afterwards when the detected bit sequences already are available [LKSB_99a, LKSB_99b].

Our semi-blind estimation method utilises the joint estimation principle combining three tasks: joint space-time equalisation, separation and detection of the multiple oversampled co-channel digital signals. Figure 10 illustrates the principle of the method.

The estimation process consists of two parts. First we estimate the basis of the desired subspace and after that we project these basis vectors to the finite alphabet (FA) constellation. Between these two steps we increase the robustness of the estimation by initialising the FA projections with user identification fields. Figure 11 shows the parts of the entire semi-blind estimation process.

### 2.4.2 Subspace Estimation (Space-Time Equalisation)

The computationally most expensive part of the algorithm is to estimate the basis vectors spanning the row space of the specially structured array data matrix. In practice this corresponds to the joint space-time equalisation of all incoming signals. Employment of the singular value decomposition (SVD) leads naturally to the optimal bit error rate performance, but the computational complexity can be decreased by using adaptive subspace tracking algorithms. With these techniques the subspace estimate is updated iteratively over the columns of the matrix instead of considering it blockwise as a whole. We have analysed the performance when the required subspace is estimated using PAST (Projection Approximation Subspace Tracking) and PASTd (Projection Approximation Subspace Tracking with deflation) techniques [Yang_95] and compared it to the optimal SVD case. The slight lack of orthonormality with tracking algorithms is eliminated by performing an additional orthonormalisation step once after the last update. The tracking methods lead to a slightly worse BER performance, but correspondingly the computational complexity is reduced maximally by the factor of 70 [LKB_99].

### 2.4.3 DILSF Algorithm

After the subspace estimation part we have to detect different desired signals by performing least-squares projections utilising known finite alphabet constellation. We call our projection algorithm Decoupled Iterative Least-Squares with Subspace Fitting, DILSF [LB_98]. It combines the ideas of
the DWILSP (Decoupled Weighted Iterative Least-Squares with Projections) [Pel_97] and the ILSF (Iterative Least-Squares with Subspace Fitting) algorithms [VTP_97]. Instead of simultaneous iteration of all symbol vectors, this approach makes the projections between the FA constellation and the obtained subspace separately for each user, which has several desirable properties. This projection approach is computationally very efficient, because during each iteration round only matrix vector multiplications are required. We continue iterations until convergence and after begin then with the estimation of the next desired signal. In our simulations we needed typically 2-3 iterations before convergence.

2.4.4 Simulations and Results

We carried out the simulations using the Geometry-based Stochastic Channel Model (GSCM) described in the previous section 2.1. and more in detail e.g. in references [MKLH_98] and [MLKS_98]. Appropriate parameter selection allows modelling of the different propagation environments. In these simulations we used a parameter set corresponding to the urban environment with base station antennas above the rooftop level. This parameter selection gives an averaged angular spread (AS) of about 3 degrees related to each nominal direction-of-arrival (DOA).

The results of our simulations show the raw bit error rates (BER) as a function of the input SNR (signal-to-noise ratio). In all simulated cases we assumed two SDMA users and averaged the BER over both of them. The SNR values were defined by the received mean power values averaged over a large number of random channel situations.

Figure 12. shows the performance with different number of antenna elements and antenna spacing. When the element number was decreased, the element spacing was increased correspondingly. This reduces the correlation between the fading signals received by the independent elements and thus improves the performance compared to the \( \lambda/2 \) spaced scenario. In this simulation the inter-element spacing was selected so that the overall length of the array was in the range of 20. Thus the element spacing was 20, 10 and 7 corresponding to the array sizes of \( M=2 \), \( M=3 \) and \( M=4 \) elements, respectively.

Figure 12 compares the performance with the fixed number of the antenna elements (\( M=8 \)) when the required subspace was estimated using SVD, PAST and PASTd algorithms. The tracking approach leads to saturation to a certain BER floor level, but the computational complexity decreased by a factor of 70.

Fig. 12. BER with different element spacing, \( M=2, 3, 4 \)

Fig. 13. BER comparison between PAST, PASTd and SVD, \( \lambda/2 \) spacing, \( M=8 \)
When traditional array processing algorithms based on DOA estimation are used, the detection of the different signals is only possible when are separable in angular domain. Our approach estimates the unknown channel response matrix, and thus also angularly overlapping signals are separable in case of different channel responses. To demonstrate this property we created the following modified channel scenario. Instead of random positioning of the mobiles we placed both users near each other (same MS-BS distance, DOA difference 2°). Additionally we used the same scattering points for both users and only local scatterers were present in the simulation. Thus, in this worst case scenario (Fig. 14) all signal components transmitted by two co-channel users were propagated via the same scattering points before arriving at the base station array.

Clearly no detection based on DOA estimation can cope with this scenario, but the different channel response matrices allowed signal separation for our algorithm. The BER performance of this scenario is shown as the broken line in Fig.15 for /2 array with 6 elements. The solid line shows the situation in which we added independent far scattering areas for both users, but local contributions propagated still via the common scattering points. This increased the separability of the channel response matrices and the performance approached that with the standard channel.

![Fig. 14. Common multipath scenario](image1.png)

![Fig. 15. BER with common multipath scenario, \( \frac{1}{2} \) spacing, \( M=6 \)](image2.png)

The performance shown in these figures is very promising especially concerning hardware realisation. The simulations show that already small number of elements with two times oversampling gives sufficient performance. Note, however, that increasing the number of the independent samples by using more array elements improved the performance further.

### 2.4.5 Testbed Software Implementation

The algorithm described above has been implemented also for AdAnt adaptive antenna testbed developed in our group.
2.5 References


"Smart Antennas for Mobile Communications Systems"


"Smart Antennas for Mobile Communications Systems"
3 PROJECT RELATED PUBLICATIONS

Papers:


[P2] Laurila J., Kopsa K., Schürhuber R., and Bonek E., "Semi-Blind Separation and Detection of Co-Channel Signals", accepted for publication in International Conference on Communications, Vancouver, Canada, June 6-10, 1999


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