Threshold List Subset Detector For Turbo MIMO Systems

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Abstract—A threshold based list detector is presented for multiple-input multiple-output (MIMO) system. The detector is based on subset-sum algorithm. The algorithm makes use of a low complexity sub optimal minimum mean square error (MMSE) detector to find the bit reliabilities, and uses these reliabilities to generate list of possible candidate data vectors. It is shown through analysis that this detector can be designed to ensure a specific bit error performance with respect to the optimum maximum likelihood detector. The proposed threshold list subset sum detector (T-LSS) is extended for coded turbo MIMO transmission. Unlike other detectors proposed in the literature, the T-LSS detector generates list for each outer iteration.

Index Terms— MIMO systems, List processing, Maximum likelihood detection, Iterative methods.

I. INTRODUCTION

It is well known that multiple transmit and receive antennas can significantly increase the data carrying capacity of wireless systems [1] - [3]. Usually a multiple-input multiple-output (MIMO) system requires a channel code to approach capacity [4]. However, for such MIMO systems, the optimal joint maximum-likelihood (ML) detection using exhaustive search is too complex and is almost impossible. Motivated by turbo decoding [5], iterative detectors and decoders, treating the channel code as the outer code and the space time mapper as the inner code, have been commonly employed in the literature. Although the iterative decoder structures are extensively investigated in the code theory literature, the design and role of the detector structure still need investigation. In this context, the authors in [6], [9] studied the iterative algorithm for MIMO systems using optimum soft-input/soft-output ML MIMO detector. Unfortunately the optimal MIMO detector complexity increases exponentially with the number of transmit antennas or/and the number of bits per constellation point.

Several suboptimal detector structures have been studied in the literature for reducing the complexity of the MIMO detector. These can be classified into linear and nonlinear detectors. Linear detectors include zero-forcing (ZF) and minimum mean-square error (MMSE) detectors, and the nonlinear receivers include decision feedback, nulling-cancelling and variants relying on successive interference cancellation. These suboptimal detectors are easy to implement but their bit error rate (BER) performance is significantly inferior to that of the optimum MIMO detector [10]. The authors in [12], [13] studied nulling-cancelling detector with iterative processing.

There has also been considerable progress in using low complexity (near) ML detection based on lattice decoding. In [20], a near optimal detection method is proposed using sphere-decoder (SD) concept, which has low complexity at high SNR. The work in [4] extends the sphere detector algorithm of [20] to coded MIMO systems with complex constellations. It is shown that for good choices of the initial radius and for sufficient list sizes, list sphere decoder (LSD) in a concatenated system can achieve a bit error rate (BER) performance close to capacity limits. However, the worst case complexity of LSD can be very high and the expected complexity is polynomial with the number of transmit antennas [4]. Besides, the LSD does not exploit channel decoder information in generating the list of candidate codewords. Based on semi-definite relaxation (SDR) of the ML problem, the authors in [14] proposed a soft Quasi ML detection for MIMO systems.

In this paper, we propose a novel threshold list subset detector (T-LSS) that extends the List subset detector for iterative turbo MIMO systems [21]. List based techniques have also been considered by other researchers in various contexts. In [16], a list-sequential detector, based on a modified stack algorithm, is discussed for MIMO systems. Detection over multiple input multiple output channels for uncoded system using Chase [25] type of algorithm has been proposed in [18], and for multiuser detection in spread spectrum systems in [28]. The T-LSS detector generates lists of candidate codewords based on the subset sum algorithm [23]. The T-LSS detector do not require any search radius as in LSD rather depends on the threshold value. Second, the lists of codewords are generated at each iteration of the receiver by taking into account the a priori information fed back from the channel decoder. Third, the candidate codeword selection in T-LSS does not directly involve channel estimation as in LSD. Our results show that for small average list sizes, the performance of T-LSS is almost same as full A Posteriori Probability (APP) detection. Moreover, the average complexity of T-LSS is relatively small.

Notation: Bold upper case (lower case) letters denote matrices (vectors). The notations $(\cdot)^T$, $(\cdot)^H$, $(\cdot)^*$, $E[\cdot]$, Re$(\cdot)$ and Im$(\cdot)$ denote transpose, Hermitian, conjugation, expectation, real and imaginary parts respectively. $A^c$ is the complement of $A$, $|| \cdot ||$ is Euclidian norm, and $\binom{m}{k}$ denotes $m!/(m-k)!k!$. 

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A MIMO system with $N_t$ transmit antennas and $N_r$ receive antennas is considered as shown in Fig. 1. At the transmitter side, the input data bits are encoded by a channel code, randomly interleaved and then mapped to modulation symbols before being transmitted by the antennas. Denoting a block of information bits by the vector $d$ and the transfer function of the channel code by $G$, the output codeword can be written as $\hat{c} = Gd$, and $c = \Pi(\hat{c})$ represents the interleaved sequence of coded bits. The symbol mapper converts this bit sequence into an M-ary symbol sequence as follows. Assume that $c$ has $LN_tM_c$ elements, where $M_c$ is the number of bits per constellation point and $L$ is a non-negative integer. The symbol mapper first partitions $c$ into $L$ subvectors, each of length $N_tM_c$, to form an $N_tM_c \times L$ matrix, $C = [c_1, c_2, \ldots, c_L]$, where $c_l = \left[c_{(l-1)N_tM_c+1}, c_{(l-1)N_tM_c+2}, \ldots, c_{(l-1)N_tM_c+M_c}\right]^T$, $1 \leq l \leq L$, and $c_j$ is the $j$-th element of $c$. Each subvector $c_l$ is then mapped to the symbol vector $\mathbf{x}^l = [x_1^l, x_2^l, \ldots, x_{N_t}^l]^T$ through a unique predetermined bit mapping scheme $x_i^l = F[c_{(l-1)N_tM_c+(i-1)M_c+1}, \ldots, c_{(l-1)N_tM_c+iM_c}]$, $1 \leq i \leq N_t$. We call each sub vector $\mathbf{x}^l$ a code bit vector. The elements of the symbol vector $\mathbf{x}$ are then transmitted by the $N_t$ transmit antennas.

Ignoring the superscript $(l)$ for simplicity, the received $N_r \times 1$ vector $r$ due to the transmission of the $N_t \times 1$ symbol vector $\mathbf{x}$ can be written as

$$r = Hx + n$$

where $H$ is a $N_r \times N_t$ complex MIMO channel matrix, and $n$ is complex additive noise vector whose elements are independent, complex-valued Gaussian variables with zero mean and variance $\sigma^2$ per each dimension.

### III. Receiver Structure

#### A. Conventional soft MIMO detector

A typical iterative receiver structure consists of an inner MIMO detector and an outer channel decoder. The MIMO detector calculates the log likelihood ratio (LLR) $L_D(c_i|r) = \log(P(c_i = 1|r)/P(c_i = 0|r))$, for each bit $c_i$, $1 \leq i \leq N_tM_c$, and sends the extrinsic LLR values $L_{ext}(c_i|r) = L_D(c_i|r) - L_A(c_i)$ to the channel decoder, where $L_A(c_i) = \log(P(c_i = 1)/P(c_i = 0))$ is the a priori information. A direct computation of detector extrinsic LLR is performed as [9]

$$L_{ext}(c_i|r) = \sum_{c^i \in \mathcal{L}_{i,c,i}} p(r|c^i) \exp \left(\frac{1}{2} c^i_T L_{A,i}[i] \right)$$

where $\mathcal{L}$ is a set containing all possible code bit vectors and is called the list. The set $\mathcal{L} \subseteq \mathcal{C}$ contains code bit vectors in the list with $c_i = 1$, $(l-1)N_tM_c + 1 \leq i \leq (l+1)N_tM_c$. $L_{A,i}[i]$ denotes the vector of all $a$ priori values by omitting the bit $i$, $c^i_{[i]}$ denotes the coded bit vector $c^i$ by removing the $i$-th bit, and $p(r|c^i)$ is the conditional probability density function (pdf).

From (2), it is clear that an exhaustive search over all possible bit vectors requires computation of (2) over a list $\mathcal{L}$ containing $2^{N_tM_c}$ candidate code bit vectors. This provides MAP detection but its complexity is too high for large $N_tM_c$. In order to reduce complexity, the authors in [4] extend the SD concept for coded turbo MIMO systems by generating a list of code bit vectors from the detector to the decoder. Although the complexity is reduced, the list generation process in [4] does not utilize the information fed back from the channel decoder. Accordingly, the work in [15] modifies the SD algorithm with a Finkle-Pohst MAP search, which is repeated for each iteration. In general, the SD based approach relies on a search radius that sometimes involves trial and error [4]. Furthermore, many floating point operations, including QR decompositions or Cholesky decompositions, are required in generating the list of candidate code bit vectors. Therefore, we propose a different soft MIMO detector structure that generates lists requiring only a few floating point operations and mostly comparisons. Besides, instead of using a search radius, we use alternative parameters which are easier to characterize.

#### B. Proposed soft MIMO detector

In our novel receiver structure, we reduce the list size significantly so that the computation of (2) is performed only for a few candidate bit words. Toward this end, we propose to optimize the list from iteration to iteration. Thus, for the $k$-th iteration between the detector and the decoder, $L_{ext}^{(k)}(c_i|r)$ is
computed as

\[ L^{(k)}(c_i | r) = \log \sum_{c^j \in \mathbb{L}^{(k)} \cap c_{i-1}} p(c^j | r^j) \exp \left( \frac{1}{2} c^T [L_{A,i}] c^j \right) \]

where \( \mathbb{L}^{(k)} \) is the list of code bit vectors in the \( k \)-th iteration. Note that unlike 2, \( \mathbb{L}^{(k)} \) does not usually contain all possible code bit vectors. The detector constructs the list based on the LLR information \( \{ \alpha_i \} \) for each bit. In the first iteration, we use an initial reliability detector to generate \( \{ \alpha_i \} \). For subsequent iterations, \( \{ \alpha_i \} \) are obtained from the channel decoder. Thus, our receiver consists of three components: (1) an initial reliability detector, (2) a list subset sum detector and (3) a channel decoder as shown in Fig. 1. The initial reliability detector and the list subset detector form the proposed MIMO detector.

1) Initial Reliability Detector: The initial reliability detector is used only during the first iteration to assist in generating the list \( \mathbb{L}^{(1)} \). It consists of a linear minimum mean squared error (MMSE) detector. Such detectors are known to have information lossless property [24]. Other detectors namely zero forcing (ZF), zero forcing with successive interference cancellation (ZF-SC), can also be used to obtain the initial reliability of bits. Let \( y = P^T r \) be the \( N_t \times 1 \) vector output of MMSE detector, where \( P = (HR_x H^T + \sigma^2 I)^{-1} H \) is the MMSE detector coefficients [10], \( R_x = E [x x^T] \), and \( I \) is the identity matrix of size \( N_r \times N_r \). Assuming MMSE output as Gaussian [22], the MMSE output is used to obtain the initial reliability of the \( N_t \) bits. The reliability of the coded bit \( c_i \) is measured by the magnitude of the log-likelihood ratio, \( \log(P(c_i = 1 | y_t) / P(c_i = 0 | y_t)) \), where \( t = [i | M_c] \). As an example, for quadrature phase-shift keying (QPSK) with constellation points \((1 + j) / \sqrt{2}, (-1 + j) / \sqrt{2}, (-1 - j) / \sqrt{2}, (1 - j) / \sqrt{2}\) representing bit pairs \((0,0), (0,1), (1,1) \), and \((1,0)\) respectively, \( \text{Im} \{ y_t \} \) and \( \text{Re} \{ y_t \} \) give the reliabilities of the first and the second bit respectively [31]. Let us denote the reliability of the coded bits by \( \{ \alpha_i \} \) and let \( \alpha_i \) be the hard decision of \( \alpha_i \).

2) List subset sum detector: The list subset sum detector takes reliability values \( \{ \alpha_i \} \) as input soft information to produce a list \( \mathbb{L}^{(k)} \) of most likely code bit vectors. This list is used to produce extrinsic LLR \( L^{(k)}(c_i | r) \) for each bit \( c_i \). This consists of two parts: a list generator and an extrinsic LLR calculator.

List generator: The motivation of list based algorithms is that flipping of \( \alpha_i \) at a few bit positions may produce the MAP code bit vector in \( \mathbb{L}^{(k)} \) of (3) with high probability. We use the MAP metric of the transmitted vector \( c \), denoted by \( J(c) \) as [27]

\[ J(c) = \sum_{i \in S_c} |\alpha_i| - \sum_{i \in S_p} |\alpha_i| = \sum_{i \notin U} |\alpha_i| - 2 \sum_{i \in S_p} |\alpha_i| \] (4)

where \( U = \{ 1, 2, \ldots, N_t M_c \} \) is the set of bit positions, \( S_c = \{ i | c_i = \alpha_i, i \in U \} \) and \( S_p = \{ i | c_i \neq \alpha_i, i \in U \} \). Since the first term in (4) is independent of the value of \( c \), \( J(c) \) depends only on the second term \( \sum_{i \in S_p} |\alpha_i| \). Hence we need to find set of vectors which minimizes the second term. i.e., the perturbation vectors should be designed in ascending order of the sum \( S = \sum_{i \in S_p} |\alpha_i| \). This problem is equivalent to the subset-sum problem [23], where the objective is to find all subsets of a set of numbers that have sum less than or equal to a given number \( V_{th} \). Let \( \mathbb{L}^{(k)} \) be the set of all perturbation vectors whose reliability sum \( S \) is below a certain threshold \( V_{th} \), and \( \gamma \) be the cardinality of \( \mathbb{L}^{(k)} \). The choice of \( V_{th} \) will be discussed in the next section.

Let us define a vector \( p_i \) as a zero element vector with a 1 at the \( i \)-th bit position. The weight of the vector \( \{ \alpha_i \} \) is defined as \( w = \sum_{i=1}^{N_t M_c} |\alpha_i| \). The list is generated as follows:

Step 1: Sort \( |\alpha_j|, j = 1, \ldots, N_t M_c \) in the ascending order. Set the size of the list \( \Lambda = 1 \), bit position \( i = 1 \), first term in the list \( v^1 \) or \( v_0 \) is \( [0 0 \ldots 0] \) and the weight \( w_0 = 0 \).

Step 2: For each vector in the list \( m = 1 \) to \( \Lambda \), create \( v^m = v^m_0 + p_i \) and modify the weight of each vector as \( w^m = w^m_0 + |\alpha_i| \).

Step 3: Merge lists \( v^m \) and \( v_0 \) to form a new list \( v_{new} \).

Step 4: If \( k = 1 \) i.e., in the first iteration between the detector and the decoder, keep only the vectors in \( v_{new} \) that have a sum less than or equal to \( V_{th} \).

Step 5: If \( k > 1 \), then sort vectors in \( v_{new} \) in ascending order according to their weights \( w_{new} \). Truncate the size of \( v_{new} \) to \( \Lambda^{(k)} \), if the size is greater than \( \Lambda^{(k)} \), where \( \Lambda^{(k)} \) is the maximum size of the list, and set the value of \( \Lambda^{(k)} \) to the size of \( v_{new} \).

Step 6: Set \( v_0 \leftarrow v_{new} \).

Step 7: Set \( i \leftarrow i + 1 \). Repeat Step 2 to 7 if \( i \leq N_t M_c \).

Step 8: Re-arrange the positions of the elements in each test vector in \( v_{new} \) back to their original positions before Step 1, and then add each vector to \( \alpha_i \) to generate the test list \( \mathbb{L}^{(k)} \).

Extrinsic LLR calculator: Once the list \( \mathbb{L}^{(k)} \) is available, the extrinsic LLR values \( L^{(k)}(c_i | r) \) for each coded bit \( c_i \). For higher number of transmit antennas, computation of (3) is very cumbersome, and max-log approximation is used as [4]

\[ L^{(k)}(c_i | r) \approx \frac{1}{2} \max_{c^j \in \mathbb{L}^{(k)} \cap c_{i+1}} \left\{ -\frac{1}{\sigma^2} ||r - H x^j||^2 + c^j T [L_{A,i}] c^j \right\} - \frac{1}{2} \max_{c^j \in \mathbb{L}^{(k)} \cap c_{i-1}} \left\{ -\frac{1}{\sigma^2} ||r - H x^j||^2 + c^j T [L_{A,i}] c^j \right\} \]

After all the code bit vectors \( c^j, 1 \leq l \leq L \), have been processed by the MIMO detector, the extrinsic LLR values associated with \( c \) are made available to the channel decoder as a priori information after de-interleaving:

\[ L^A(c) = \Pi^{-1} \{ L^{ext}(c) \} \] (6)
C. Channel Decoder

The decoder considered in this paper is a soft-input soft-output (SISO) convolutional decoder based on the BCJR algorithm [30]. This decoder is based on trellis structure, where a branch metric computation uses the soft information $L_{\text{A}}(\hat{c})$ coming from the detector. Based on forward and reverse recursions of BCJR, the LLR for each coded and data bit is obtained. The a priori information $L_{\text{A}}(\hat{c}_i)$ is removed from the LLR of each coded bit to produce extrinsic information $L_{\text{ext}}(\hat{c}_i)$. Finally, the extrinsic information is fed back to the detector as a priori information after interleaving as

$$L_{\text{A}}(c) = \Pi\{L_{\text{ext}}(\hat{c})\} \quad (7)$$

The a priori information $L_{\text{A}}c_i$ for each bit $c_i$ is used by the MIMO detector as described in Section III A. The iteration between the detector and the decoder are repeated to decrease the BER. After the last iteration, the LLR of data bits are subjected to hard decision to produce final data decisions.

IV. Performance Analysis

We consider QPSK modulation. The probability of an error $e$ in bit $c_i$ can be written as

$$P_b(c_i) = \sum_{k=0}^{1} P(e|c_i = k)P(c_i = k) \quad (8)$$

Assuming bits 0 and 1 to be equally likely and $P(e|c_i = k)$ to be same for $k = 0$ and 1. Similar to the error analysis presented in [31], and assuming that the output of MMSE detector is Gaussian distributed [32], $P_b$ can be written as

$$P_b \approx P_3 + (1 - P_3)P_{\text{ML}} \quad (9)$$

where

$$P_3 = \frac{1}{N_tM} \sum_{i=1}^{N_tM} Q\left(\frac{V_{\text{th}} + |\mu_i|}{\sigma_i}\right) \quad (10)$$

Where $\mu_i$ and $\sigma_i$ represents the mean and variance of each bit at the MMSE detector output. Note that when $V_{\text{th}}$ is large, the algorithm performs a tree search for almost all bits and hence $P_b \approx P_{\text{ML}}$. This agrees with (9). Selection of $V_{\text{th}}$ is done by solving the following equation,

$$\sum_{i=1}^{N_tM} Q\left(\frac{V_{\text{th}} + |\mu_i|}{\sigma_i}\right) = \left(\frac{\epsilon P_{\text{ML}}}{1 - P_{\text{ML}}}\right) N_tM $$

where $\epsilon$ is a design parameter that controls the performance of the method, and it is given by $P_b = (1 + \epsilon)P_{\text{ML}}$.

A. Implementation Issues

In computing $V_{\text{th}}$, three parameters, $\mu_i$, $\sigma_i$ and $P_{\text{ML}}$ are needed. The parameters $\mu_i$ and $\sigma_i$ are obtained from the MMSE filter coefficients [32]. Finding $P_{\text{ML}}$ is not straightforward. One can use $P_{\text{ML}}$ values obtained through numerical simulations for studying the behavior. However, in a practical use of the algorithm, one has to find $P_{\text{ML}}$ on-line. In our work, we propose to use a matched filter (MF) bound given by

$$P_{\text{MF}} = Q(\sqrt{2\gamma}) \quad (12)$$

where $\gamma$ is the average received signal to noise ratio (SNR).

V. Numerical Results and Discussions

A MIMO system with $N_t$ transmit and $N_r$ receive antennas is considered. The Complex Gaussian random MIMO channel is assumed to be ergodic. The channel information is assumed to be known at the receiver only. QPSK modulation is considered for all the cases. Unless specified $\epsilon$ equal to 0.01.

Fig 2 shows the BER plot for uncoded system with symmetrical configuration for $2 \times 2$, $4 \times 4$, $6 \times 6$ and $8 \times 8$ systems. Also plotted the BER plot with full search (MLD). It can be seen that with T-LSS we can reach the same performance as that of MLD. The average list $S_{\text{avg}}$ required for T-LSS symmetrical configuration is shown in Fig 3. It can be seen that we are getting huge reduction of list size at high $E_b/N_o$. For example, for a $4 \times 4$ system at $E_b/N_o = 14$dB, the BER is equal to $10^{-4}$, the average list size equal to 34.78, as compared to 256 for MLD.

Fig 4 shows the BER plot with $4 \times N_r$, for different values of $N_r$. It can be seen that the T-LSS detector works for any of the combinations unlike the SD, or original V-BLAST algorithm. Fig 5 shows the list size required for the T-LSS for these configurations at $E_b/N_o = 14$dB.

Fig. 6 shows the BER plot for the iterative MIMO system. A rate 1/2 convolutional code with constraint length 7 with polynomials [147, 117]in octal notation is considered. Also shown is the plot with full list size for each iteration. For iterative T-LSS, in the first iteration the list is generated from the T-LSS algorithm with the design is based on MF. For the other iterations the list size is fixed and it is equal to 32.0. It can be seen that the the total list size is 131 as compared to that of 1024 of full search, the performance is almost equal to that of full search.

VI. Conclusions

Threshold based list subset detector is presented. The proposed detector’s performance is very close to that of MLD.
and the complexity is very less. Semi analytical performance is given for the proposed detector. A systematic procedure is given for the design of the detector. The T-LSS detector is extended for MIMO systems concatenated with a channel code to achieve the capacity. The future work include design of capacity approaching limiting irregular LDPC codes for T-LSS based detector. Another approach may be studying the performance for frequency selective fading channels.

REFERENCES