MULTI-BRANCH MMSE DECISION FEEDBACK DETECTION ALGORITHMS WITH ERROR PROPAGATION MITIGATION FOR MULTI-ANTENNA SYSTEMS

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ABSTRACT

In this work we propose novel decision feedback (DF) detection algorithms with error propagation mitigation capabilities for multi-input multi-output (MIMO) spatial multiplexing systems based on multiple processing branches. The novel strategies for detection exploit different patterns, orderings and constraints for the design of the feedforward and feedback filters. We present constrained minimum mean-squared error (MMSE) filters designed with constraints on the shape and magnitude of the feedback filters for the multi-branch MIMO receivers and show that the proposed MMSE design does not require a significant additional complexity over the single-branch MIMO design. The proposed multi-branch MMSE DF detectors are compared with several existing detectors via simulations. The main contributions of this work are as follows: 1) Multi-branch MMSE decision feedback detectors; 2) MMSE filter expressions with shape and magnitude constraints; 3) A study of the proposed and existing MIMO detectors.

1. INTRODUCTION

Multiple transmit and receive antennas in wireless communication systems can offer significant multiplexing[1][6] and diversity gains[3]. In a spatial multiplexing configuration, the system can obtain substantial gains in data rate. The capacity gains grow linearly with the minimum number of transmit and receive antennas, and the transmission of individual data streams from the transmitter to receiver[1]. In order to separate these streams, a designer must resort to MIMO detection techniques. The optimal maximum likelihood (ML) detector can be implemented using the sphere decoder (SD) algorithm[4]. However, the computational complexity of this algorithm depends on the noise variance, the number of data streams to be detected and the signal constellation, resulting in high costs for low signal-to-noise ratios (SNR), large MIMO systems and large constellations. The complexity requirements of the ML detector and the SD algorithm have motivated the development of numerous alternative strategies for MIMO detection. The linear detector[5], the successive interference cancellation (SIC) approach used in the VBLAST systems[6] and the decision feedback (DF) detectors[7][8] are techniques that can offer an attractive trade-off between performance and complexity. An often criticized aspect of these sub-optimal schemes is that they typically do not achieve the diversity of the ML and SD algorithms. This motivated the investigation of detectors such as lattice-reduction-based schemes[9][10] and calls for new cost-effective algorithms with near-ML or ML performance.

In this work we propose novel DF detection strategies for MIMO spatial multiplexing systems based on multiple processing branches and error propagation mitigation. Prior work on DF schemes includes the DF detector with SIC (S-DF)[9][10] and the DF receiver with PIC (P-DF)[11], combinations of these schemes[11][12][13] and mechanisms to mitigate error propagation[14][15]. The proposed detector employs multiple feedforward and feedback filters and yields multiple decision candidates. The proposed structure exploits different patterns and orderings and selects the candidate and branch which yield the estimates with the highest likelihood. We present constrained minimum mean-squared error (MMSE) filters designed with constraints on the shape and the magnitude of the feedback filters for the multi-branch MIMO receivers. We show that the proposed MMSE design does not require a significant additional complexity since it relies on similar filter realizations but with different constraints on the feedback filters. The proposed multi-branch MMSE DF detectors are compared with several existing detectors via simulations. The main contributions of this work are as follows: 1) Multi-branch MMSE decision feedback detectors; 2) MMSE filter expressions with shape and magnitude constraints; 3) A study of the proposed and existing MIMO detectors.

2. SYSTEM MODEL

Let us consider a spatial multiplexing MIMO system with NT transmit antennas and NR receive antennas, where NR ≥ NT. At each time instant [i], the system transmits NT symbols which are organized into an NT × 1 vector s[i] = [s1[i], s2[i], . . . , sNT[i] ]T taken from a modulation constellation A = {a1, a2, . . . , aN}, where (·)T denotes transpose. The symbol vector s[i] is then transmitted over flat fading channels and the signals are demodulated and sampled at the receiver, which is equipped with NR antennas. The received signal after demodulation, matched filtering and sampling is collected in an NR × 1 vector r[i] = [r1[i], r2[i], . . . , rNR[i] ]T with sufficient statistics for detection and given by

$$r[i] = Hs[i] + n[i],$$

where the NR × 1 vector n[i] is a zero mean complex circular symmetric Gaussian noise with covariance matrix E[s[n][n]H[n]] = σ2nI, where E[·] stands for expected value, (·)H denotes the Hermitian operator, σ2n is the noise variance and I is the identity matrix. The symbol vector s[i] has zero mean and a covariance matrix E[s[i][s]H[i]] = σ2sI, where σ2s is the signal power. The elements hniR,nR,i of the NR × NT channel matrix H are the complex channel gains from the nR-th transmit antenna to the nR-th receive antenna.

3. MULTI-BRANCH MMSE DF DETECTORS

In this section, we detail the proposed multi-branch MMSE decision feedback (MB-MMSE-DF) structure for MIMO systems. The proposed MB-MMSE-DF scheme, shown in Fig. 1, employs multiple signal processing branches with appropriate shape constraints that modify the design of both feedforward and feedback filters. The detector exploits different patterns and orderings for the design of the feedforward and feedback filters. The aim is to mitigate the error propagation and approach the performance of the optimal ML detector. The proposed MB-MMSE-DF scheme can achieve the full di-
versity available in the system by increasing the number of branches and, therefore, the number of candidate symbols prior to detection.

The MB-MMSE-DF employs multiple feedback forward and feedback filters such that it can obtain different local maxima of the likelihood function associated with the ML detector. In order to detect each transmitted data stream, the proposed MB-MMSE-DF detector linearly combines the feedback filter \( w_{j,l} \) corresponding to the \( j \)-th data stream and the \( l \)-th branch with the received vector \( \mathbf{r}[i] \), substracts the remaining interference by linearly combining the feedback filter \( f_{j,l} \), with the \( N_T \times 1 \) vector of initial decisions \( \hat{s}_{j,l}^{\text{opt}}[i] \) obtained from previous decisions. This input-output relation is given by

\[
z_{j,l}[i] = \mathbf{w}_{j,l}^H \mathbf{r}[i] - f_{j,l}^H s_{j,l}^{\text{opt}}[i],
\]

where the input to the decision device for the \( i \)-th symbol and \( j \)-th branch is the \( L \times 1 \) vector \( z_{j,l}[i] = [z_{j,l,1}[i] \ldots z_{j,l,L}[i]]^T \). The number of parallel branches \( L \) that yield detection candidates is a parameter that must be chosen by the designer. In this context, the optimal ordering algorithm conducts an exhaustive search \( L = N_T + 1 \) and is clearly very complex for practical systems when \( N_T \) is significantly large. Our goal is to employ a reduced number of branches and yet achieve near-ML or ML performance. The proposed MB-MMSE-DF detector selects the best branch according to

\[
l_{\text{opt}} = \arg \min_{1 \leq k \leq L} \text{iMSE}(s_k[i], w_{j,l}, f_{j,l}), \quad j = 1, \ldots , N_T
\]

where iMSE\((s_k[i], w_{j,l}, f_{j,l})\) corresponds to the instantaneous MMSE produced by the pair of filters \( w_{j,l} \) and \( f_{j,l} \). The final detected symbol of the MB-MMSE-DF detector is obtained by using the optimal branch:

\[
\hat{s}_j[i] = Q_z(z_{j,l_{\text{opt}}}[i] = Q_{z_{j,l_{\text{opt}}}}(w_{j,l}^H \mathbf{r}[i] - f_{j,l_{\text{opt}}}^H s_{j,l_{\text{opt}}}^{\text{opt}}[i]), \quad j = 1, \ldots , N_T
\]

where \( Q_z(\cdot) \) is a slicing function that makes the decisions about the symbols, which is drawn from an M-PSK or a QAM constellation.

### 3.1 MMSE Filter Design

The design of the MMSE filters of the proposed MB-MMSE-DF detector is equivalent to determining feedback filters \( w_{j,l} \) with dimensions \( N_T \times 1 \) and feedback filters \( f_{j,l} \) with \( N_T \times 1 \) elements subject to certain shape and magnitude constraints on \( f_{j,l} \) in accordance with the following optimization problem

\[
\begin{align*}
\min & \quad \text{MSE}(s_j[i], w_{j,l}, f_{j,l}) = E[|s_j[i] - w_{j,l}^H \mathbf{r}[i] + f_{j,l}^H \hat{s}_{j,l}^{\text{opt}}[i]|^2] \\
\text{subject to} & \quad S_{j,l} f_{j,l} = v_{j,l} \quad \text{and} \quad \|f_{j,l}\|^2 = \gamma_{j,l} ||f_{j,l}\|^2 \\
\text{for} & \quad j = 1, \ldots , N_T \quad \text{and} \quad l = 1, \ldots , L,
\end{align*}
\]

where the \( N_T \times N_T \) shape constraint matrix is \( S_{j,l} \) and \( v_{j,l} \) is the resulting \( N_T \times 1 \) constraint vector and \( f_{j,l}^* \) is a feedback filter without constraints on the magnitude of its squared norm.

By resorting to the method of Lagrange multipliers, computing the gradient vectors of the Lagrangian with respect to \( w_{j,l} \) and \( f_{j,l} \), and equating them to null vectors and rearranging the terms we obtain for \( j = 1, \ldots , N_T \) and \( l = 1, \ldots , L \)

\[
\begin{align*}
w_{j,l} & = R^{-1}(p_j + Q f_{j,l}), \quad (6) \\
f_{j,l} & = \beta_{j,l} \Pi_{j,l}(Q^H w_{j,l} - t_j) + (I - \Pi_{j,l})v_{j,l}, \quad (7)
\end{align*}
\]

where

\[
\Pi_{j,l} = I - S_{j,l}^H (S_{j,l}^* S_{j,l})^{-1} S_{j,l}
\]

is a projection matrix that ensures the shape constraint \( S_{j,l} \) and \( \beta_{j,l} = (1 - \alpha_{j,l})^{-1} \) is a factor that adjusts the magnitude of the feedback, \( 0 \leq \beta_{j,l} \leq 1 \) and \( \alpha_{j,l} \) is the Lagrange multiplier. The relationship between \( \beta_{j,l} \) and \( \gamma_{j,l} \) is not in closed-form even though we have \( \beta_{j,l} = 0 \) and \( \beta_{j,l} = 1 \) for \( \gamma_{j,l} = 0 \) (standard linear MMSE detector) and \( \gamma_{j,l} = 1 \) (standard MB-MMSE-DF detector), respectively. The \( N_R \times N_R \) covariance matrix of the input data vector is

\[
R = E[\mathbf{r}[i] \mathbf{r}[i]^H], \quad p_j = E[\mathbf{v}[i] \mathbf{v}[i]^H], \quad Q = E[\mathbf{r}[i] \hat{s}_{j,l}^{\text{opt}}[i]^H], \quad \text{and} \quad t_j = E[\hat{s}_{j,l}^{\text{opt}}[i] \hat{s}_{j,l}^{\text{opt}}[i]^H] = (N_T \times 1 \text{vector of correlations between } \hat{s}_{j,l}^{\text{opt}}[i] \text{ and } \hat{s}_{j,l}^{\text{opt}}[i]^H].
\]

Substituting (7) into (6) and then further manipulating the expressions for \( v_{j,l} = 0 \), we arrive at

\[
w_{j,l} = (R - \beta_{j,l} \Pi_{j,l}(Q^H) \Pi_{j,l} - t_j), \quad (9)
\]

\[
f_{j,l} = \beta_{j,l} \Pi_{j,l} Q (R - \beta_{j,l} \Pi_{j,l} Q^H) \Pi_{j,l} - t_j).
\]

The above expressions only depend on statistical quantities, and consequently on the channel matrix \( H \), the symbol and noise variance \( \sigma_s^2 \) and \( \sigma_n^2 \), respectively, and the constraints. However, the matrix inversion required for computing \( w_{j,l} \) is different for each branch and data stream, thereby rendering the scheme computationally less efficient. The expressions obtained in (6) and (7) are equivalent and only require iterations between them for an equivalent performance.

Simplifying the equations in (6) and (7), using the fact that the quantity \( t_j = 0 \) for interference cancellation, \( v_{j,l} = 0 \), and assuming perfect feedback (\( s = \hat{s} \)) we get

\[
w_{j,l} = (HH^H + \sigma_n^2(\sigma_s^2 I)^{-1})^{-1} \left( \delta_j + f_{j,l} \right), \quad (11)
\]

\[
f_{j,l} = \beta_{j,l} \Pi_{j,l} (\sigma_s^2 H^H w_{j,l}), \quad (12)
\]

where \( \delta_j = [0 \ldots 0 \ 1 \ 0 \ldots 0]^T \) is a \( N_T \times 1 \) vector with a one in the \( j \)-th element and zeros elsewhere. The proposed MB-MMSE-DF detector expressions above require the channel matrix \( H \) (in practice an estimate of it) and the noise variance \( \sigma_n^2 \) at the receiver. In terms of complexity, it requires for each branch \( l \) the inversion of an \( N_R \times N_R \) matrix and other operations with complexity \( O(N_R^3) \). However, the expressions obtained in (6) and (7) for the general case, and in (11) and (12) for the case of perfect feedback, reveal that the most expensive operations, i.e., the matrix inversions, are identical for all branches. Therefore, the design of filters for the multiple branches only requires further additions and multiplications of the matrices. Moreover, we can verify that the filters \( w_{j,l} \) and \( f_{j,l} \) are dependent on one another, which means the designer has to iterate them before applying the detector.

The MMSE associated with the pair of filters \( w_{j,l} \) and \( f_{j,l} \) and the statistics of data symbols \( s_j[i] \) is given by

\[
\text{MMSE}(s_j[i], w_{j,l}, f_{j,l}) = \sigma_s^2 - w_{j,l}^H R w_{j,l} + f_{j,l}^H f_{j,l}
\]

where \( \sigma_s^2 = E[|s_j[i]|^2] \) is the variance of the desired symbol.
3.2. Design of Cancellation Patterns and Ordering

We detail the design of the shape constraint matrices $S_{j,l}$ and vectors $v_{j,l}$, motivate their choices and explain how the ordering of the data is obtained. By pre-storing matrices for the $N_T$ data streams and for the $L$ branches of the proposed MB-MMSE-DF detector, a designer can exploit different patterns of cancellation and orderings. Specifically, we are interested in shaping the filters $f_{j,l}$ for the $N_T$ data streams and the $L$ branches with the matrices $S_{j,l}$ such that resulting constraint vectors $v_{j,l}$ are null vectors. This corresponds to allowing feedback connections of only a subgroup of data streams. For the first branch of detection ($l = 1$), we can use the SIC approach used in the VBLAST and

$$S_{j,l} f_{j,l} = 0, \quad l = 1$$

$$S_{j,l} = \begin{bmatrix} 0_{j-1} & \quad 0_{j-1,N_T-j+1} & \quad I_{N_T-j+1} \\ 0_{N_T-j+1,j-1} & \quad 0_{j-1} \\ I_{N_T-j+1} & \end{bmatrix}, \quad j = 1, \ldots, N_T,$$  

(14)

where $0_{m,n}$ denotes an $m \times n$-dimensional matrix full of zeros, and $I_m$ denotes an $m$-dimensional identity matrix. For the remaining branches, we adopt an approach based on permutations of the structure of the matrices $S_{j,l}$, which is given by

$$S_{j,l} f_{j,l} = 0, \quad l = 2, \ldots, L$$

$$S_{j,l} = \phi_l \begin{bmatrix} 0_{j-1} & \quad 0_{j-1,N_T-j+1} & \quad I_{N_T-j+1} \\ 0_{N_T-j+1,j-1} & \quad 0_{j-1} \\ I_{N_T-j+1} & \end{bmatrix}, \quad j = 1, \ldots, N_T,$$

(15)

where the operator $\phi_l[\cdot]$ permutes the columns of the argument matrix such that one can exploit different orderings via SIC. These permutations are straightforward to implement and allow the increase of the diversity order of the proposed MB-MMSE-DF detector.

An alternative approach for shaping $S_{j,l}$ for one of the $L$ branches is to use a PIC approach and design the matrices as follows

$$S_{j,l} f_{j,l} = 0, \quad l = 1$$

$$S_{j,l} = \text{diag}(\delta_j), \quad j = 1, \ldots, N_T,$$  

(16)

The PIC requires the use of an initial vector of decisions taken with the feedback filters $w_{j,l}$. The ordering for the proposed MB-MMSE-DF detector is based on determining the optimal ordering for the first branch, which employs a V-BLAST type SIC, and then uses phase shifts for increasing the diversity for the remaining branches. The proposed ordering for $l = 1, \ldots, L$ is given by

$$\{o_1, \ldots, o_{N_T, l}\} = \arg \min_{o_1, \ldots, o_{N_T}} \sum_{l=1}^{L} \sum_{j=1}^{N_T} \text{MMSE}(s_j[i], w_{j,l}, f_{j,l}).$$

(17)

This algorithm finds the optimal ordering for each branch. For the case of a single branch detector this corresponds to the optimal ordering of the V-BLAST detector. The idea with the multiple branches and their orderings is to attempt to benefit a given data stream or group for each decoding branch. With this approach, a data stream that for a given ordering appears to be in an unfavorable position can benefit in other parallel branches by being detected in a more favorable situation, increasing the diversity of the proposed detector.

4. MULTISTAGE DETECTION FOR THE MB-MMSE-DF

In this section, we present a strategy based on iterative multi-stage detection [I] that gradually refines the decision vector, combats error propagation and improves the overall performance. We incorporate this strategy into the MB-MMSE-DF scheme and then investigate the improvements to detection performance. An advantage of multistage detection that has not been exploited for the design of MIMO detectors is the possibility of equalizing the performance of the detectors over the data streams. Since V-BLAST or DF detection usually favors certain data streams (the last detected ones) with respect to performance, it might be important for some applications to yield uniform performance over the data streams. Specifically, the MB-MMSE-DF detector with $M$ stages can be described by

$$z_{j,l}^{(m+1)}(i) = w_{j,l}^H r[i] - f_{j,l} \hat{s}_{j,l}^{o(m)}[i], \quad m = 0, 1, \ldots, M,$$  

(18)

where the MMSE filters $w_{j,l}$ and $f_{j,l}$ are designed with the approach detailed in the previous subsection, $M$ denotes the number of stages and $\hat{s}_{j,l}^{o(m)}[i]$ is the vector of tentative decisions from the preceding iteration that is described by:

$$\hat{s}_{k,j,l}^{o(1)}[i] = Q\left(w_{j,l}^H r[i]\right), \quad k = 1, \ldots, N_T,$$  

(19)

$$\hat{s}_{k,j,l}^{o(m)}[i] = Q\left(z_{j,l}^{(m)}[i]\right), \quad m = 2, \ldots, M,$$  

(20)

where the number of stages $M$ depends on the scenario.

In order to equalize the performance over the data streams population, we consider an M-stage structure. The first stage is an MB-MMSE-DF scheme with filters $w_{j,l}$ and $f_{j,l}$. The tentative decisions are passed to the second stage, which consists of another MB-MMSE-DF scheme with similar filters but use the decisions of the first stage and so successively. The output of the second stage of the resulting scheme is

$$z_{j,l}^{(m+1)}[i] = [T w_{j,l}]^H r[i] - [T f_{j,l}] H_{j,l} \hat{s}_{j,l}^{o(m)}[i]$$

(21)

where $z_{j,l}^{(m+1)}[i]$ is the output of $j$th data stream after multistage detection with $M$ stages. $T$ is a square permutation matrix with ones along the reverse diagonal and zeros elsewhere. When using multiple stages, it is beneficial to demodulate the data streams successively and in reverse order relative to the first branch of the previous MB-MMSE-DF detector. The role of reversing the cancellation order in successive stages is to equalize the performance of the users over the population or at least reduce the performance disparities.

5. SIMULATIONS

In this section, we assess the bit error rate (BER) performance of the proposed and analyzed MIMO detection schemes, namely, the sphere decoder (SD), the linear [5], the VBLAST (SIC) [6], the S-DF [7] with MMSE estimators and the proposed MB-MMSE-DF techniques without and with error propagation mitigation techniques for the design of MIMO detectors. We also consider the lattice-reduction aided versions of the linear and the VBLAST detectors [9], which are denoted LR-MMSE-Linear and LR-MMSE-SIC, respectively. The channels’ coefficients are taken from complex Gaussian random variables with zero mean and unit variance and QPSK modulation is employed. We average the experiments over 100000 runs, use packets with $Q = 200$ symbols and define the signal-to-noise ratio as $SNR = 10 \log_{10} N_T \sigma_n^2 / \sigma_a^2$, where $\sigma_n^2$ is the variance of the symbols and $\sigma_a^2$ is the noise variance.

Let us first consider the proposed MB-MMSE-DF detector and evaluate the number of branches $L$ that should be used for a MIMO system with $N_T = N_R = 4$ antennas with $\gamma_{jl} = 0$. We also compare the proposed user ordering algorithm against the optimal ordering approach, briefly described in Section 3, that tests $N_T! = 24$
possible branches and selects the most likely estimate. We designed the MB-MMSE-DF detectors with \( L = 1, 2 \) and 8 parallel branches, using one branch with the PIC of (16) for \( L > 1 \), and compared their BER performance against the SNR with the existing schemes. The results in Fig. 2 show that the MB-MMSE-DF detector outperforms the linear one by a substantial margin and is comparable with the VBLAST for \( L = 1 \). The performance of the MB-MMSE-DF improves as the number of parallel branches increases, resulting in improvements for more than \( L = 1 \) branches. For the case of \( L = 24 \), we obtain a performance identical to the optimal ML detector and for \( L = 8 \), we get a performance within 1.5 dB from the optimal ML detector computed with the SD.

In the next experiment, shown in Fig. 3, we compare the BER performance of the proposed MB-MMSE-DF detector with \( M = 2 \) stages, \( L = 4 \) (3 SICs and 1 PIC shaping matrices) with perfect channel estimation and error propagation mitigation. We include in addition to the previous experiment the LR-MMSE-Linear and LR-MMSE-SIC detection schemes [9] in the comparison. The results depicted in Fig. 3 for a scenario with perfect channel estimates shows that the proposed MB-MMSEDF detector achieves a performance which is very close to the optimal ML implemented with the SD and outperforms the linear, the VBLAST, the LR-MMSE-Linear and LR-MMSE-SIC detectors by a significant margin.

6. CONCLUSIONS

We proposed the MB-MMSE-DF detector for MIMO systems based on multiple feedback branches. We also proposed the design of MMSE filters subject to shape and magnitude constraints and the use of multi-stage detection for error propagation mitigation. The MB-MMSE-DF detector was compared with existing detectors and was shown to approach the ML detector performance. Future work will investigate low-complexity design of the filters, channel estimation and the use for multiuser and multi-cell MIMO systems.

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