Improved Detection Technique for the Uncoded MIMO Systems Using an Efficient K-best Algorithm.

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Abstract—This paper presents a new algorithm for spatially multiplexed MIMO detection that exploits the resources available in the search procedure to enhance the error performance of the K-best approach of search. The proposed algorithm exploits the heuristics of the nodes and it is referred as the Heuristic K-best algorithm (HK-best). Unlike the conventional K-best algorithm, the HK-best algorithm sort the visited nodes in each layer based on the path metric and the heuristic. Simulation results shows a gain of 2dB compared to the conventional K-best algorithm for Symbol Error Rate (SER) equal to 10-6 and a 17% computational complexity reduction. In addition, the HK-best conserves the constant computational complexity in contrast to the other variants of the K-best algorithm.

Keyword-MIMO system, low complexity detection, Tree search, K-best Algorithm, heuristic

I. INTRODUCTION

Multiple input Multiple output (MIMO) system [1,2] is one of the major technologies adopted by current wireless communication standards such as IEEE 802.11n, 802.16e and Third Generation Partnership Project Long-Term Evolution (3GPP LTE). With arrays antennas on both the transmitter and the receiver sides, the MIMO technology increases the channel information capacity which can be used as a means of increasing the data rate or the reliability of the system [2]. However, these improvements can be achieved without any trade-off with either bandwidth or signal power but with an additional signal processing and computations in the receiver which limits the Qos of the application in real time system [3].

To attain the possible enhancement in data rate, the architecture of spatial multiplexing MIMO transmission (Bell Labs Layered Space-Time Architecture BLAST) is employed by transmitting an independent data streams over different antennas. On the receiver side, different algorithms are proposed in the literature to optimally recover the transmitted signals.

Maximum likelihood ML [4,5] detection scheme has shown to be the optimal detection technique but with an NP hard complexity because of the exhaustive search over all the possible combinations. Thus the ML search is constraint with such inflexibility up to certain extend for practical implementations.

However; both of the linear detection algorithms family, such as Zero Forcing (ZF) and minimum mean square error (MMSE) [2], and the successive interference cancellation (SIC) detectors family [6] reduce greatly the computational complexity but suffer from significant error performance.

By representing the MIMO signal detection as a tree search [7], wide range of optimal and suboptimal techniques are proposed with different tradeoffs performance complexity. In such kind of representation, the proposed algorithms are classified, based on their tree exploration, on three different categories: depth first, breadth first and best first category. For all the algorithms, the problem is reformulated to find the short path from the top to the bottom of the tree, where each node is weighted by its distance from the top.

The sphere decoding algorithm (SDA) [8,9] and its variants [10-12] have been proposed for the depth first tree exploration. By limiting the search within a hyper sphere, this technique results in an optimal error performance and reduced computational complexity. Nevertheless, the SDA algorithm is not efficient for hardware implementation because of the non constant and non predictable detection complexity, hence a non constant decoder throughput.

To overcome the drawbacks of the SDA, the suboptimal k-best algorithm was proposed in [13,14] and it is also known as QRD-M algorithm. The K-best algorithm performs the breadth-first tree exploration and retains only a constant number of the promising nodes at each layer, based on their weights, and referred as survivor nodes. As a result, the K-best algorithm has a constant and a predictable detection complexity and guarantees a manageable hardware realization i.e. it facilitates the parallel and pipelined processing [15]. However, the suboptimality is caused by the hard condition of retaining k nodes and discarding the rest although the fact that the discarded nodes may contain the correct one to lead to the ML solution. Alternatively, several variants have been proposed in the literature to improve the error performance of the K-best algorithm by changing the number of survivor nodes as in [16-18]. However those improvements are achieved at the expense of the constant complexity, where the proposed algorithms are characterized by a non predictable complexity.

Since the performance loss of K best algorithm is directly related to selecting the most promising nodes, we propose a new K-best algorithm that improves the selection of the k best nodes using a new weight. Motivated by the work in [19], the new weight includes the conventional weight of the node and an estimation of the remained distance to the bottom, which called the heuristic. However, adding an admissible heuristic to the node weight proves to better evaluate the nodes [20]. As a result, the new algorithm, termed Heuristic K-best algorithm HK-best, improves the error performance of the conventional K-best algorithm and inherits its constant complexity and the manageable hardware realization.

The rest of the paper is organized as follows. Section II introduces the signal model. Section III gives an overview of the QRD-M algorithm. The proposed algorithm and simulation results are described in Sections IV and V, respectively. Section VI gives the conclusions.

II. SYSTEM MODEL AND MIMO DETECTION BASED ON TREE SEARCH

A. MIMO system model

We consider a spatially multiplexed MIMO system with N_t transmitter antennas and N_r receiver antennas operating within Rayleigh fading channel. The received signal vector can be expressed as:

$$y_c = H_c \times s_c + v_c \tag{1}$$

Where y_c is (N_r × 1)-dimensional vector represents the received signal, s_c is (N_t × 1)-dimensional vector represents the transmitted signal its elements drawn from a set of complex elements such as M-QAM constellation, where M is the modulation order, H_c is ($N_r \times N_t$) matrix represents the channel with independent and identically distributed (i.i.d.) Gaussian entries with zero mean and unitary variance and v_c is (Nr ×1)-dimensional vector of noise with an i.i.d complex entries with zero mean and variance σ_n^2 . For simplicity, the number of transmit and receive antennas are assumed to be symmetrical, i.e. $N_t = N_r$, the channel state information is assumed to be known to the receiver.

The equivalent real presentation of the system (1) is defined by**:**

$$\begin{bmatrix} \Re(y_c) \\ \Im(y_c) \end{bmatrix} = \begin{bmatrix} \Re(H_c) & -\Im(H_c) \\ \Im(H_c) & \Re(H_c) \end{bmatrix} \times \begin{bmatrix} \Re(s_c) \\ \Im(s_c) \end{bmatrix} + \begin{bmatrix} \Re(v_c) \\ \Im(v_c) \end{bmatrix} \tag{2}$$

Where $\Re(*)$ and $\Im(*)$ denote the real and the imaginary parts of its elements. The equivalent real representation of the system model in (2) is presented as follows:

$$y = H \times s + v \tag{3}$$

Where: $y \in R^n$, $s \in R^m$, $H \in R^{n \times m}$, $v \in R^n$ with $n = 2 \times N_r$, $m = 2 \times N_t$

B. MIMO detection based on tree search:

In the MIMO detection, the maximum likelihood ML detection achieves the optimal bit error rate performance by solving the minimization problem:

$$\hat{s} = \arg\min_{s \in \Omega^m} \| y - Hs \|^2 \tag{4}$$

Where: Ω is the constellation in the real valued system model, for example, in 16-QAM $\Omega = \{+3, +1, -1, -3\}$.

The ML detection makes an exhaustive search over all the candidates of "**s**". Hence, the complexity of the detection increases exponentially with the number of antennas and the modulation order M and returns it impractical for real time implementations.

By applying the **QR** decomposition on the channel matrix, (4) is reformulated by the equivalent expression (5).

$$\hat{s} = \arg\min_{s \in \Omega^m} \| y - Hs \|^2 \quad \text{with} \quad P(s) = \|y' - Rs\|^2 \quad \text{and} \quad y' = Q^H R \tag{5}$$

Where **Q** is a unitary matrix and **R** is an upper triangular matrix.

Because of the upper triangular matrix **R**, P(s) in (5) can be calculated in a recursive process as shown in (6). Thus, the MIMO detection is reformulated.

$$P(s_k^l) = P(s_{k-1}^l) + B(s_k^l) \quad \text{with} \quad B(s_k^l) = (y'_k - \sum_{j=k}^{m} r_{k,j} s_j)^2 \tag{6}$$

Where: y'_k and s_j are the real elements of $\mathbf{y}$ and $\mathbf{s}$ respectively and $r_{k,j}$ is the (k, j)-entry of $\mathbf{R}$.

$s_k^m = (s_k, \ldots, s_m)^T$ is a partial symbol vector and its entries, possible transmitted symbols, are searched layer by layer in a tree of m layers as presented in Figure1 . Each symbol s_k is presented as a node on layer l , with $l = m - k + 1$ and it takes a possible value from Ω . Every node s_k is weighted with the path metric $P(s_k^m)$ (the partial Euclidian distance PED up to the l th layer) and the branch metric $B(s_k^m)$. The optimal solution of (4) is the vector s_1^l (in the last layer: $l = m$) which has the smallest path metric $P(s_1^m)$.

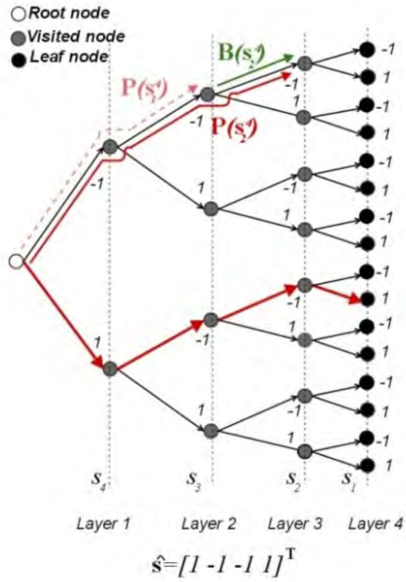
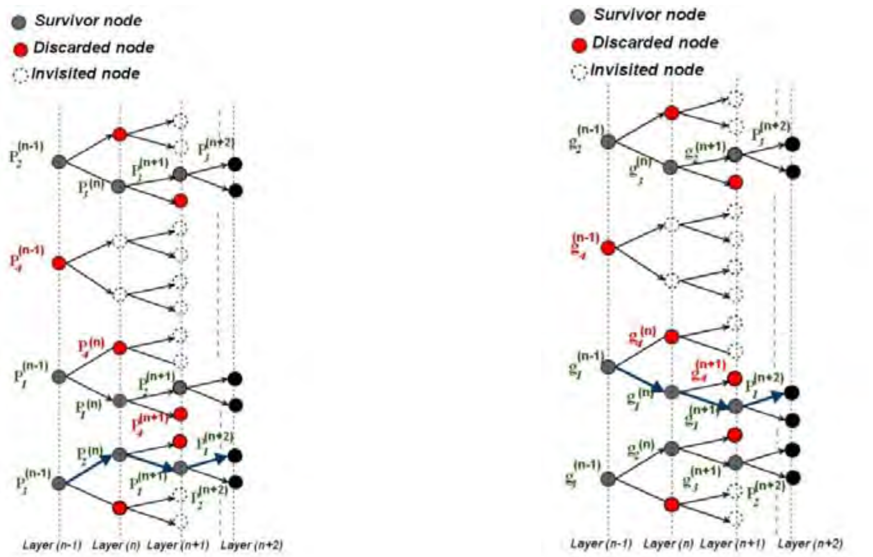


Fig. 1. Tree search for 2 x 2 MIMO detection and 16-QAM



(a) (b)

Fig. 2. Tree search procedure (a) K-best algorithm and (b) HK-best algorithm

III. K-BEST ALGORITHM

With the aim of reducing the computational complexity of the ML detection and fixing the throughput of the detection, The K-best algorithm is proposed for the breadth-first detection category. It traverses the detection tree layer by layer in the forward direction only. In contrast to visiting all the nodes for each layer, the k-best algorithm selects only a finite set of the best nodes and eliminates the rest. More specifically, the visited nodes for each layer are sorted in an increasing order of their PEDs and the K nodes those have the smallest PED are selected and referred as survivor nodes. For the next layer, only the corresponding child nodes of the K survivor nodes are visited. Fig2 a. shows the search procedure for the K-best algorithm.

IV. PROPOSED HK-BEST ALGORITHM

It is clear that restricting the number of survivor nodes to K and discarding the rest is the cause of performance lose where the discarded nodes may include nodes that contribute in the search. In this section, we propose a new algorithm that performs the selection process. In contrast of sorting the nodes for their PEDs, the proposed algorithm includes an estimated *admissible* heuristic (not over-estimating the real distance) of each node to the sorting process and selects the K best nodes. It is proved in [20] that if the heuristic is *admissible*, the shortest path is guaranteed. The more accurate is the estimate, the better performance of the algorithm can be achieved

The idea of including a heuristic in the MIMO tree detection have been applied in the work [19] on the Dijkstra's algorithm [21] (best first category). The admissible heuristic is based on look-ahead (LA) technique developed without involving an exhaustive search.

TABLE I
THE HK-BEST ALGORITHM

Algorithm 1 : The HK-best algorithm

Input : y', R, s, Ω

Output: $\hat{s}$

1 **Take the root** s_0 **on layer** $l = 0$ **as the start node, initial the list of survivor nodes v=0**

2 **for mother ← v(1) to v(length(v))**

3 **Expand the mother node to its child nodes** $\forall s \in \Omega$ **and calculate the PED eq. (6) and the Heuristic eq. (11)**

$$P(s_k^l) = P(s_{k-1}^l) + B(s_k^l)$$

$$g(s_k^m) = h(s_k^m) + P(s_k^m)$$

4 **end**

5 **Sort all the nodes of v in an ascending order of g**

6 **If length (v) is less than K then**

7 **Keep all the nodes of v**

8 **else**

9 **Keep the K smallest nodes of v**

10 **end**

11 **If** $l \neq m$ **then**

12 **Return to step2**

13 **end**

14 **return the first ement in v as the estimated** $\hat{s}$

$$\hat{s} = v(1)$$

Consider a node $s_k^m = (s_k, \ldots, s_m)^T$ in layer $l = m - k + 1$, the known path metric from the top to this node is expressed (7):

$$\mathrm{P}(s_k^m) = \sum_{j=k}^{m} \mathrm{B}(s_j^l) \quad (7)$$

and the unknown is the remind path metric from the node to the bottom, it can be expressed by(8):

$$\mathrm{P}(s_1^{k-1}) = \sum_{j=1}^{k-2} \mathrm{B}(s_j^{k-1}) \quad (8)$$

The condition of admissibility implies that any estimated metric less or equal to $\mathrm{P}(s_1^{k-1})$ can be considered as an admissible heuristic. This condition is satisfied by the minimum branch metric of the next layer.

$$\min_{s_{k-1}\in\Omega} \mathrm{B}(s_{k-1}^m) = \min_{s_{k-1}\in\Omega} (y'_{k-1} - \sum_{j=k-1}^{m} r_{k-1,j} s_j)^2 \quad (9)$$

By taking in consideration that all the elements: $y'_k,...,y'_m$, $s_k,...,s_m$ and $r_{k-1,k},...,r_{k-1,m}$ in the second part of (9) are common for all the calculations, the minimization in (9) is achieved by finding the value of s_{k-1} that solves the minimization in (10):

$$\min_{s_{k-1}\in\Omega} (y'_{k-1} - r_{k-1,k-1} s_{k-1})^2 \quad (10)$$

Which is given by only the partial zero forcing and slicing $\left[y'_{k-1} / r_{k-1,k-1} \right]_\Omega$

As a result, the heuristic adopted in this work is expressed by (11)

$$\mathrm{h}(s_k^m) = (y'_{k-1} - \sum_{j=k-1}^{m} r_{k-1,j} s_j)^2 \quad \text{with} \quad s_{k-1} = \left[y'_{k-1} / r_{k-1,k-1} \right]_\Omega \quad (11)$$

Hence, the weight of each node in the HK-best algorithm is given by (12)

$$\mathrm{g}(s_k^m) = \mathrm{h}(s_k^m) + \mathrm{P}(s_k^m) \quad (12)$$

Figure2, b illustrates the search procedure of the proposed HK-best algorithm, and Table 1 presents the HK-best algorithm.

V. COMPUTATIONAL COMPLEXITIES

In order to compare the proposed HK-best and the conventional K-best, this section analyses the computational complexity for each algorithm. The system model presented in Section II represents a real equivalent system; therefore the computation complexity is defined as the number of real operations while obtaining a solution. Each real operation is equal to one flop which is considered as representative unit of required computational complexity. In this analysis, the computations of QR decomposition are not considered, since it is performed for both the K-best and HK-best. Only the computational complexity of the tree search expansion is considered.

We define:

$\mathrm{I}_l^{(*)}$ is the number of visited nodes in layer l for algorithm (*)

$|\Omega|$ is the number of elements of the real constellation set.

$\mathrm{I}_{tot}^{(*)}$ is the total the total number of visited nodes during the MIMO detection using the algorithm (*) where:

$$\mathrm{I}_{tot}^{(*)} = \sum_{l=1}^{m} \mathrm{I}_l^{(*)} \quad (13)$$

$\mathrm{C}(s_k^m)$ is the computational cost of visiting one node in layer l where $k = 1,2,...,m$.

C^* is the total computational cost of the algorithm (*).

A. Complexity of K-best:

In the K-best algorithm, only the path metric $\mathrm{P}(s_k^m)$ is computed and its computational complexity $\mathrm{C}\left[\mathrm{P}(s_k^m)\right]$ is the main contributor in the total complexity.

$$\mathrm{C}(s_k^m) = \mathrm{C}\left[\mathrm{P}(s_k^m)\right] \quad (14)$$

The branch metric $\mathrm{B}(s_k^m)$ of node in layer l is represented by Eq (6).; hence, the cost of computing $\mathrm{B}(s_k^m)$, noted by $\mathrm{C}\left[\mathrm{B}(s_k^m)\right]$, is expressed by (15):

$$\mathrm{C}\left[\mathrm{B}(s_k^m)\right] = \begin{cases} m-k+2 = l+1 & \text{multiplication} \\ m-k+1 = l & \text{addition} \end{cases} \quad (15)$$
$$= 2l+1 \quad \text{flops}$$

By summing up $\mathrm{B}(s_k^m)$ and $\mathrm{P}(s_{k-1}^m)$, the cost $\mathrm{C}\left[\mathrm{P}(s_k^m)\right]$ is represented by Eq. (16) and the cost of each node in presented by Eq.(17)

$$\mathrm{C}\left[\mathrm{P}(s_k^m)\right] = 2(l+1) \quad \text{flops} \quad (16)$$

$$\mathrm{C}(s_k^m) = 2(l+1) \quad \text{flops} \quad (17)$$

Therefore, the total number of computational cost in K-best algorithm is expressed by Eq. (18):

$$\mathrm{C}^{K-best} = \sum_{l=1}^{m} 2\, \mathrm{I}_l^{(K-best)}(l+1) \quad \text{flops} \quad (18)$$

B. Complexity of HK-best:

Similar to the K-best, the HK-best visits the same number of nodes and computes for each node its path metric $\mathrm{C}\left[\mathrm{P}(s_k^m)\right]$ and summing up its heuristic $\mathrm{C}\left[\mathrm{h}(s_k^m)\right]$.

$$\mathrm{C}(s_k^m) = \mathrm{C}\left[\mathrm{P}(s_k^m)\right] + \mathrm{C}\left[\mathrm{h}(s_k^m)\right] \quad (19)$$

As described above, the heuristic is equal to the branch metric of the next layer after computing the partial zero forcing and slicing; hence, the additional computational complexity is expressed by Eq. (20) and the cost of each node is expressed by eq.(21):

$$\mathrm{C}\left[\mathrm{h}(s_k^m)\right] = (2l+3)+2 \quad \text{flops} \quad (20)$$

$$\mathrm{C}(s_k^m) = 2(l+1) + 2l+5$$
$$= 4l+7 \quad (21)$$

Therefore, the total number of computational cost in HK-best algorithm is expressed by Eq. (22):

$$C^{HK-best} = \sum_{l=1}^{m} \mathrm{I}_l^{(HK-best)}(4l+7) \quad \text{flops} \quad (22)$$

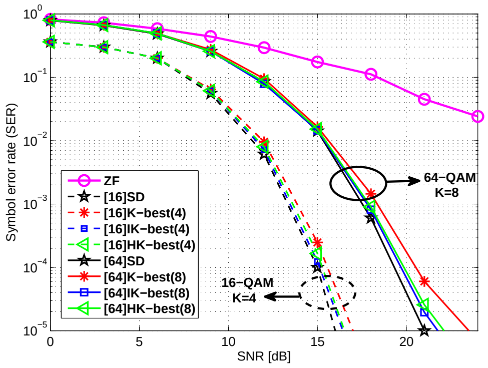
Since the heuristic of the current survivor node is an estimated branch metric of its related nodes in the next layer (child nodes), we can employ this calculated metric, expressed in Eq.(11), to calculate the branch metric of the nodes in the next layer and avoid a large amount of additional complexity. Rather than the value of s_{k-1} in Eq.(11), the rest of elements and their calculations are the same for the branch metric $\mathrm{B}(s_{k-1}^m)$, hence, the result of these calculations is restored from eq.(11), which conserves a large amount of additional computations, and only the calculation of the elements related to s_{k-1} cost an additional computation, because s_{k-1} takes a new values from Ω.

VI. Simulation and Results

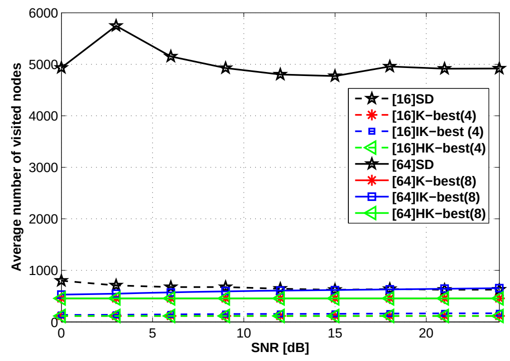
The aim of this section is to compare the performance and the complexity of the proposed HK-best algorithm over the conventional K-best algorithm in MIMO signal detection and its variant IK-best proposed in [18]. Computer simulations were conducted, assuming perfect channel estimate. The entries of the channel matrix are independently and identically distributed (i.i.d.) Gaussian with zero mean and unitary variance. The SER is employed to realize and compare the error performance of the system with different signal detection schemes, while the average number of visited nodes and flops are calculated to evaluate the computational complexity.

In this experiment, an uncoded 4 × 4 MIMO systems with modulation order of 16−QAM and 64−QAM are considered. Five detection algorithms where used and compared on these systems: ZF, SD, K-best, IK-best and HK-best. The ML curve is from the conventional SD. In order to compare fairly the K-best and its variant over the proposed HK-best, the algorithms are not combined with the SD and the channel detection ordering is not included.

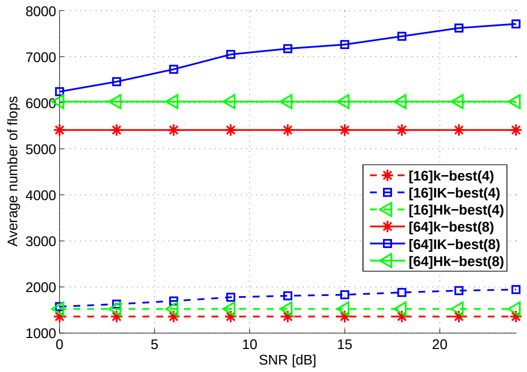
For both MIMO systems with16-QAM and 64-QAM, it is shown in Fig 3.a that the proposed HK-best algorithm improves the error performance of the conventional K-best for SNR ranging from 9dB up to 25dB and the SER curve of the HK-best algorithm is nearly superposed on the curve of the IK-best. Compared to the conventional K-best, the SNR gain is about 1 dB and 2 dB for 16-QAM and 64-QAM respectively, For an



(a)



(b)



(c)

Fig. 3. 4 x 4 MIMO system with 16-QAM and 64- QAM modulation. (a) The error performance comparison. (b) The average number of visited nodes. (c) The number of flops required to output the detected signal.

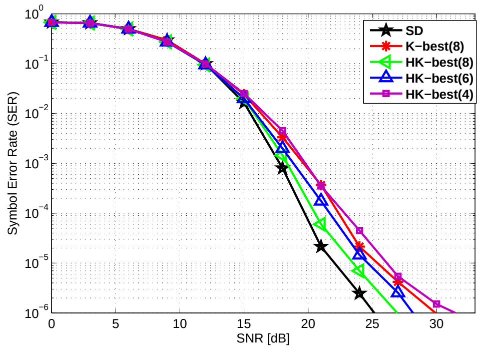
SER = 10-5. for the high SNR regime we can observe an increasing in the performance gain. As the SNR increases, the K best nodes selected in the top layers are more likely to end to the ML solution, in addition to that, adding the heuristics to the cost performs the selecting process, so the gain in the error performance occurs grater for the high SNR regime.

Figure 3.b illustrates the number of visited nodes in function of the SNR. As shown in the figure, the proposed HK-best algorithm visits a constant number of nodes in detection process which equals the K-best algorithm nodes. In contrast to that, the IK-best algorithm visits a varied number of nodes according to the noise level. For all SNR regime, the HK-best visits about 450 node and 110 nodes for 64-QAM and 16-QAM respectively. Contrary to the SD algorithm, which visits a varied large number of nodes in function of the SNR regime, it ranges between 5000 to 5800 nodes for 64-QAM and 600 to 800 for 16-QAM, while the number of nodes visited by the IK-best algorithm ranges between 135 and 165 node for 16-QAM and ranges between 530 and 660 node for 64-QAM.

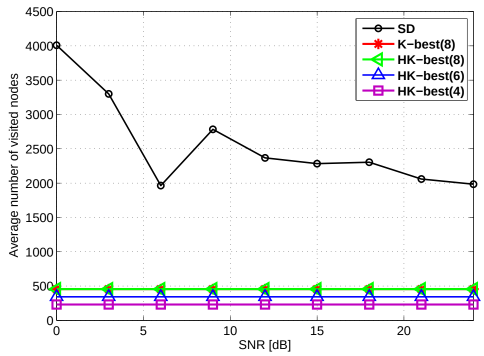
However, the proposed HK-best inherits the main advantage of the constant complexity, provided by the K-best algorithm, because of maintaining the condition of fixing the number of survivor nodes regardless of the noise level. In contrast, the IK-best lose this important advantage because of varying the number of survivor nodes according to the noise level[.].

Figure 3.c shown the number of flops required in MIMO detection using K-best, IK-best and HK-best algorithms. The HK-best involves an additional computations and it costs about 1520 and 6010 flops instead of 1360 and 5400 flops for 16-QAM and 64-QAM respectively. However, the additional computational complexity of HK-best is much lower than that of the IK-best algorithm especially for high SNR regime. As the SNR increases, the gain in term of computational cost increases compared to the IK-best and it ranges between 4% and 22%.

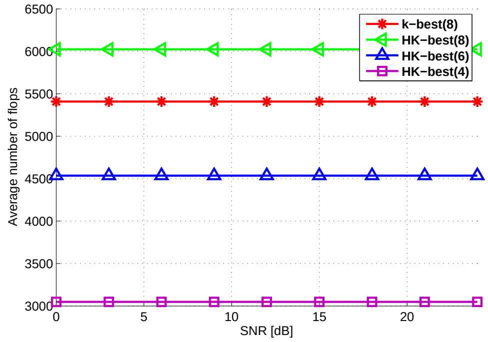
Figure 4 illustrates the impacts of the number of survivor nodes (value of K) on the error performance and the computational complexity. As the Fig 4.a shows, both the HK-best (8) and HK-best(6) have a better error performance compared to the conventional K-best. For a BER= 10^{-6}, the figure shows that the HK-best (8) algorithm has an SNR gain of 3 dB compared to the K-best (8), while the HK-best (6) has a gain of 2 dB.



(a)



(b)



(c)

Fig. 4. 4 x 4 MIMO system with 64-QAM modulation order and k=8, 6, 4. (a) The error performance comparison. (b) The average number of visited nodes. (c) The number of flops required to output the detected signal.

However, selecting a smaller number of survivor nodes degrades the error performance as for the HK- best(4) compared to the HK-best(8). In this case, the new proposed weight is not sufficient to express the best nodes and it conducts to a poorer error performance.

Fig 4.b shows the impact of the constant K on the total number of visited nodes for the detection process. It is clear that the number of visited nodes for the HK-best is proportional to the number of the constant K. Regardless the value of K, both the conventional K-best and the proposed HK-best algorithms maintain the constant complexity detection.

In Fig 4.c, the impact of K on the computational complexity is illustrated. However, the HK-best (8) has a grater computational complexity compared to K-best(8), while both HK-best(6) and HK-best(4) have a lower computational complexity. Both HK-best(6) and HK-best(4) reduce the computational complexity of the K-best(8) by about 17% and 44% respectively.

From Fig 4.a and Fig 4.c, it can be seen that the HK-best (6) outperform the K-best(8) in term of error performance and it reduces its computational complexity by about 17%.

VII. CONCLUSION

In this paper, an effective algorithm for MIMO signal detection with near optimal performance has been proposed. The results demonstrate the potential superiority of the proposed HK-best over the conventional K-best and its variant IK-best. By considering K=6 in the HK-best, the HK-best improves the error performance of signal detection and reduces the computational complexity by about 17% compared to the conventional K-best, in addition it conserves the constant and the predictable detection complexity contrary to the IK-best algorithm. This favors the application of HK-best algorithm for practical implantation and hardwar realization.

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