Low Effort MIMO Detector for Frequency Selective Indoor Channels

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Abstract—A new MIMO detector for frequency selective indoor channels is proposed. The detector is based on a two-stage detection followed by a decision feedback equalizer (DFE). The first detection stage is assured by a linear equalizer subsequently followed by a decision unit. The second step is a reduced search (RS) around the solution acquired by the linear equalization, which will be performed in an efficient way at the different transmitted data streams. The RS will be adjusted depending on the search probability at each level. The DFE is applied in order to remove the effect of the inter symbol interferences (ISI) caused by the channel dispersion as it has been observed in the indoor measurements. The RS method provides a near ML performance while it demands a fixed computational effort which is determined by the number of operations and limited by the hardware resources. Compared to some of the most important MIMO detectors, such as for example V-BLAST and sphere decoder, in simulations as well as in field measurements our approach exhibits a near ML performance in terms of BER while its computational effort always remains distinctly lower.

Index Terms—MIMO, Line-of-sight, frequency selective channel, RS detector

I. INTRODUCTION

Multiple Input Multiple Output (MIMO) transmission systems promise higher data rates and better reliability for a given signal to noise ratio and a fixed bandwidth [1], [2]. The maximum likelihood (ML) detector is the optimum detector in terms of minimizing the bit error rate (BER) for MIMO systems, but stays not feasible in practice due to its extremely high computational effort. Various approaches have reached a near ML performance with reduced computational effort by applying a linear equalization to the received signal and a ML correction of the unreliable symbols [3], [4]. These approaches do not only suffer from still high computational effort, but they also use reliability checks of high complexity. Otherwise, the sphere decoder (SD) provides ML performance with reduced complexity compared to the ML detector. The SD derived in [5], [6] is based on a successive layer detection considering decreased search radius which results in a reduced number of candidates. However, the SD presents a variable complexity, depending on the noise level and the channel conditions. The SD complexity converges to an exponential complexity for a bad conditioned channel matrix and low signal-to-noise ratio (SNR) which makes its implementation unfeasible in practice.

To overcome this drawback, a new method called reduced search (RS) ML has been proposed in [7], which is based on a linear detection providing the starting search sets followed by a RS ML. The search sets are adjusted by the RS algorithm depending on the search probabilities at the different levels. The method provides a near ML performance while it demands a fixed computational effort which consequently determines the needed hardware resources. As the effort remains constant the hardware is optimally exploited marking a crucial benefit compared to different proposals in [3], [4] which allow for a varying effort and therefore only deal with a mean effort as the essential performance criterion. The RS approach has already been derived in [7] for flat fading channels and will be extended in this paper to frequency selective indoor channels applying a decision feedback equalizer (DFE) in order to remove the effect of the inter symbol interferences (ISI) caused by the channel dispersion. The indoor channels are characterized by dominant line-of-sight (LOS) components which are usually present in the in-room office scenario and contribute the significant capacity part [8].

Hence, the rest of the paper is structured as follows: In section II, the MIMO system model is presented. In section III, the proposed RS detector is described. In section IV, we compare the performance of the RS algorithm to some other MIMO detectors by applying them to the commonly used simulated flat Rayleigh channel as most of the results of other detectors are available only for this type of channel. In section V, the measurements were performed in a real indoor frequency selective channel using a real $4 \times 4$ MIMO communication test bed so that we are closer to the practical circumstances. The performance of the RS algorithm will again be analyzed and compared to the performance of other common detectors. Finally, our work will be concluded in section VI.

II. SYSTEM MODEL

We consider a symmetric MIMO system consisting of $M$ transmit (Tx) and $M$ receive (Rx) antennas and a frequency selective channel which will be described in discrete time representation. The complex channel coefficients include the channel phase information. Assuming the channel to be time invariant over a burst, the channel impulse response (CIR) is of the form $H[l] = \sum_{k=0}^{K-1} H_k \delta[l - k]$, where the sum is evaluated over the $K$ different transmission paths consisting of $(K - 1)$ reflected signal parts and one LOS...
signal component indicated by the index \( k = 0 \). The complex matrix \( H_k \in \mathbb{C}^{M \times M} \) denotes the \( k \)-th MIMO transmission path. We define \( s[l] = [s_1[l], ..., s_M[l]]^T \in \mathbb{A}^M \) to be the transmitted vector consisting of \( M \) data symbols arbitrary chosen from the quadrature amplitude modulation (QAM) constellation \( \mathbb{A} \) with the same probability of occurrence. \( \mathbf{R}_s = \mathbb{E}[s[l]s[l]^H] \in \mathbb{R}^{M \times M} \) denotes the covariance matrix of the transmitted vector, where \( \sigma_{n,m}^2 \) denotes the Tx power of the \( m \)-th Tx antenna. The received signal vector \( x[l] \) can be expressed as:

\[
x[l] = \sum_{k=0}^{K-1} H_k s[l-k] + n[l] \in \mathbb{C}^M,
\]

where \( n[l] \in \mathbb{C}^M \) denotes the additive white noise. We assume the noise to be zero-mean complex Gaussian with covariance matrix \( \mathbf{R}_n = \mathbb{E}[n[l]n[l]^H] = \text{diag}(\sigma_{n,1}^2, ..., \sigma_{n,M}^2) \in \mathbb{R}^{M \times M} \), where \( \sigma_{n,m}^2 \) denotes the noise power at the \( m \)-th Rx antenna.

**III. DETECTION ALGORITHM**

In this section, we will briefly describe the proposed RS algorithm for flat fading channel. Then, we generalize the algorithm to the frequency selective indoor channel as it has been observed in the measurements.

**A. Flat fading channel**

In this case the CIR has only one transmission path and can also be written as \( H[l] = H_0 \delta[l] \). For ease of notation, time index \([l]\) is dropped in this subsection. The RS detector is an approach based on a linear detection providing the starting solution followed by a RS ML. The search sets are adjusted by the RS algorithm depending on pre-computed search probabilities at each level. The method provides a near optimal complexity as the linear equalizer used for the flat fading channel. The calculation of the noise power at the equalizer output \( \eta = \mathbf{G} \mathbf{n} \in \mathbb{C}^M \), which is expressed at the \( i \)-th level by \( \eta_i = \sum_{q=1}^{M} |g_{iq}|^2 \sigma_{n,q}^2 \), has the following noise power at level \( i \)

\[
\sigma_{\eta_i}^2 = \sum_{q=1}^{M} |g_{iq}|^2 \sigma_{n,q}^2.
\]

The calculation of the noise power at the equalizer output offers the possibility to calculate the search probabilities at the different levels. Consequently, a larger search set will be needed for the symbols belonging to the least reliable levels and a smaller search set for the symbols belonging to the most reliable levels is expected. The block diagram of the RS detection scheme is illustrated in Figure 1.

The RS solution, already derived in [7], is obtained according to

\[
\hat{s}_{RS} = \arg \min_{\hat{s} \in S} ||x - H \hat{s}||^2,
\]

where \( S = S_1 \times \ldots \times S_M \) is a subset of \( \mathbb{A}^M \) and denotes the set of calculated hypotheses over all levels whose cardinality equals the total number of candidates supported by the hardware resources.

**B. Frequency selective channel**

The RS algorithm will be now extended to the case of a frequency selective indoor channel. In this paper we focus on measured indoor channels utilizing a real MIMO transmission test bed. The equipment will be explained in more detail in section V. Figure 2 exemplarily shows a typical, measured discrete time MIMO channel represented by its \( 4 \times 4 \) channel impulse responses in a bandwidth of \( 4 \) MHz.

The performed measurements show that the number of the transmission paths \( K \) is strongly limited in such a bandwidth and can thus be restricted to 2. Consequently, there are the LOS MIMO transmission path with strong power and one MIMO reflected signal part. The remaining samples of the CIRs are at noise level.

An extended RS algorithm for the measured channel model is illustrated in Figure 3. For the first detection step we again refer to a linear equalizer which takes into account only the effect of the dominant LOS signal parts. This results in a simple design of the linear equalizer which has the same complexity as the linear equalizer used for the flat fading channel. In the second step, the RS algorithm will be applied for the data detection. In the third step, we apply to the DFE in order to remove the ISI effect caused by the channel dispersion

\[
y[l] = \sum_{k=0}^{K-1} H_k s[l-k] + n[l] - \sum_{k=1}^{K-1} H_k \hat{s}[l-k].
\]
As the measured MIMO indoor channel has two taps, equation (4) can be written as

$$y[l] = H_0 s[l] + H_1 s[l-1] + n[l] - H_1 s[l-1].$$

(5)

An efficient removal of the ISI effect would be possible for a very low BER at the RS output. In this case we get a flat channel model ($y[l] = H_0 s[l] + n[l]$) and the RS algorithm works in similar way as it has already been indicated in subsection III-A. Otherwise, an incorrect detection at the RS output stays also possible even if the previous symbols are not detected correctly. Consequently, the new detection scheme presents a promising approach for strong LOS frequency selective indoor channels without a significant increase of the computational effort compared to the flat fading case.

IV. PERFORMANCE ANALYSIS BASED ON SIMULATIONS

For comparison purposes, the following simulation assumptions will be considered. We consider a flat Rayleigh fading channel, resulting in a channel matrix $H \in \mathbb{C}^{M \times M}$, containing uncorrelated complex Gaussian fading gains with unit variance. The channel matrix is additionally scaled by $1/\sqrt{M}$ as usual. A perfect channel knowledge at the Rx is assumed. Figure 4 illustrates some simulation results of the ZF RS algorithm compared to the results of ZF V-BLAST (Vertical Bell Laboratories Layered Space Time) derived according to [9], SD based on the Schnorr-Euchner enumeration derived from [5], [6] and ML. We refer to a $3 \times 3$ system using 16 and 64 QAM. The computational effort $\mathcal{F}$ is given for each detector. $\mathcal{F}$ denotes the maximum effort limited by the hardware resources for each detector. We observe that the ZF RS achieves near ML performance in both constellations, but with an effort reduction factor of 2 compared to the SD and a factor of 600 compared to the ML in the case of 64 QAM. We note that the computational effort $\mathcal{F}_{\text{ZF RS}}$ is not an average effort over different realizations like in [3], [4], which does not present a performance measure for a practical implementation. $\mathcal{F}_{\text{ZF RS}}$ is the maximum effort that would be needed, and stays also valid for a lower signal-to-noise ratio (SNR) and for bad conditioned matrices. The other ZF RS curves in the Figure show a relatively good performance although the computational effort is significantly reduced. We get an effort reduction of 20 compared to SD and 6000 compared to ML with a performance loss of about 0.5 dB at a BER of $10^{-2}$ using 64 QAM.

V. PERFORMANCE ANALYSIS BASED ON MEASUREMENTS

In this section, we show the performance of the extended RS detector in a real frequency selective indoor channel so that we are close to the real circumstances. We will firstly explain the used performance evaluation parameters, then we describe the measurement procedure, and finally we present the performance analysis derived from the measurements.

A. Basic calculation of the MIMO channel capacity and MIMO mutual information

For the analysis of MIMO channels the channel capacity generally is the most meaningful performance measure. According to [1] and [2] for a MIMO system consisting of $M$ Tx antennas and $M$ Rx antennas, if uncorrelated transmit signals are presumed, the time invariant channel spectral efficiency $C$, which denotes the channel capacity normalized by the transmission bandwidth (unit [Bit/s/Hz])$^1$, for a frequency selective MIMO-channel in the absence of channel knowledge at the Tx is calculated

$$C = \frac{1}{B} \int_{B} \log_2 \left( \det \left( I_M + R_n^{-1} \overline{H}(f) R_s \overline{H}^H(f) \right) \right) \, df,$$

(6)

where $\overline{H}(f)$ denotes the channel matrix in frequency domain and $B$ is the transmission bandwidth. $I_M \in \mathbb{N}^{M \times M}$ abbreviates the identity matrix.

For the evaluation we have calculated for each scenario the channel capacity $C$ as well as the mutual information $T$ (also called transinformation). The system mutual information has been measured after equalizing the received data with the extended RS detector derived in III-B as well as with other common equalizers such as the minimum mean square error (MMSE) and V-BLAST derived from [9] and computing the current BER. The mutual information $T$ is calculated over the different transmitted data streams. The $M \times M$ transmission system is considered as a system with $M$ independent binary symmetric channels (BSCs)$^2$. Each symbol of the data stream

$^1$We use the terms "capacity" and "spectral efficiency" synonymously, here.

$^2$The spatial correlation of the noise that can occur after the equalizer has not been taken into account in this consideration.
is composed of $\chi$ binary bits where $\chi$ denotes the number of bits per symbol for the chosen QAM constellation (6 in the 64-QAM case). Based on the definition of the mutual information in [10], $T$ is approximately calculated according to

$$T = \chi \sum_{m=1}^{M} \left[ 1 + p_m \log_2(p_m) + (1 - p_m) \log_2(1 - p_m) \right], \quad (7)$$

where $p_m$ is the measured BER which has arisen during the transmission of the $m$-th data stream by comparing the binary data at the input and the output of the BSC.

B. Scenario description and measurement procedure

In the following we discuss statistical results which we obtained from measurement campaigns within different indoor environments. We only summarize the most important results and conclusions by means of exemplarily depicted curves showing cumulative capacity as well as mutual information distribution functions (CDFs). We have summarized the most important technical key features in table I.

<table>
<thead>
<tr>
<th>MIMO system order</th>
<th>4 × 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>carrier frequency</td>
<td>2.35 GHz</td>
</tr>
<tr>
<td>measurement bandwidth</td>
<td>4 MHz</td>
</tr>
<tr>
<td>resolution</td>
<td>12 Bit</td>
</tr>
<tr>
<td>measurement SNR</td>
<td>&gt;35 dB</td>
</tr>
<tr>
<td>maximum transmit power per antenna</td>
<td>10 dBm</td>
</tr>
<tr>
<td>number of transmitted bursts per antenna</td>
<td>50</td>
</tr>
<tr>
<td>number of data symbols per burst</td>
<td>1400</td>
</tr>
<tr>
<td>transmission time per burst</td>
<td>500 μs</td>
</tr>
<tr>
<td>used constellation</td>
<td>64-QAM</td>
</tr>
<tr>
<td>maximum number of measurement shots</td>
<td>200</td>
</tr>
<tr>
<td>Tx-Rx distance</td>
<td>3m</td>
</tr>
<tr>
<td>antenna spacing $d_T = d_R$</td>
<td>30cm</td>
</tr>
</tbody>
</table>

**TABLE I**

**KEY TECHNICAL DATA OF THE MIMO DATA TRANSMISSION TEST BED.**

Otherwise, the measurements have been performed in a large office depicted in Figure 5 for illustration, also showing its dimension as well as its special property in terms of furniture and materials. The office was equipped with a number of equidistantly spaced rows of single-person working desks with a large, metal blackboard in the front and huge panorama windows at the rear. We fixed center distance between the Tx and Rx antenna array by 3m in order to keep the LOS signal component invariant in terms of its path loss.

Furthermore, the different antenna arrangements achieving maximum and minimum LOS capacities have been illustrated in Figure 5 by LOS orthogonal channel and LOS keyhole channels, respectively. The LOS orthogonal channel is obtained by a broadside antenna arrangement of Tx and Rx where the antenna spacings have exactly been optimized for a 4 × 4 MIMO system according to [11].

C. Measurement results

Figure 6 shows two calculated capacity CDFs for the orthogonal and keyhole channels. A capacity gap between the optimum LOS configuration and an arrangement which leads to a pure LOS channel of almost keyhole channel transfer matrix (CTM) condition is observed. In comparison to the optimum the 90% outage capacity decreases about 10%. Nevertheless, the capacity which is obtained in the keyhole LOS setup is far from the real keyhole capacity. This is the result of the impinging reflections which increase the CTM condition number and therefore avoid a pure keyhole channel.

Besides, the extended RS algorithm as well as some commonly used MIMO detectors MMSE and MMSE V-BLAST have been applied for every measurement resulting in respective mutual information CDFs for the different antenna arrangements. Starting the discussion of the results, from Figure 6 we at first note that the value of the measured mutual information remains clearly lower than the theoretical calculated capacity. For the best-performing equalizer we observe a gap of 30%. This effect is caused by different reasons. The first one concerns the calculation of the mutual information: although it is known that within a single QAM reason. The first one concerns the calculation of the mutual information: although it is known that within a single QAM
the hard-decision strategy at the Rx. As no soft information is taken into account, clearly a noteworthy part of the information keeps unexploited. The use of error correcting codes should clearly increase the measurable mutual information. Generally, it is worth to note that all mutual information values are limited by the used constellation which is 24 Bit/s/Hz in our case. We additionally observe a mutual information degradation of MMSE and MMSE V-BLAST compared to the RS detector, especially for keyhole channels. Thus, the 90% outage RS mutual information (about 18 Bit/s/Hz) shows a gain of about 40% compared to MMSE (12.5 Bit/s/Hz) and 20% compared to MMSE V-BLAST (15 Bit/s/Hz). One reason for the mutual information degradation is the fact that MMSE and MMSE V-BLAST equalizers for some channel situations do not properly exhibit the noise correlation produced by the equalizer at the different levels. This drawback is also a main reason for the deterioration of many MIMO equalizers in low-rank MIMO channels compared to their high-rank counterparts where we observe only a slight decrease of the mutual information. We additionally note that the V-BLAST detector suffers from possible error propagation through its successive interference cancellation. Otherwise, contrarily to the MMSE V-BLAST, where the information about the noise correlation will be provided in an unidirectional way, from the already detected levels to detect the next levels, the RS algorithms present an approach where the noise correlation will be exploited in an efficient way between all different levels.

Figure 6 shows two types of RS detectors: the ZF RS and the MMSE RS. The ZF RS detector is the detector derived in section III and illustrated by the block diagram in Figure 3. We observe a mutual information degradation of the ZF RS for a small number of channel realizations. The Figure shows for some measurement scenarios a very low mutual information achieved by the ZF RS where the MMSE and V-BLAST show a mutual information of about 4 Bit/s/Hz. This measured mutual information is still very low and stays far from the computed capacity. A closer inspection of the CTM condition number shows that the LOS transmission path matrix $H_0$ is singular which explains the strong degradation of the RS ZF. The other equalizers also suffer from a strong noise correlation between the different levels at their output so that the achieved mutual information stays very low. In order to avoid the invertibility problem of the ZF equalizer for some channel realizations at the first detection step we have used the MMSE equalizer which is expressed by

$$G = R_nH_0^T(H_0R_nH_0^T + R_n)^{-1} \in \mathbb{C}^{M \times M}. \quad (8)$$

Otherwise, the MMSE equalizer suffers from the biased detection effect, so that the symbol reliability check of the RS algorithm derived in [7] presents only an approximation in this case and therefore the MMSE RS achieves a slight mutual information degradation compared with the ZF RS in the most channel realizations.

In the legend of Figure 6, the computational effort $\mathcal{F}$ is given for the corresponding detector. We observe that the RS detectors need less than half the effort required by the MMSE V-BLAST and about 30% effort enhancement compared to the MMSE equalizer. We again note that the used RS equalizers do not use the common Toeplitz matrix for frequency selective channels with its large dimension. Consequently, we get a remarkable complexity reduction for the RS algorithms with a relatively high performance. Due to the extremely high computational effort of the ML detector which is in the order of $10^{16}$, we did not implement it as a reference curve in Figure 6.

VI. CONCLUSION

A novel MIMO detector for frequency selective indoor channels was presented. The detector is capable of combining a near ML detection performance with a very low computational effort. Furthermore, the RS algorithm is optimized for practical implementation as it enables a performance analysis as well as an effort adjustment which is determined by the maximum effort limited by the available hardware resources. The method outperforms different common proposals resulting in an improved performance with less complexity. In fact, the measurements performed in an indoor office show that the 90% outage RS mutual information presents a gain of about 20% compared to MMSE V-BLAST with less than half of the computational effort.

REFERENCES