VLSI Implementation of Optimal K-Best Sphere Decoder

Nishit M Vankawala, Komal M Lineswala, Prof. Rakesh Gajre

Abstract— **MIMO system provides spatial multiplexing gain and diversity gain. Maximum likelihood solution is optimal decoder for MIMO systems. However, computational complexity of such lattice decoder is high in terms of hardware implementation. Moreover, throughput is also variable. In this paper, Sphere Decoding algorithm is used which provides an ease in terms of computational complexity and also throughput is constant. For real time applications, constant throughput is efficient. Hence, Sphere Decoder provides more efficient and realizable hardware. Such algorithm increase speed on chip and can be extended such that operation is performed using less no. of cycles. For a 4-transmit and 4-receive antennas system using QAM, a higher decoding throughput in terms of Mbps and low BER for MIMO system can be achieved. Also BER performance decoding throughput in terms of Mbps of Sphere Decoder is close to Maximum Likelihood solution.**

Index Terms— **lattice decoding, Sphere decoding, Maximum Likelihood, k-best SD, breadth first search.**

I. INTRODUCTION

This section gives introduction of MIMO Detection and its various literatures. It introduces MIMO system and tradeoff between Spatial multiplexing gain and Diversity gain. Section II gives general classification of MIMO Decoders and various techniques employing them. It also highlights pros and cons of mentioned techniques. Section III gives detailed idea of Sphere decoding and tree traversal and radius reduction based on constraints of SD. It describes difference between depth-first and breadth-first tree search. Section IV shows lattice decoders and algorithm implemented for k-best with and without sorting techniques. Section V shows hardware architecture and various Simulation results.

A. MIMO Decoders

Recently, need of higher transmission rates with less transmission errors have increased in wireless communication. Hence use of multiple antennas for communication is need of an hour. Hence, next-generation wireless networks have emerged to offer higher transmission rates with less error. Multiple antenna systems increase spectral efficiency of the system through the use of diversity techniques and SM (Spatial Multiplexing) scheme.

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In [1] a basic transmit diversity scheme is developed for two transmit antennas, while in [2] the diversity gain is increased using four transmit antennas with orthogonal codes. In past researches, the channel is assumed to be uncorrelated and at the receiver maximum-likelihood detection is employed together with combining techniques. On the other hand, the spectral efficiency of the system is increased by employing spatial multiplexing (SM) [3] which permits the opening of multiple spatial data pipes between transmitter and receiver without any additional bandwidth or power requirement. MIMO systems introduce a spatial dimension to existing rate adaptation algorithms that implies to decide MIMO transmission type, STBC, spatial multiplexing or hybrid approaches, as well as modulation and coding type. However, in MIMO systems, correlations may occur between channel coefficients due to insufficient antenna spacing and the scattering properties of the transmission environment. This may lead to significant degradation in system performance. In this regard, adding more antennas to the base-station and/or the subscriber unit require more spatial dimension at the base station and/or the subscriber unit in order to have an uncorrelated channel between antenna elements. Hence, it would not be feasible to design higher order MIMO systems in small handsets. On the other hand the use of dual-polarized antenna elements is introduced as a space and cost-effective alternative that is used to transmit information symbols through vertical and horizontal polarizations without any additional power and bandwidth requirement. In communication with dual-polarized antenna elements, the information streams are sent through vertical and horizontal polarizations of the antenna elements at the same time and frequency.

However as pointed out in [4], imperfections of transmit and/or receive antennas and XPD factor, which is the power ratio of the co-polar and cross-polar components, degrades the system performance considerably. In [5], a system employing one dual-polarized antenna at the transmitter and one dual-polarized antenna at the receiver is presented and the error performance of 2-antenna SM and STBC transmission schemes are derived for this virtual MIMO system. Notice that, in [5], a single-input single-output (SISO) system is enabled with MIMO capabilities through the use of dual-polarized antennas. In IEEE 802.11n and WiMAX systems, 2×1 and 2×2 antenna configurations are used with Alamouti and SM transmission techniques, however, although it is defined in the standards, higher order MIMO systems are not used due to the space problem. The system throughput is controlled by both these two MIMO options and modulation and coding schemes (MCS) defined in the standards. However, when dual-polarized antenna elements are used at both link ends, a virtual 4×4 MIMO system is obtained where the hybrid MIMO options can also be carried out to maximize detection performance and multiplexing gain of the system.

In combination of virtual 4×4 MIMO system with MCS's including large constellation size; a tremendous computational effort is required when the optimal detection techniques are employed at the receiver, especially for SM and hybrid transmission techniques. On the other hand, we need a low complexity but an effective receiver.

Recently, a lot of research efforts have done in order to suppress undesired transmission effects through low complexity iterative equalization methods based on the joint use of linear MMSE filtering and SIC process. For instance, in [6] multiple access interference are cancelled out for CDMA systems while in [7] ISI effects are suppressed for single antenna systems. However, when the channel memory length is large, employing equalization at time domain would require a considerable computational effort due to the matrix inversion. Therefore, frequency domain equalization is introduced in the literature and through [8][9] low complexity iterative frequency domain equalization is studied. Moreover, equalization task is performed at frequency domain in OFDM systems where frequency-selective fading channels become frequency-flat fading channels by sending the symbols through orthogonal subcarriers. By adding at least channel length cyclic prefix to the system, OFDM technology solves the ISI problem. Due to that reason, OFDM is used as a standard technique in IEEE 802.11n WiMAX systems. When combining four dual-polarized MIMO transmission techniques with MCS's introduced in IEEE 802.11n and WiMAX standards, a transmission channel can be fully utilized via a proper adaptive switching mechanism. In this regard, we employ the standard link adaptation technique, given in [10] where SNR information is defined as a link quality indicator and the transmission parameters are adapted to the current channel conditions according to the SNR knowledge.

Diversity gain and spatial multiplexing gain are related to system coverage range and data rate, respectively. Both gains can be improved using a larger antenna array. However, given a MIMO system, there is a fundamental trade-off between these two gains. In the diversity-multiplexing space, repetition code, Alamouti code, and space-time code use data redundancy to increase diversity at the price of losing spatial multiplexing gain. In contrast, Bell Labs Layered Space Time (BLAST) algorithm, Singular Value Decomposition (SVD), and QR decomposition allocate data-streams in different Eigen-modes to maximize spatial multiplexing gain while sacrificing diversity gain, as shown in Fig. 1.

Sphere decoding is a decoding scheme that can extract both diversity and multiplexing gains. With flexibility in coding and modulation, sphere decoder can effectively explore the entire tradeoff curve as shown in Fig.1.

B. *Basic Model for MIMO System*

Our equivalent complex-valued discrete-time baseband system model is as follows.

$$y = Hs + n \qquad (1)$$

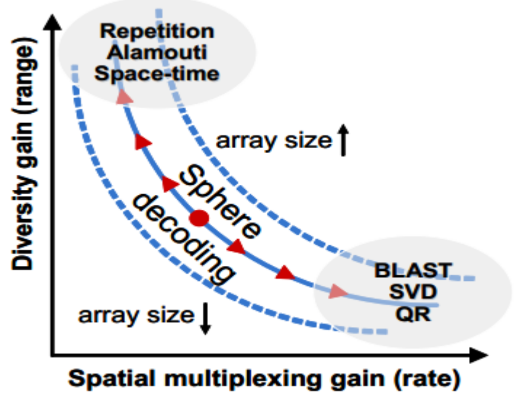

Fig.1. Diversity v/s Multiplexing tradeoff in MIMO communications [11].

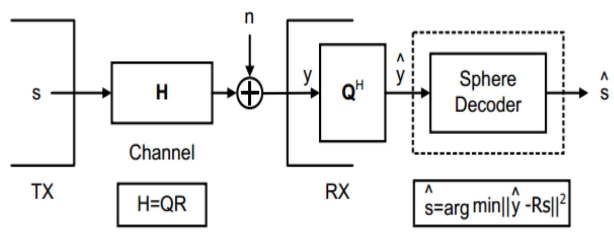

Fig. 2. Basic Model of MIMO System [11]

where H denotes the M_r x M_t channel matrix, s= [s_1 s_2 ......s_{Mt}] is the M_t-dimensional transmit signal vector, and n stands for the M_r-dimensional additive i.i.d. circularly symmetric complex Gaussian noise vector. The entries of s are chosen independently from a complex constellation Ȯ with Q bits per symbol, i.e. $Ȯ=2^Q$. The set of all possible transmitted vector symbols is denoted by $Ȯ^{Mt}$. The corresponding uncoded transmission rate is R= M_t Q bits per channel use (bpcu).

II. CLASSIFICATION OF MIMO DECODERS

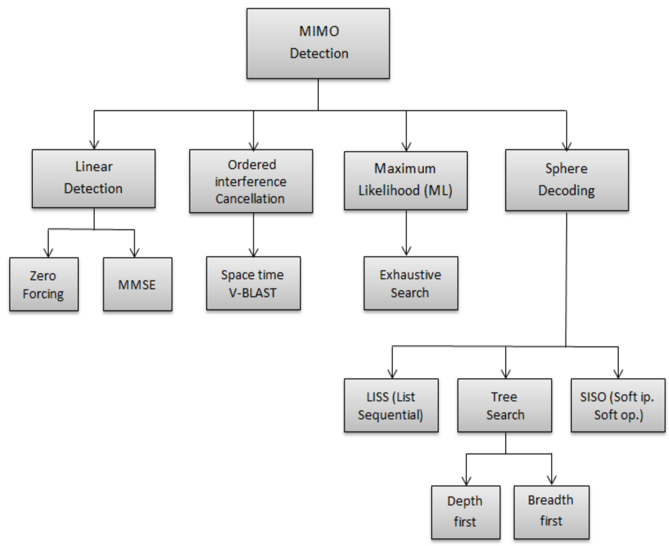

Fig. 3. Classification of MIMO Decoder

We assume that the receiver has acquired knowledge of the channel H (e.g., through a preceding training phase). Algorithms to separate the parallel data streams corresponding to the transmit antennas can be divided into four categories.

1. Linear detection methods invert the channel matrix using a zero-forcing (ZF) or minimum mean squared error (MMSE) criterion. The received vectors are then multiplied by the channel inverse, possibly followed by slicing. The drawback is, in general, a rather poor bit-error-rate (BER) performance.

2. Ordered successive interference cancellation decoders such as the vertical Bell Laboratories layered space-time (V-BLAST) algorithm show slightly better performance, but suffer from error propagation and are still suboptimal.

3. Maximum-likelihood (ML) detection, which solves

$$\hat{s} = \arg\min \| y-Hs \|^2 \qquad s \in \dot{O}^{Mt} \tag{2}$$

is the optimum detection method and minimizes the BER. A straightforward approach to solve (2) is an exhaustive search. Unfortunately, the corresponding computational complexity grows exponentially with the transmission rate R, since the detector needs to examine 2^R hypotheses for each received vector. While the implementation of exhaustive-search ML has been shown to be feasible in the low rate regime R<= 8 bpcu, complexity quickly becomes unmanageable as the rate increases. For example, in a 4 x 4 system (i.e. M_r=M_t=4) with 16-QAM modulation (corresponding to R= 16 bpcu), 65,536 candidate vector symbols have to be considered for each received vector.

4. Sphere decoding (SD) solves the ML detection problem [12][13]. While the algorithm has a nondeterministic instantaneous throughput, its average complexity was shown to be polynomial in the rate [14] for moderate rates, but still exponential in the limit of high rates. However, these asymptotic results do not properly reflect the true implementation complexity of the algorithm, which for most practical cases is still significantly lower than an exhaustive search. The algorithm is thus widely considered the most promising approach toward the realization of ML detection in high-rate MIMO systems. Ever since its introduction in and its application to wireless communications in [13], reduction of the computational complexity of the algorithm has received significant attention [13][15]. However, most modifications of the algorithm proposed in the literature so far have been suggested with digital signal processor (DSP) implementations in mind. Little attention has been paid to the efficient VLSI implementation of the SD algorithm and the associated performance tradeoffs.

III. BASICS OF SPHERE DECODING

In this section, we briefly review the basics of SD, and we outline what we consider to be the corresponding state of the art. Our description summarizes the original algorithm [16], introduced by Pohst, and its subsequent extensions and improvements [13][17][15]. We distinguish four key concepts, which we describe in the following.

A. Sphere Constraint

The main idea in SD is to reduce the number of candidate vector symbols to be considered in the search that solves (2), without accidentally excluding the ML solution. This goal is achieved by constraining the search to only those points Hs that lie inside a hyper sphere with radius r around the received point y. The corresponding inequality is referred to as the sphere constraint (SC)

$$d(s) < r^2 \qquad \text{where } d(s) = \|y-Hs\|^2 \tag{3}$$

B. Tree Pruning Strategies

Only imposing the SC (3) does not lead to complexity reductions as the challenge has merely been shifted from finding the closest point to identifying points that lie inside the sphere. Hence, complexity is only reduced if the SC can be checked other than again exhaustively searching through all possible transmit vector symbols $s \in \dot{O}^{Mt}$. Two key elements allow for such a computationally efficient solution

1. Computing Metric

The channel matrix H in (3) can be triangularized using a QR decomposition according to H=QR, where the M_r x M_t matrix

$$d(s) = c + \| \hat{y} - Rs \|^2 \qquad \text{where } \hat{y} = Q^H y = Rs^{ZF} \tag{4}$$

where s^{ZF} is the zero-forcing (or unconstrained ML) solution $s^{ZF} = H^I y$ (H^I is pseudo-inverse of H). The constant c is independent of the vector symbol and can hence be ignored in the metric computation. In the following, for simplicity of exposition, we set c=0. If we build a tree such that the leaves at the bottom correspond to all possible vector symbols s and the possible values of the entry s_{Mt} define its top level i (i=1, 2….M_t), we can uniquely describe each node at level by the partial vector symbols $s^{(i)} = [s_i\ s_{i+1}\ \ldots s_{Mt}]$.

Now, we can recursively compute the (squared) distance d(s) by traversing down the tree and effectively evaluating in (3) in a row-by-row fashion. We start at level i=M_t and set $T_{Mt+1}(s^{Mt+1}) = 0$ .The partial (squared) Euclidean distances (PEDs) $T_i(s^{(i)})$ are then given by

$$T_i(s^{(i)}) = T_{i+1}(s^{(i+1)}) + | e_i(s^{(i)}) |^2 \tag{5}$$

With i=M_t, M_t-1….1, where the distance increments of $| e_i(s^{(i)})|^2$ can be obtained as

$$| e_i(s^{(i)}) |^2 = | \hat{y}_i - \Sigma R_{ij} s_j |^2 \tag{6}$$

We can make the influence of S_i more explicit by writing

$$| e_i(s^{(i)}) |^2 = | b_{i+1}(s^{(i+1)}) - R_{ii} s_i|^2 \tag{7}$$

$$b_{i+1}(s^{(i+1)}) = \hat{y}_i - \Sigma R_{ij} s_j \tag{8}$$

where i+1<=j<= M_t. Finally d(s) is the PED of the corresponding leaf: d(s) =T_1(s). Since the distance increments $|e_i(s^{(i)})|^2$ are nonnegative, it follows immediately that whenever the PED of a node violates the (partial) SC given by

$$T_i(s^{(i)}) < r^2 \quad (9)$$

then the PEDs of all of its children will also violate the SC. Consequently, the tree can be pruned above this node. This approach effectively reduces the number of transmit vector symbols (i.e. leaves of the tree) to be checked.

2. Tree Traversal and Radius Reduction

When the tree traversal is finished, the leaf with the lowest $T_1(s)$ corresponds to the ML solution. The traversal can be performed breadth-first or depth-first. In both cases, the number of nodes reached and hence the decoding complexity depends critically on the choice of the radius r. The k-best algorithm [18] [19] approximates a breadth-first search by keeping only up to k nodes with the smallest PEDs at each level. The advantage of the k-best algorithm over a full (depth-first or breadth-first) search is its uniform data path and a throughput that is independent of the channel realization and the SNR. However, the k-best algorithm does not necessarily yield the ML solution.

In a depth-first implementation, the complexity and dependence of the throughput on the initial radius can be reduced by shrinking the radius r whenever a leaf is reached. This procedure does not compromise the optimality of the algorithm, yet it decreases the number of visited nodes compared to a constant radius procedure. As an added advantage of the depth-first approach with radius reduction, the initial radius may be set to infinity, alleviating the problem of initial radius choice. However, in contrast to the k-best algorithm, a depth-first traversal does not yield a deterministic throughput. Hence breadth first algorithm is used for real-time application.

C. *Accountable sets*

The admissible set of children $s^{(i)}$ of a particular parent $s^{(i+1)}$ in the tree is simply defined by the constellation points s_i for which the PED satisfies $T_i(s^{(i)}) < r^2$.In the case of real-valued constellations, one can determine the boundaries of an admissible interval using (5) in conjunction with (4) and the partial SC (8). All admissible children are then contained within these boundaries. Unfortunately, in the practically more relevant case of complex-valued constellations, admissible intervals cannot be specified. A solution for QAM constellations that is frequently found in the literature is to decompose the M_t-dimensional complex signal model into a $2M_t$ –dimensional real-valued problem according to

$$\begin{bmatrix} R\{y\} \\ I\{y\} \end{bmatrix} = \begin{bmatrix} R\{H\} & -I\{H\} \\ I\{H\} & R\{H\} \end{bmatrix} \begin{bmatrix} R\{s\} \\ I\{s\} \end{bmatrix} + \begin{bmatrix} R\{n\} \\ I\{n\} \end{bmatrix} \quad (10)$$

This approach results in a tree that is twice as deep as the original tree (corresponding to the complex-valued formulation) with a smaller number of children per node. The number of leaves remains unchanged. However, we will argue later that performing SD directly on the complex constellation is more efficient in VLSI implementations.

D. *Optimum Ordering*

With radius reduction, it is desirable to find candidate solutions that lie close to the ML solution as early as possible in order to shrink the sphere as fast as possible and hence expedite the tree pruning. A scheme proposed by Schnorr and Euchner [17] and modified for the finite lattice case in [15] traverses the members of the admissible sets in ascending order of their PEDs. In the case of real-valued lattice constellations, given a starting point and an initial direction, this ordering is predefined. The decoder starts with the center of the admissible interval and proceeds to the boundaries in a zigzag fashion. As shown in [15], there is no need to explicitly compute the boundaries; instead, due to the Schnorr–Euchner (SE) ordering, it is sufficient to terminate once the SC is violated. In the case of complex-valued constellations, SE ordering is still possible even without the real-valued decomposition (10). However, depending on the constellation, no obvious predefined order may exist. Hence explicit sorting of the admissible children by their PEDs may be required, incurring a high implementation complexity.

IV. Typical Lattice Decoder For MIMO Detection

A. *Lattice Decoder*

A typical lattice decoder for MIMO detection consists of a pre-processing unit, a pre-decoding unit and a decoding unit, as shown in Fig. 4. The preprocessing unit takes the estimated channel matrix H, and generates its inverse H^{-1}, a triangular matrix L, and a correspondingly optimal ordering p if needed. The task of the pre-decoding unit is simply to generate a zero forcing (ZF) point $z = (H^{-1}x)^T$ as an initial estimate for the decoding unit. The computational complexity of the pre-decoding unit is omitted in the following complexity analysis for all the lattice decoders. The differences among various lattice decoders for MIMO detection depend largely on the design of the decoding unit.

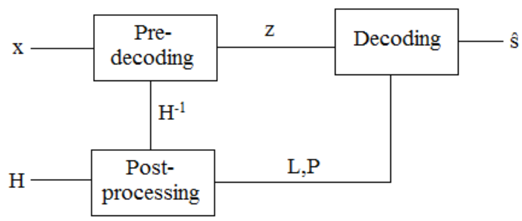

Fig. 4. Typical Lattice Decoder [20]

In a lattice decoder, an n=2 M-dimensional lattice is decomposed into n sublattices. Let k be the dimension of the sublattice that is currently being investigated, and y the orthogonal distance between two points in the adjacent sub lattices. The objective of the decoder is to search for the lowest possible squared distance bestdist between (k=n)-dimensional and (k=1)-dimensional sublattice [12].

In theory, the BER performance of the SE and the SD algorithms should be the same for MIMO detection, since the difference between the SE and the SD lies in the searching order among the sublattices [12]. According to the searching direction instead, the lattice decoders can be divided into two types, the depth-first type with variable throughput and the breadth-first type with fixed throughput.

B. *Breadth first algorithm*

Instead of the metric-first and depth-first mixed searching scheme, the breadth-first searching scheme can also be employed for MIMO detection. The breadth-first algorithm searches for the bestdist in the forward direction only, but the best K candidate newdist are kept at each level of the sublattice. Hence, the breadth-first algorithms can result in a constant decoding throughput. A strict breadth-first algorithm should keep K as large as possible without compromising on the optimality, compared with the exhaustive-search ML algorithm. However, limiting K can reduce the complexity of the breadth-first algorithm [18] [21] [22] that is called K-best algorithm. The bit-error rate (BER) performance of the K-best algorithm is expected to be close to that of the ML algorithm if K is sufficiently large, as in the well-known M-algorithm for sequential decoding.

The principle of the K-best type of algorithm is outlined as below.

1. At the root sublattice, initialize one path with metric zero.
2. Extend each survivor path, retained from the previous sublattice, to M_c contender paths, and update the accumulated metric for each path.
3. Sort the contender paths according to their accumulated metrics, and select the K-best paths.
4. Update the path history for each retained path, and discard the other paths.
5. If the iteration arrives at the end sublattice, stop the algorithm. Otherwise, go to Step 2.

The best path at the last iteration is, thus, the hard decision output of the decoder. The advantage of the K-best algorithm over the sequential algorithm is its fixed throughput, since it is easily implemented in a parallel and a pipelined fashion.

C. Modified Breadth first algorithm

This algorithm provides more efficient way to implement considering set of all points in accountable set. The algorithm (for e.g. is for r=R radius) consists of following steps

1. Taking center of sphere, find distance of all points in accountable sets. The point with largest distance is considered apex point (say A) for tree search.
2. Now taking radius r=R1 (R1<R), draw sphere from center and then consider all points lying within r=R1 (say hl1). Find distance of all this points from A. The point with minimum distance is selected and other points are pruned.
3. Continue the process with r=R2 (R2<R1<R) and find minimum metric point.
4. Continue the process until most likelihood solution is obtained.

V. Hardware Implementation of MIMO Decoders

Fig. 5 shows the uncoded BER performance of the k-Best algorithm for K=5 compared to the ML algorithm. Three observations can be made: First, the figure shows a significant BER performance loss in the high SNR regime. However, in the range of interest (16-20 dB) the loss is small. Furthermore, Simulations of coded BER showed good results with K=5; also, it is stated that K=5 is reasonable. Second, fig. 5 clearly shows a BER performance advantage of the RVD algorithm compared to operating directly on the complex valued constellation points. Third, the simplified norm k-Best algorithm (l^1-norm) leads to almost the same BER performance as the squared l^2-norm k-Best algorithm.

A. K- Best Architecture

The K-Best detector is pipelined such that one layer of the tree is always processed in one pipeline stage (Fig. 6). Each stage consists of a metric computation unit (MCU), a K-Best unit (KBU) that determines the K smallest PEDs, and a Register bank L_k where the K smallest nodes of the previous layer are stored. Together, they form a computation unit. Resource sharing is applied such that the K nodes at the input of the stage are processed one after the other. In each cycle the MCU delivers the PEDs of all children of a parent node in L_k .These PEDs need to be sorted into a list $\overline{L_k}$ where the K smallest PEDs found so far are stored. After K iterations, all children of the nodes in L_k have been computed by the MCU. The KBU has determined the K smallest PEDs and delivers them to the next pipeline stage. In total, $2M_T$ almost identical copies of the computation unit form the $2M_T$ pipeline stages of the detector.

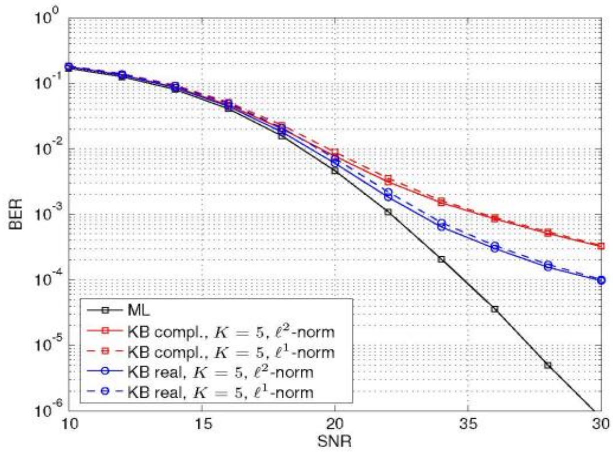

Fig. 5. Uncoded BER performance comparison between ML algorithm and different alternatives of k-Best algorithm [23]

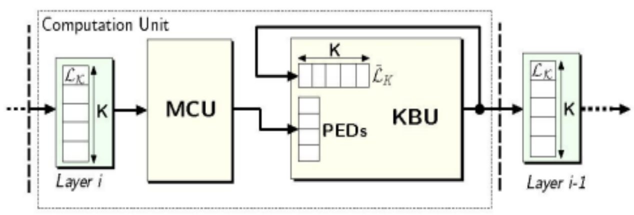

Fig. 6. One of $2M_T$ pipeline stages of the K-best VLSI architecture [23].

In hardware implementation, depth-first is realized in a folding-like architecture because only one node is visited at a time during the tree search process. In this case, an extra memory to record the visited nodes is required, for the trace-back operation. K-best is realized in a multi-stage pipelined way, because no trace-back is needed. To process K data paths at the same time, parallel architecture is applied. Fig.7 illustrates the basic architectures of these two search schemes, and Table 1 summarizes their comparison in terms of circuit metrics and algorithmic performance.

For the sphere decoder operating with a large antenna array, the biggest challenge in the implementation is reducing area of the design. Using the number of (complex) multipliers as a first order area estimate, the number of multipliers needed in the folding and multi-stage architectures are M and M(M+1)/2, respectively , where M is the number of transmit antennas. Expanding a 4x4 system to a 16x16 system, relative area increases from 4 to 16 for the folding architecture and 10 to 136 for the multi-stage architecture. To keep the area within a reasonable value, folding technique is considered. The second design challenge is operating frequency for the folded architecture.

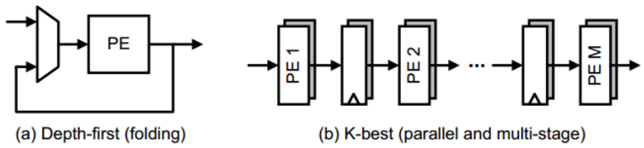

Fig. 7. Basic architecture of (a) depth-first and (b) K-Best algorithm [11].

Table 1. Comparison of depth-first and K-best Algorithm

	Area	**Through put**	**Latency**	**Radius Shrinking/ Tree Pruning**	**Perform ance**
Depth-first	Small	Variable	Long	Yes	ML
K-best	Large	Constant	Short	No	Near-ML

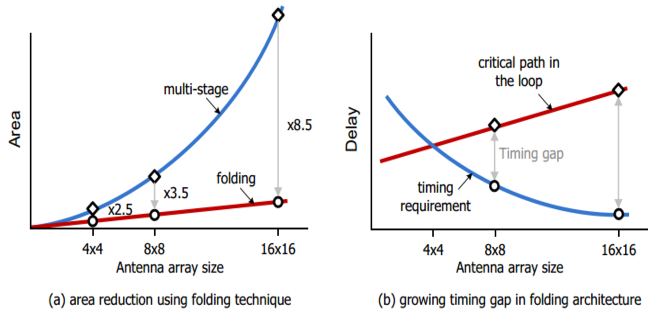

Fig. 8. Design challenge and tradeoff for large antenna size. Impact of antenna array size on (a) area and (b) critical path delay [11].

The K-Best detector is pipelined such that one layer of the tree is always processed in one pipeline stage (Fig. 8). Each stage consists of a metric computation unit (MCU), a K-Best unit (KBU) that determines the K smallest PEDs, and a Register bank L_k where the K smallest nodes of the previous layer are stored. Together, they form a computation unit. Resource sharing is applied such that the K nodes at the input of the stage are processed one after the other. In each cycle the MCU delivers the PEDs of all children of a parent node in L_k .These PEDs need to be sorted into a list $\overline{L_k}$ where the K smallest PEDs found so far are stored. After K iterations, all children of the nodes in L_k have been computed by the MCU. The KBU has determined the K smallest PEDs and delivers them to the next pipeline stage. In total, $2M_T$ almost identical copies of the computation unit form the $2M_T$ pipeline stages of the detector.

Table 2. Implementation of k- Best Algorithm for 4x4 systems with 16- QAM Modulation (without pre-processing)

Reference	**Proposed architectures [23]**				**[18]**	**[17]**	**[24]**
Technology [µm]	0.25				0.35	0.35	0.25
Norm	l^2		l^1		l^2	l^2	l^2
K	5	10	5	10	5	10	10
Core Area Sc1	90	132	68	110	91	52	215[2]
Core Area Sc2	115	157	93	135			
Throughput [Mb/s]	376	80	424	83	53	10	40
Loss compared to ML [dB]	0.4	0.1	0.75	0.4	0.4	0.1	0.1
Latency [cycles]	49	89	49	89	240	1280	320
Max.clock[MHz]	117	50	132	52	100	100	100

VI. CONCLUSION

This paper includes different techniques of MIMO Detection and from survey we can conclude that K-Best Algorithm with sort free method gives best result keeping in mind hardware implementation and BER is close to that of Maximum Likelihood (ML) solution. We can further decrease area and power consumption by using selective multipliers and better combination of adders and shifters. We can also use better tree search algorithms keeping in mind sphere used for decreasing computation complexity.

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