Tree-Based Adaptive Spatial Detection for Adaptive Modulated MIMO Systems

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***Abstract*—Adaptive Multiple-Input Multiple-Output (MIMO) systems achieve a much higher information rate than conventional fixed schemes due to their ability to adapt their configurations according to the wireless communications environment. However, current adaptive MIMO detection schemes exhibit either low performance (and hence low spectral efficiency) or huge computational complexity. In particular, whilst deterministic Sphere Decoder (SD) detection schemes are well established for static MIMO systems, exhibiting deterministic parallel structure, low computational complexity and quasi-ML detection performance, there are no corresponding adaptive schemes. This paper solves this problem, describing a hybrid tree based adaptive modulation detection scheme. Fixed Complexity Sphere Decoding (FSD) and Real-Values FSD (RFSD) are modified and combined into a hybrid scheme exploited at low and medium SNR to provide the highest possible information rate with quasi-ML Bit Error Rate (BER) performance, while Reduced Complexity RFSD, B-Chase and Decision Feedback (DFE) schemes are exploited in the high SNR regions. This algorithm provides the facility to balance the detection complexity with BER performance with compatible information rate in dynamic, adaptive MIMO communications environments.**

***Index Terms*—Adaptive Modulation MIMO, Hybrid Detection, FSD/RFSD, Detection Ordering, Performance Complexity Trade-off**

I. Introduction

The maximum information rate of a communication system, i.e. its Shannon capacity, adapts with the environment in terms of the average SNR and channel condition [1]. In environments such as this, Adaptive Multiple-Input Multiple-Output (A-MIMO) systems can outperform their fixed counterparts by adapting their configurations in terms of aspects such as number of activated antennas [2] [3], modulation types [4][5], coding schemes [6] and transmit power [7]. However, whilst detection of the symbols impinging on a MIMO receiver is a key factor in the overall performance of a MIMO configuration, current Adaptive Modulation (AM) schemes apply either low Bit Error Ratio (BER) detection algorithms such as Zero Forcing (ZF) or Minimum Mean Square Error (MMSE) [2] (leading to either low spectral efficiency) or highly complex BER-optimal algorithms such as Maximum Likelihood Detection (MLD) [8].

The Fixed-Complexity Sphere Decoder (FSD) [9] and Real-valued FSD (RFSD) [10] are quasi-ML, deterministic detection algorithms which exhibit much lower computational complexity than MLD, and are well suited to embedded implementation [11][12]. However, conventional FSD and RFSD are unable to consider the variation in modulation schemes when ordering received signals according to their robustness and hence directly applying these to AM-MIMO systems will lead to BER degradation. In addition, whilst they exhibit good BER performance (hence the high spectral efficiency), their computational complexities grow rapidly with the number of antennas or QAM constellation size. When this complexity becomes so severe as to become more critical than detection performance, lower complexity detection algorithms with similar structure should be applied to redress the complexity/performance imbalance. Such adaptive hybrid detection approaches do not currently exist.

In this paper, we present such a scheme: a novel tree-based hybrid detection algorithm for AM-MIMO systems. Specifically, we make three main research contributions.

1) We demonstrate how weight metrics representing different modulation schemes can be integrated into the FSD/RFSD channel matrix ordering process.
2) We present a novel adaptive detection algorithm, which adapts its behaviour amongst a number of pre-defined tree-based detection schemes to balance the spectral efficiency, BER and detection complexity according to the channel conditions.
3) By applying the modified FSD/RFSD in 1) and algorithm selection methods in 2), we present a novel AM and Adaptive Algorithm (AA) for a 4×4 MIMO system based on the BER simulation results, which shows good capability in balancing the information rate, BER and complexity.

The remainder of this paper is as follows. Section II introduces the AM-MIMO system and the tree-based detection candidates. Section III shows how to modify the FSD/RFSD in the ordering process for hybrid modulated AM-MIMO systems and a tree-based adaptive spatial detection approach is proposed in Section IV. Finally, Section V applies the proposed approaches to a 4×4 AM MIMO system to reveal the capability of the hybrid detection in balancing the information rate, BER and detection complexity.

II. Background

A. Adaptive Modulated MIMO System

In a spatially multiplexed MIMO system with m_t transmit antennas and n_r receive antennas ($m_t \leq n_r$) operating on quasi-static flat fading channels [13], the n_r-element received vector $\mathbf{y} = (y_1, y_2, ..., y_{n_r})^T$ is given by equation (1).

$$\mathbf{y} = \mathbf{Hs} + \mathbf{n} \tag{1}$$

In equation (1), $\mathbf{s} = (s_1, s_2, ..., s_{m_t})^T$ is the transmitted QAM symbol vector with normalized transmit power $E[|s_i|^2] = 1/m_t$, $\mathbf{n} = (n_1, n_2, ..., n_{n_r})^T$ is the vector of independent and identically distributed (i.i.d) complex additive white Gaussian noise (AWGN) with variance of $\sigma^2 = N_0$, and $\mathbf{H}$ is the $n_r \times m_t$ Rayleigh fading channel matrix, where h_{ij} denotes the transform function from transmit antenna j to receive antenna i with $E[|h_{ij}|^2] = 1$.

In an adaptive MIMO system, the transmitter updates its configuration in terms of the number of activated antennas [2][3], modulation constellation sizes [4][5], transmit power [7] and coding schemes [6], according to the average SNR and channel condition [1] of the communication environment, endeavouring to achieve the highest possible information rate with guaranteed BER performance [5]. Of these, only adaptive antenna and adaptive modulation schemes influence the behaviour of detection algorithms, and given the expense (in terms of area and monetary cost) of highly complex RF chain [14], we concentrate on uncoded AM-MIMO systems with square *M*-ary Quadrature Amplitude Modulations (QAM). The architecture of a generic AM-MIMO systems is illustrated in Fig. 1 [5].

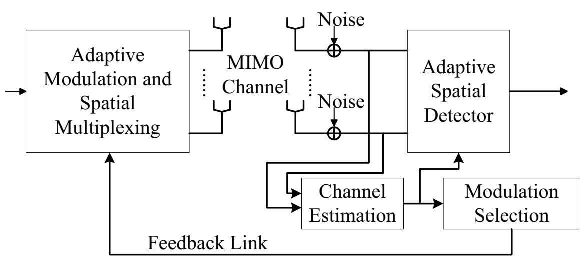


Fig. 1. AM System Architecture For Flat Fading MIMO Channels

As shown in Fig. 1, the transmitter adjusts its modulation types on each transmit antenna according to the suggested modulation schemes based on feedback from the receiver. Perfect feedback and channel state information are assumed at the receiver. In [5], the AM system described shows that a limited range of modulation modes, with successive constellation size increments, i.e. adjacent modes change from the smaller constellation size to the next-highest order *M*-QAM that can provide the required spectral efficiency. For example, AM modes for a 4×4 MIMO system with *M*-QAM (up to 64-QAM) can be set as in Table I.

The AM scheme is defined by 2 steps before feeding back to the transmitter: firstly, according to the average SNR at the receiver and a pre-calculated error rate pattern, a specific AM mode is selected, e.g. one of the mode in Table I is selected for a 4×4 AM MIMO system; secondly, each transmit antenna is assigned to one *M*-QAM constellation specified in the selected mode. As described in [5], the channel conditions

TABLE I
ADAPTIVE MODES

Antenna	Modes and Modulations (M-QAM)								
	1	2	3	4	5	6	7	8	9
Tx1	4	4	4	4	16	16	16	16	64
Tx2	4	4	4	16	16	16	16	64	64
Tx3	4	4	16	16	16	16	64	64	64
Tx4	4	16	16	16	16	64	64	64	64

of the m_t transmit antennas are ranked by calculating $\|\mathbf{h_i}\|^2$ of the channel matrix $\mathbf{H}$, where $\mathbf{h_i}$ is the i^{th} column of $\mathbf{H}$. Higher order QAM schemes are assigned to transmit antenna indices with larger $\|\mathbf{h_i}\|^2$.

Ideally, to retrieve the transmitted symbol vector, $\mathbf{s}$, from the received vector, $\mathbf{y}$, ML detection [8] is used to compare the received symbols with every combination of transmitted symbols, with the most likely candidate selected. However the huge complexity of ML detection makes it practically infeasible. Instead, sub-optimal detection algorithms, such as ZF, MMSE, Vertical Bell Laboratories Layered Space-time (V-BLAST) [15], are applied in building practical implementations. Deterministic SDs are particularly attractive due to near-optimal performance and reduced complexity as compared to MLD [9].

B. Tree-based Spatial Detection Algorithms

1) Fixed-Complexity Sphere Decoder: FSD [9] is a deterministic SD algorithm employing a breadth-first tree search behaviour. It not only provides quasi-ML BER performance, but also has low computational complexity compared with MLD and a highly parallel structure, which enables highly efficient implementations.

In the detection process, FSD firstly determines the detection ordering by permuting the columns of the channel matrix, as described in Function **FSD_Ordering**.

Function $\mathbf{H_{order}}$= FSD_Ordering($\mathbf{H}$)

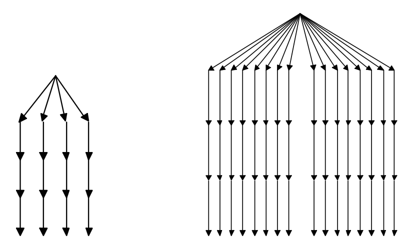
1 $NFS = \lceil \sqrt{m_t} - 1 \rceil$;
2 $\mathbf{\hat{H}_{m_t}} = \mathbf{H}$;
3 **for** $i = m_t : -1 : 1$ {
4 $\quad \mathbf{D_i} = \mathtt{diag}[(\mathbf{\hat{H}_i} \cdot \mathbf{\hat{H}_i^T})^{-1}]$;
5 $\quad$ **If** $i > (m_t - NFS)$ {
6 $\quad\quad index(i) = \arg\max_{index \in \partial}(\mathbf{D_i})$;
7 $\quad$ **else**
8 $\quad\quad index(i) = \arg\min_{index \in \partial}(\mathbf{D_i})$;
9 $\quad$ }
10 $\quad \mathbf{\hat{H}_{i-1}} = Remove(\mathbf{\hat{H}_i}, \mathbf{\hat{h}_i}(index(i)))$;
11 }
where $\partial = [1, 2m_t] - index(i+1 : 2m_t)$;
12 $\mathbf{H_{order}} = \mathbf{H}(index)$;

FSD operates in two phases: Full Search (FS) and Single Search (SS). The Number of FS (NFS) layers is firstly calculated in line 1 [16]. By applying the V-BLAST ordering metrics [15], the ordering metric is specified in line 4, where $\mathtt{diag}$ indicates the diagonal elements of a matrix. During the first NFS iterations, the index of the largest elements of $\mathbf{D_i}$ are sorted to the end of the vector $index$ (line 6), whilst the remainder are selected in a converse strategy (line 8). At the end of each iteration, the selected column is removed from $\mathbf{H_i}$, indicated by the *Remove* function in line 10. Next, $\mathbf{H}$ is ordered by the $index$.

Subsequently, FSD decomposes the ordered channel matrix $\mathbf{H_{order}}$ in equation (1) into an orthogonal matrix and a upper triangular matrix using QR decomposition. The objective function of the FSD algorithm is then defined as the (squared) Euclidean Distance (*Euc*) between the ZF and SD estimation results, given by equation (2).

$$Euc = \|\mathbf{R}(\mathbf{s_{zf}} - \mathbf{s})\|^2 \tag{2}$$

In (2), $\mathbf{s_{zf}}$ and $\mathbf{s}$ are the detected ZF and detecting SD vectors respectively. $\mathbf{R}$ is derived by QR decomposition of $\mathbf{H}$ and its upper triangular nature allows the Euclidean Distance to be calculated by working backwards through the rows of $\mathbf{R}$ from $i = m_t$ to form a tree searching structure. Finally, the candidate vector, $\mathbf{s}$, provides the smallest Euc is selected as the hard detection results. Note that different modulation types have different tree structures, e.g. the searching tree in detecting pure 4QAM and 16QAM modulated 4×4 MIMO are shown in Fig. 2(a) and Fig. 2(b) respectively, where the roots of the trees are the ZF detected symbols and each arrow represents an Accumulative Partial Euclidean Distance (APED) calculation.

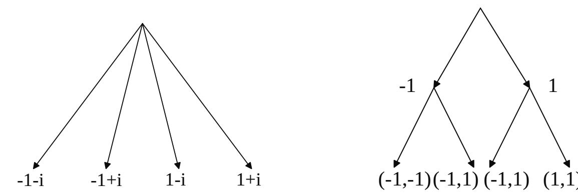


(a) Tree for 4QAM (b) Tree for 16QAM

Fig. 2. Detection Tree for FSD

Although FSD provides quasi-ML performance when all transmit antennas apply the same modulation type, it shows BER degradation if we directly apply the channel matrix ordering method in Function **FSD_Ordering** in hybrid modulated AM system.

2) Real-valued FSD: Whilst the FSD algorithm assumes complex-valued received symbols, in reality the real and imaginary parts of each received symbol are orthogonal and may hence be processed independently [17]. Real-Valued FSD (RFSD) [10] decomposes the complex-valued FSD tree into a real-valued tree, which doubles the depth but shrinks the breadth of the original tree. More specifically, in the new RFSD algorithm, the worst $\widetilde{NFS} = \lceil \sqrt{2m_t} - 1 \rceil$ real layers are ordered to the upper layers of the decode tree for fully expansion, with the remainder undergoing single expansion. Fig. 3 illustrates the effect of this change in converting a single layered 4 QAM complex detection tree into a double layered 2 PAM real tree.



(a) Uncut 4QAM FSD tree (b) Uncut RFSD tree

Fig. 3. 4QAM FSD/RFSD Processing

The finer FS granularity RFSD enables by searching the real and imaginary parts of each symbol independently enables a huge complexity reduction by eliminating unnecessary FS layers - indeed [10] shows that RFSD maintains quasi-ML whilst saving over 70% of the computational complexity of FSD for all practical MIMO cases except m_t = 3, 4 and 9. As such, a low-complexity AM decoder should be able to operate in *both* FSD and RFSD modes.

3) Sub-optimal Low-Complexity Detectors: Decision-Feedback (DFE) or Successive Interference Cancellation (SIC) [18] apply a V-BLAST ordering [15] to detect symbols from the strongest to weakest layer. After cancelling the previous detected layers, only the best candidate in current layer is maintained. B-Chase [18] generates l candidates from the first detection layer, and the l subsequent detections operated in parallel in expanding their descendants. As with FSD/RFSD, both DFE and B-Chase have tree search structures, trading-off the BER of the received signal by adapting search complexity via maintaining a variable number of search paths.

FSD and RFSD provide quasi-ML performance by applying FS strategies, i.e. $NFS = \lceil \sqrt{m_t} - 1 \rceil$ and $\widetilde{NFS} = \lceil \sqrt{2m_t} - 1 \rceil$ respectively for higher order QAM systems, or systems with high SNR. In the case where either excessivley computationally complex detection, or simplified detection given a high quality wireless communications channel are encountered, FSD/RFSD with reduced NFS/$\widetilde{NFS}$ or even lower complexity schemes such as B-Chase or DFE are all desirable to balance BER and detection complexity. There is no AM detection scheme which can integrate all these approaches in general, or tree-based detection schemes in particular. In Section IV we derive the first such adaptive modulation and detection approach.

III. Modified FSD/RFSD in AM System

A. Weight Metrics in Ordering the Hybrid Modulated MIMOs

In contrast to V-BLAST and other conventional nulling and cancellation detection algorithms, the key feature of FSD and RFSD is to fully expand the candidates of the worst distorted symbols at the top layers of the detection tree. Since conventional FSD and RFSD are designed for fixed MIMO systems with identical modulation schemes at each transmit antenna, the worst distorted layers are equivalent to those layers with the worst channel conditions, as described in line 4 of the function **FSD_Ordering**. However, as the modulation types on each transmit antenna are adaptive in AM-MIMO systems, hybrid modulations can appear. Since different constellations exhibit different error robustness, the robustness of a transmitted symbol should be defined by considering both channel condition and the applied constellation type.

Hence, besides measuring the robustness of the transmit symbols with the channel conditions in function **FSD_Ordering**, additional weight metrics should be added on each detection layer according to the applied constellations. Thus, the equation in line 2 of the function **FSD_Ordering** is updated to (3).

$$\hat{\mathbf{H}}_{\mathbf{m_t}} = \mathbf{H} * \mathbf{W}, \quad (3)$$

In (3), $\mathbf{W}$ is a diagonal matrix representing the robustness of the applied constellations. Note that the weight matrix $\mathbf{W}$ is only applied in finding the detection ordering rather than the detection process itself. The values on the diagonal of $\mathbf{W}$ are derived via experiment.

B. Weight Metrics for FSD and RFSD

The ultimate purpose of permuting the ordering of the detection scheme is to obtain the lowest possible BER, by diminishing the influence of the worst distorted symbols via FS, and reducing the error propagation of the remainder via SS. Hence we strive to obtain, via experiment, the appropriate weight metrics to best represent the robustness between different constellations and provide the lowest BER.

Since higher-order M-QAM schemes exhibit higher error rate than lower-order ones, the modulation type with the larger constellation size dominates the error rate of the MIMO system. Hence, as described in Table I, an AM system with high spectral efficiency generally applies at most two adjacent QAM constellations in each mode [5]. Therefore the elements of $\mathbf{W}$ only have to reflect the robustness ratio between those two adjacent constellations, e.g. $w_1 = \frac{robust_{4QAM}}{robust_{16AQM}}$ and $w_2 = \frac{robust_{16QAM}}{robust_{64AQM}}$ for M-ary QAM candidates, where $M =$ 4, 16 and 64 for our case. The columns of the $\mathbf{H}$ which exploit lower order QAM are multiplied by either w_1 or w_2, while the remainder are unweighted (i.e. weighted by 1). For example, for mode 2 and 6 are shown as equation (4). Note that within this expression, we assume the higher order QAM is transmitted on the 4^{th} transmit antenna.

$$\mathbf{W_2} = \begin{bmatrix} w_1 & 0 & 0 & 0 \\ 0 & w_1 & 0 & 0 \\ 0 & 0 & w_1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}; \quad \mathbf{W_6} = \begin{bmatrix} w_2 & 0 & 0 & 0 \\ 0 & w_2 & 0 & 0 \\ 0 & 0 & w_2 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (4)$$

Since the constellation points from lower-order QAMs have a higher average power than the higher-order ones, the weights w_1 and w_2 should have values larger than 1. Hence, we enumerate the weight elements from 1 to 5 with a step of 0.05 to find the value that brings the lowest BER.

Firstly, we configure the MIMO system with 4 transmit and receive antennas. The wireless channels are set as quasi-static flat fading channels as described in Section II-A. We select mode 2 and mode 6 in Table I as the testing configurations, since both of them contain only one higher order QAM layer, where the biased ordering will effectively remove the errors from the less robust higher order modulated symbol and bring significant performance improvement. Overall, 12500 frames with 300 symbols per frame are tested at fixed SNRs to give the BER results in Fig. 4.

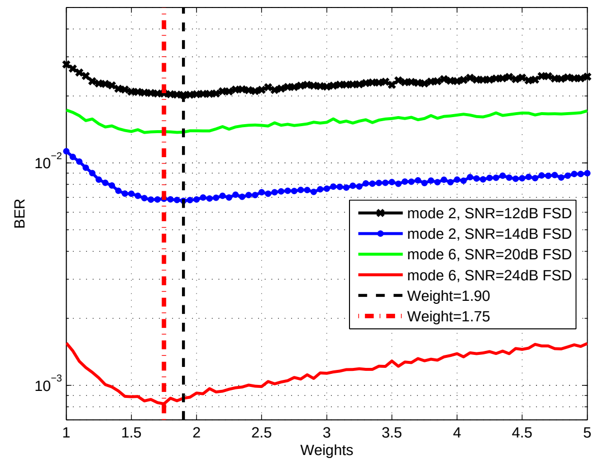


Fig. 4. BER of FSD in a 4×4 AM-MIMO with Varying Weights

Fig. 4 shows that applying the appropriate weighting scheme dramatically improves the BER in contrast with the unweighted cases. The minimum BER observed for mode 2 in FSD appears at $w_1 = 1.90$, while the $w_2 = 1.75$ brings the best BER for mode 6. Note that a higher SNR value results in a more significant BER improvement, e.g. 39.80% and 46.04% BER improvement under $SNR = 14$ and 24 for mode 2 and mode 6, respectively. However, flexibility in the SNR does does not change the weights for either modes 2 or 6.

Furthermore, Fig. 5 shows that the BER adapts as the weight updates, by applying RFSD on both 4×4 and 6×6 AM-MIMO system where 4×4 MIMO is modulated as in mode 2 in Table I and the 6×6 MIMO set with 4 4-QAM and 2 16-QAM constellations. The simulation results show that the weights within the same range results in the best BER performance for both the hybrid modulated 4×4 and 6×6 MIMO systems when applying RFSD.

Intuitively, lower weights emphasise on the channel condition, whilst higher values overestimate the effect of the modulation. Hence neither scheme provides minimum BER performance. The experiment shows the weight metrics, i.e. $w_1 = 1.90$ and $w_2 = 1.75$ for 4/16-QAM and 16/64-QAM modulated MIMO systems respectively, provide the best BER performance for both FSD and RFSD regardless of average SNR and number of antennas. In other words, the weight metrics reflect the robustness of the constellations. Next, we

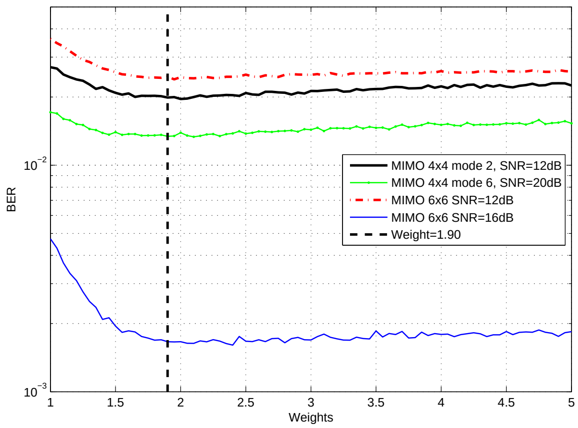


Fig. 5. BER of RFSD in an AM-MIMO System with Varying Weights

will exam the efficiency in trading-off the performance and complexity by adding the weights.

C. Weighting Performance/Complexity Trade-Off

The weight matrix employed during ordering translates into higher BER performance in the hybrid modulated MIMO systems. By applying the obtained weight metrics onto the 4×4 AM-MIMO system with configuration as described in Section III-B, the BER curves for each hybrid modulation modes of Table I are as shown in Fig. 6. Since FSD works better than RFSD when $m_t = 4$ [10], we apply FSD as the near-optimal detection algorithm.

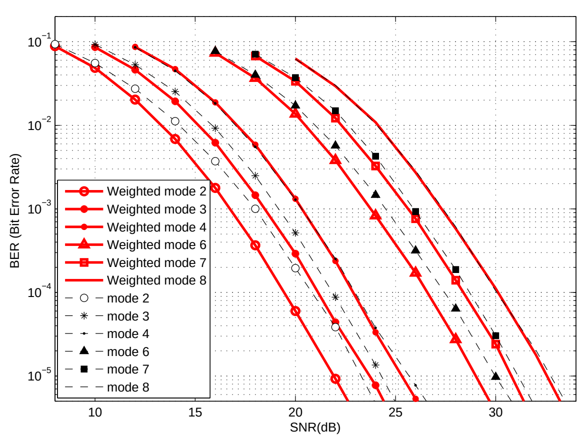


Fig. 6. Variation of BER with SNR of FSD in a 4×4 AM-MIMO

As shown in Fig. 6, the weight metrics provide significant performance improvement when only one transmit antenna works on a high-order QAM, such as in modes 2 and 6, which shows almost 2dB and 1dB SNR improvement at BER=10^{-5}, respectively. This is because the 16/64 QAM dominates the errors in mode 2/6; thus, with the bias between modulations the detector is prone to fully expending the only layer with higher-order QAM. However, when the system is dominated by high-order QAMs, the weight metric will not affect the BER as in modes 4 or 8. This is because the higher-order QAM dominates the errors and fully expanding only one higher order QAM cannot prevent errors propagating through single expanding the rest of the high-order QAM layers.

However, this modulation ordering imposes additional complexity. For example, without the bias on the modulations, mode 2 exploits a detection tree such as that in Fig. 2(a). However, for large weighting factors, the detection tree morphs into the structure shown in Fig. 2(b). In other words, employing ($w > 1$) imposes extra complexity in the detection process. Hence, the smallest weight that provides the best BER is preferred in the detecting hybrid AM-MIMOs. Table II shows the complexity increment in terms of real operations in detecting m_t mixed QAM symbols by adding the weight metrics.

TABLE II
COMPLEXITY INCREMENT IN TERMS OF REAL OPERATIONS BY ADDING THE WEIGHTS

Mode	Unweighted		Weighted		Complexity Increment	
	$\pm$	$\times$	$\pm$	$\times$	$\pm$	$\times$
2	323	208	632	371	95.67%	78.37%
3	323	208	922	525	185.45%	152.4%
4	323	208	1083	610	235/29%	193.27%
6	1139	640	1977	1084	73.57%	69.37%
7	1139	640	3160	1710	177.44%	167.19%
8	1139	640	4013	2162	252.33%	237.81%

As Table II shows, the complexity increases as the proportion of the higher-order modulation grows, i.e. mode 2 or 6 provides the most significant performance improvement with the lowest complexity increment, whilst modes 4 or 8 experience a factor three complexity without much performance improvement. The ranges $w_1 \in [1, 1.90]$ and $w_2 \in [1, 1.75]$ are particularly interesting, since they improve the BER performance with relatively low extra complexity. On the other hand, this trade-off is only efficient in the AM-MIMO configurations where smaller constellations dominate, i.e. we prefer this weight only in efficient modes, such as 2 or 6, and insist the original weight, i.e. $w = 1$, for inefficient modes, such as modes 4 or 8.

Note that, although [19] describes a similar weighting scheme for cancellation-based detectors, its weight derivation process is unclear and the derived coefficients (equivalent to $w_1 = 2.23$ and $w_2 = 2.04$) enable far less efficient performance-complexity trade-off than the coefficients proposed in this paper.

IV. TREE BASED ADAPTIVE DETECTION ALGORITHM

Besides the variation in AM modes, a variety of detection algorithms can be employed in AM-MIMO to provide lower complexity detection options, which is particularly useful when detection complexity is the most crucial issue or the system works in a high SNR region. Since the breadth of the FSD/RFSD detection tree grows as the constellation size increases, higher-order QAM modulation leads to larger detection complexity. When this becomes a system bottleneck, sub-optimal detection schemes can be exploited to reduce this complexity, at the cost of lower BER performance. Further, if the average SNR is large enough, sub-optimal detection algorithms may still achieve the required BER in the AM mode with the highest-order QAM candidates, and so it is unnecessary to apply high performance detection at the cost of huge complexity. Thus, a serial of sub-optimal detection algorithms can be applied to make this trade-off for AM MIMOs.

Since both FSD and RFSD are near-optimal detection algorithms, B-Chase, DFE/SIC and FSD/RFSD with a reduced number of FS layers can be used as sub-optimal approaches to trade-off performance and complexity. In targeting the highest possible information rate of a MIMO system, a possible algorithm selection method is proposed in Table III.

TABLE III
ADAPTIVE DETECTION ALGORITHMS

Trans. antennas	Average SNR			
	$<$SNR$_1$	[SNR$_1$,SNR$_2$]	[SNR$_2$,SNR$_3$]	$>$SNR$_3$
m_t =3, 4, 9	FSD	RFSD	B-Chase	DFE/SIC
$m_t \neq$3, 4, 9	RFSD		B-Chase	DFE/SIC

FSD can be used to achieve near-optimal detection when required, i.e. in the low SNR region ($\overline{SNR} \leq SNR_1$) when $m_t = 3, 4, 9$, whilst RFSD can be applied in the remainder of the m_t cases. In addition, because RFSD provides finer granularity for full search, it can be used as sub-optimal detection algorithm by full searching $\widetilde{NFS} < \lceil\sqrt{2m_t} - 1\rceil$ layers. Furthermore, B-Chase with K^2 maintained branches (where K is an integer number) is selected to make a further trade-off complexity and performance at higher SNR. Finally, DFE/SIC (i.e. the tree with a single maintained branch) is used if SNR is sufficiently high ($\overline{SNR} > SNR_3$). Adapting the thresholds represented by $SNR_1 - SNR_3$ can be achieved either by the BER estimation method of the QAM-MIMO system [5] or from simulated BER results. We demonstrate the latter, in the context of an AM and AA example for a 4×4 MIMO in Section V.

V. Case Study: Adaptive High Performance Detectors on AM MIMO System

We apply the proposed weighted FSD/RFSD and the adaptive spatial detection algorithm for an AM-MIMO system. Table III indicates that FSD is applied only at $m_t = 3, 4$ and 9, and 4×4 MIMO system is one of the most widely applied system setting in modern wireless standards, e.g. IEEE 802.11n. Without loss of generality, we set our system as a 4×4 MIMO system in this case study. We exploit squared M-QAMs (M up to 64) as the candidate constellations, and setting the adaptive modulation modes as shown in Table I.

Since $m_t = 4$, according to Table III, FSD is used as the near-optimal detector; RFSD, B-Chase and DFE are applied as the sub-optimal detection algorithms. In targeting the maximum spectral efficiency by the chosen detection algorithms, the near-optimal scheme, i.e. FSD, will be applied as long as higher information rate is achievable (the weights in determining the ordering, as described in Section III, are applied only on modes 2, 3, 6 and 7), whilst the sub-optimal algorithms are only used when the average SNR is sufficiently high to saturate the information rate within the candidate modulation modes.

Fig. 7 shows the results of a Monte Carlo simulation of the candidate detection algorithms with variety of modulation modes on SDM 4×4 AM-MIMO systems over quasi-static flat Rayleigh fading channels, as described in Secion II-A. We process 10^5 frames of 300 symbols each for each configurations.

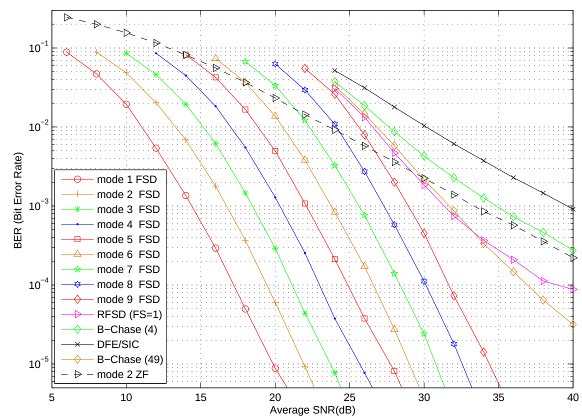


Fig. 7. BER performance of FSD over Adaptive Modulated MIMO 4×4

By adding weight metrics between different modulations for ordering the detection tree, the BER performance of FSD from different modes reveals steady gaps, i.e. roughly 2 dB, between adjacent modes. In other words, since the information rate gap between adjacent modes is 0.5 bits per channel use, the FSD provides a good trade-off between the spectral efficiency and required average SNR, i.e. as 1 dB average SNR increment achieves roughly 0.25 extra bits per channel use, within the adaptable SNR range, e.g. from 14.4 dB to 28.9 dB in targeting BER of 10^{-3} for this example.

If the average SNR is sufficiently high, e.g. $\overline{SNR} >$ 28.9 dB, the information rate is saturated by the candidate modulations. Then, the sub-optimal detection algorithms can be applied to further trade off the detection complexity with BER performance. As indicated in Fig. 7, the RFSD with a single NFS layer in mode 9, which has comparable complexity to B-Chase with 8 branches, outweighs the BER from B-Chase with 49 maintained branches; thus we apply RFSD as the sub-optimal algorithm instead of B-Chase with more than 8 candidates.

The thresholds (in terms of average SNR) of the adaptive modulation schemes and candidate algorithm selection method in targeting BER of 10^{-3} are indicated in Table IV. Note that although ZF has very low complexity, its BER performance is much worse than those tree-based algorithms. Hence, it offers much lower information rate [4]. For example, in targeting $BER = 10^{-3}$, the ZF at mode 2 is only enabled from $SNR =$ 33.4 dB (as described in Figure 7), whilst mode 9 is activated in the flexible tree-based algorithm at the same SNR. Hence, the information rate of the applied tree-based detector (24 bits per channel use) is three times the ZF (8 bits per channel use). In addition, the space-time coding can be combined with ZF [2], yet this technique dramatically decreases the throughput from SDM MIMO systems. Furthermore, this AM and AA approach reveals a practical detection complexity in building efficient implementations [12], unlike MLD methods [5].

TABLE IV
EXAMPLE OF ADAPTIVE MODULATIONS MODES AND DETECTION ALGORITHMS AS THE AVERAGE SNR CHANGES

Averg. SNR	Mode	Algo.	Averg. SNR	Mode	Algo.
$[14.4, 16.7]$	1	FSD	$[25.6, 27.4]$	7	FSD
$[16.7, 18.5]$	2	FSD	$[27.4, 28.9]$	8	FSD
$[18.5, 20.3]$	3	FSD	$[28.9, 31.4]$	9	FSD
$[20.3, 22.1]$	4	FSD	$[31.4, 34.9]$	9	RFSD
$[22.1, 23.8]$	5	FSD	$[34.9, 39.6]$	9	B-Chase (4)
$[23.8, 25.6]$	6	FSD	>39.6	9	DFE/SIC

Besides defining the AM and AA scheme from the simulation results, the adaptive solutions can be obtained by the accurate BER prediction methods as well, e.g. the optimal uncoded BER estimation in [5] and the sub-optimal DFE in [3].

VI. CONCLUSION

In this paper, we have presented a hybrid modulated MIMO nulling and cancellation detection approach employing tree-based detection algorithms, i.e. FSD and RFSD. We have shown how channel matrix weighting factors may be determined via experimentation and applied during ordering to reduce the BER for tree-based detection schemes. Further, we have proposed a novel adaptive detection algorithm that consists of a series of tree-based detection candidates, enabling the AM system to balance the BER and detection complexity. By applying the proposed ordering method and detection algorithm selection techniques, a novel AM and AA scheme was presented based on the simulation results for a 4×4 AM MIMO system, which shows a good trade off among the achievable information rate, BER performance and detection complexity.

REFERENCES

[1] A. Goldsmith and P. Varaiya, "Capacity of fading channels with channel side information," *IEEE Transactions on Information Theory*, vol. 43, no. 6, pp. 1986–1992, 1997.

[2] R. Heath and D. Love, "Multimode Antenna Selection for Spatial Multiplexing SystemsWith Linear Receivers," *IEEE Transactions on Signal Processing*, vol. 53, no. 8, pp. 3042–3056, Aug. 2005.

[3] H. Zhang, H. Dai, Q. Zhou, and B. L. Hughes, "On the Diversity Order of Spatial Multiplexing Systems With Transmit Antenna Selection: A Geometrical Approach," *IEEE Transactions on Information Theory*, vol. 52, no. 12, pp. 5297–5311, Dec. 2006.

[4] P. Sebastian, H. Sampath, and A. Paulraj, "Adaptive Modulation for Multiple Antenna Systems," *Conference Record of the Thirty-Fourth Asilomar Conference on Signals, Systems and Computers (Cat. No.00CH37154)*, vol. 1, no. 1, pp. 506–510, 2000.

[5] F. Kharrat-Kammoun, S. Fontenelle, and J. Boutros, "Accurate Approximation of QAM Error Probability on Quasi-Static MIMO Channels and Its Application to Adaptive Modulation," *Information Theory, IEEE Transactions on*, vol. 53, no. 3, pp. 1151–1160, 2007.

[6] M. Dorrance, "Adaptive Discrete-Rate MIMO Communications with Rate-Compatible LDPC Codes," *Communications, IEEE*, vol. 58, no. 11, pp. 3115–3125, 2010.

[7] T. Yoo, "Capacity and Power Allocation for Fading MIMO ChannelsWith Channel Estimation Error," *Information Theory, IEEE Transactions on*, vol. 52, no. 5, pp. 2203–2214, 2006.

[8] V. Tarokh, N. Seshadri, and A. Calderbank, "SpaceTime Codes for High Data Rate Wireless Communication: Performance Criterion and Code Construction," *IEEE Transactions on Information Theory*, vol. 44, no. 2, pp. 744–765, Mar. 1998.

[9] L. Barbero and J. Thompson, "Fixing the Complexity of the Sphere Decoder for MIMO Detection," *IEEE Transactions on Wireless Communications*, vol. 7, no. 6, pp. 2131–2142, Jun. 2008.

[10] C. Zheng, X. Chu, J. McAllister, and R. Woods, "Real-Valued Fixed-Complexity Sphere Decoder for High Dimensional QAM-MIMO Systems," *Signal Processing, IEEE Transactions on*, vol. 59, no. 9, pp. 4493–4499, 2011.

[11] X. Chu and J. McAllister, "FPGA Based Soft-core SIMD Processing: A MIMO-OFDM Fixed-Complexity Sphere Decoder Case Study," in *Field-Programmable Technology (FPT), 2010 International Conference on*, 2010, pp. 479–484.

[12] X. Chu, J. McAllister, and R. Woods, "A Pipeline Interleaved Heterogeneous SIMD Soft Processor Array Architecture for MIMO-OFDM Detection," in *The 7th International Symposium on Applied Reconfigurable Computing*, Belfast, 2011, pp. 129–140.

[13] I. Telatar, "Capacity of Multi-antenna Gaussian Channels," *European transactions on telecommunications*, vol. 10, no. 6, pp. 585–596, 1999.

[14] P. Uthansakul, N. Promsuwanna, and M. Uthansakul, "Performance of Antenna Selection in MIMO System Using Channel Reciprocity with Measured Data," *International Journal of Antennas and Propagation*, vol. 2011, pp. 1–10, 2011.

[15] P. Wolniansky, G. Foschini, G. Golden, and R. Valenzuela, "V-BLAST: An Architecture for Realizing Very High Data Rates Over the Rich-Scattering Wireless Channel," *Signals, Systems, and Electronics, 1998. ISSSE 98. 1998 URSI International Symposium on*, pp. 295–300, 1998.

[16] J. Jalden, L. G. Barbero, B. Ottersten, and J. S. Thompson, "The Error Probability of the Fixed-Complexity Sphere Decoder," *IEEE Transactions on Signal Processing*, vol. 57, no. 7, pp. 2711–2720, Jul. 2009.

[17] U. Fincke and M. Pohst, "Improved Methods for Calculating Vectors of Short Length in a Aattice, Including a Complexity Analysis," *Mathematics of computation*, vol. 44, no. 170, pp. 463–471, 1985.

[18] D. L. Milliner, E. Zimmermann, J. R. Barry, and G. P. Fettweis, "A Framework for Fixed Complexity Breadth-First MIMO Detection," *2008 IEEE 10th International Symposium on Spread Spectrum Techniques and Applications*, pp. 129–132, Aug. 2008.

[19] J. Kim, S. Bahng, and Y.-o. Park, "A New Detection Method for MIMO Systems with Differently Modulated Layers," *Advanced Communication Technology, 2009. ICACT 2009. 11th International Conference on*, vol. 2, pp. 1228–1232, 2009.