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應用於多天線偵測之叢集演算法

The Study of Cluster Based MIMO Detection

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摘要

為了能夠有效的利用頻寬，高維度的 QAM modulation 以及多輸入多輸出 (MIMO) 的傳輸系統，已經被很多無線通信系統所廣泛地使用。目前多輸入多輸出偵測器已有各種的方法被提出，並且可分成三類演算法：次於效能最佳化的演算法、接近效能最佳化的演算法、演能最佳化的演算法。

在這篇論文我們提出了多層級叢集為基礎的多輸入多輸出偵測演算法。此演算法透過多層級的 N-QAM 星狀圖結構將傳送的信號分割成叢集，並且藉由多階層的樹狀結構來搜尋叢集，偵測出正確的傳送信號。另一方面，我們在多層級叢集為基礎的演算法中，採用了分支限界的技術還有相位偵測技術來降低演算法複雜度。

在 IEEE 802.11n 的系統平台而且符合 TGN 所規範的通道模型中模擬。模擬結果指出此演算法與 K-Best 球狀解碼器相比，可以較低的複雜度完成相同的系統效能。因此，此演算法為多輸入多輸出系統提供了具有低複雜度、接近效能最佳化的偵測演算法。

Abstract

Recently, multiple-input multiple-output (MIMO) architecture has been applied widely in many wireless communication systems because of its high spectrum efficiency. Various approaches are explored for the MIMO detection, which can be classified to three categories: sub-optimal, near-optimal and optimal solution.

We propose the multilevel cluster-based MIMO detection algorithm by partitioning the transmitted MIMO signal vectors into clusters with the multilevel N-QAM structures in each dimension. Our method detects correct transmitted signal vector by searching the corresponding clusters in hierarchical tree structure. Moreover, both branch and bound and phase detection techniques are addressed to archive low complexity design.

Through simulation in IEEE 802.11n platform with TGn channel E, it indicates the complexity of proposed algorithm is less than the K-best SD with the same performance. Hence, the proposed algorithm provides a near-optimal solution with low computation complexity design for wireless MIMO system.

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Chapter 1

Introduction

Recently, multiple-input multiple-output (MIMO) architecture has been applied widely in many wireless communication systems because of its high spectrum efficiency. To exploit the spectrum efficiency, large number of antennas and/or high order QAM constellations are often employed, which leads a challenge to design the MIMO detection with acceptable complexity and sub-optimal performance.

Various approaches are explored for the detection of MIMO signals [1]. For linear detection approaches, Zero-Forcing (ZF) or Minimum Mean Square Error (MMSE) uses the inverse of estimated channel response to extract the desired signals. Both of these two approaches are simple to implementation, but with the enhancing channel noise which induce large performance degradation. Another category is the nonlinear approaches such as V-BLAST and the maximum likelihood detection (MLD). The V-BLAST algorithm using ordered successive interference cancellation with QR decomposition [2]. The MLD algorithm gains the optimal performance with the intractable computation complexity [3]. The sphere decoder (SD) methods [4] attempted to reduce the search set by searching the candidates that lie within the radius, which still provides the ML performance. However, the radius of SD varies with the channel realization which makes its complexity is higher in the low SNR region. Some methods [5]-[7] reduce the search set by employing the multilevel structure of the N-QAM constellations. The multilevel structure decomposes N-QAM demodulation naturally into a sequence of sub-demodulations with a hierarchical order, which has been widely investigated for complexity reduction purpose [8].

In this paper, we develop a novel algorithm that detects the received MIMO symbol vectors by partitioning the multi-dimensional symbols into clusters according to the multilevel N-QAM structures in each dimension. In [5], this work identified the M most significant QAM symbol combinations by SGA algorithm and exploits the multilevel structure of QAM constellations to reduce complexity with depth-first searching and breadth-first searching. In [6] and [7], both of these two works detected the likelihood MIMO symbols in the multi-dimensional MIMO symbol set which perform hierarchical QPSK searching within full constellation of symbol points. Nevertheless, [6] did not show its feasibility by simulation results and [7] has an error floor for low bit error rate (BER).

The remainder of this paper is organized as follows. The system assumptions with problem statement are addressed in Section II. The proposed multilevel cluster-based algorithms are described on example in Section III. The complexity reduction strategies are described in Section IV. Performance and complexity are evaluated and compared with different approaches in Section V. Finally, Section VI gives conclusions.

Chapter 2

System Assumptions

A. System Description

Consider a $N_T \times N_R$ spatial multiplexing MIMO system, where N_T and N_R are the number of transmitted and received antennas. The data is encoded by scrambler, convolutional code, puncture, interleaver, *N*-QAM modulation and transmitted over the N_T antennas simultaneously. Assuming perfect timing and frequency synchronization, the received baseband signal for $N_T \times N_R$ MIMO system is modeled as following:

$$\boldsymbol{y} = H\boldsymbol{x} + \boldsymbol{n} \tag{1}$$

where $\boldsymbol{x} = \left[x_1, x_2, ..., x_{N_T} \right]^T$ ($[*]^T$ means transpose), x_i is the transmitted signal modulated with *N*-QAM constellation in the *i*-th transmitted antenna in the transmitted signal space; $\boldsymbol{y} = \left[y_1, y_2, ..., y_{N_R} \right]^T$ denote the received symbol vector in the received signal space, and $\boldsymbol{n} = \left[n_1, n_2, ..., n_{N_R} \right]^T$ indicates an independent identical distributed (i.i.d.) complex zero-mean Gaussian noise vector with variance σ^2 per dimension. Moreover, the frequency selective fading [9] is represented by the $N_R \times N_T$ channel matrix *H*, whose elements h_{ij} represent the complex transfer function from the *j*-th transmit antenna to the *i*-th receive antenna. We assume that the receiver knows the channel matrix perfectly, and that $N_R = N_T$ in this paper.

B. Problem Statement

To employ large number of antennas and/or high order QAM constellations, the MLD requires unacceptable computation to exhausted search the most likelihood symbol combination. To overcome the complexity problem, finding the likelihood candidates according to the multilevel structure of the N-QAM constellations can significantly reduce the search space. The partition rule of multilevel N-QAM structure is described as an example of 64-QAM constellation in Fig. 1(a) The 64 constellation points are firstly partitioned into four distinct sets according to the four quadrants of I-Q plane. Each quadrant comprises a 16-QAM constellation and is coupled to a square point which is a mean value of the sixteen points. The quadrants can be further partitioned into four sub-sets (4-QAM) recursively. The four constellation points in each of 4-QAM constellations are coupled to a star point which is a mean value of the four points.

More accurately, the definitions for the mean symbols of multilevel structure in *N*-QAM constellation are as follows. The *N*-QAM constellation can be recursive partitioned to L levels where $L = \log_4 N$. The $P^{\ell,i}$ is a subset of constellation points which are in the partition *i* at level ℓ $(\ell = 1, 2, \ldots, L)$. The set of mean symbols at level ℓ can be defined as $S^{\ell} \triangleq \left\{ s_1^{\ell}, s_2^{\ell}, \cdots, s_{N_\ell}^{\ell} \right\}$, where s_i^{ℓ} is the mean symbol of $P^{\ell,i}$ and $N_\ell = 4^{1-\ell} \times N$. For ℓ=1, s_i^1 is the constellation point in N-QAM constellation. The relation between s_i^{ℓ} and its coupled constellation points is expressed as

$$s_i^{\ell} = \frac{\left(\sum_{s_j^1 \in P^{\ell,i}} s_j^1 \right)}{\left(N / 4^{(L-\ell+1)} \right)} \tag{2}$$

For MIMO multi-dimensional symbols, the transmitted symbol vector is $\boldsymbol{x}^1 = \left[s_1^1, s_2^1, \ldots, s_{N_T}^1 \right]^T$ for transmitted antennas $1, 2, \cdots, N_T$. The ℓ-th level mean symbol vectors can be defined as $\boldsymbol{x}^{\ell} \triangleq \left[s_1^{\ell}, s_2^{\ell}, \cdots, s_{N_T}^{\ell} \right]^T$ and obtain with multilevel

N-QAM structure of each dimension in transmitted symbol vector. The set of all possible mean symbol vectors at level ℓ is $X^{\ell} \triangleq \left\{\boldsymbol{x}^{\ell,\, i}\right\}_{i=1,2,\cdots,N_{\ell}^{N_T}}$.

The aim of the multilevel MIMO detection is to find the nearest *N*-QAM symbol combination ($\boldsymbol{x}^{1,\, i}$) by hierarchical search strategy. [5] found the M most possible QAM symbol combinations by SGA algorithm with depth-first searching or breadth-first searching for multilevel 64 QAM structure. The SGA algorithm translate MIMO symbols uses the zero forcing output as a reference estimation to find the likelihood approximation vectors in transmitted signal space, which leads the risks of performance degradation caused by zero forcing. [7] tries to detect the likelihood transmitted signals in the received signal space which does not need the help of inversion of channel matrix. However, a serious systematic error which causes error floor at low BER is mentioned. Such systematic error is generated due to the cross-talk elements in channel matrix H, which makes the nearest mean vector with the minimum Euclidian distance in the transmitted signal space doesn't always imply that it is still the nearest one in the received signal space. The following equation shows such mismatch of signal detection between transmitted signal space and received signal space.

$$\left\|\left(H\boldsymbol{x} - H\boldsymbol{x}^{\ell}\right)\right\|^2 = \left\|H\left(\boldsymbol{x} - \boldsymbol{x}^{\ell}\right)\right\|^2 = \left(\boldsymbol{x} - \boldsymbol{x}^{\ell}\right)^H H^H H \left(\boldsymbol{x} - \boldsymbol{x}^{\ell}\right) \qquad (3)$$

For MIMO channel, $H^H H$ only ensures its diagonal elements are positive real value, which leads $\left\|\left(H\boldsymbol{x} - H\boldsymbol{x}^{\ell}\right)\right\|^2$ is not necessarily proportional to $\left\|\left(\boldsymbol{x} - \boldsymbol{x}^{\ell}\right)\right\|^2$. Thus, our problems associated with multilevel cluster-based MIMO detection are to overcome the systematic error in the received signal space and to design of near ML performance algorithm with low complexity cost.

Chapter 3

Multilevel Cluster-Based MIMO Detection

A. Principles of Reducing Search Space

Instead of exhausted searching all possible transmitted vectors in the MLD, this work proposes a hierarchical search according to the multilevel structure of *N*-QAM constellation. We first divide the set of all possible transmitted symbol vectors into different level of clusters according to the *N*-QAM multilevel partition rule. The Cluster *i* at level ℓ is a group of similar transmitted symbol vectors with mean vector $\boldsymbol{x}^{\ell,i}$, which is defined as $C^{\ell,i} \triangleq \left\{\boldsymbol{x}^1 \mid s_i^1 \in P^{\ell,i}\right\}_{i=1,2,\cdots N_T}$. The divisions are recursively to form a multilevel cluster tree in Fig 1(b). The root node represents the set of all possible transmitted symbol vectors and other nodes are the means of clusters. Each node at layer ℓ extends 4^{N_T} nodes to next layer ($\ell-1$). The breadth-first search is applied to search the correct transmitted vectors in the multilevel cluster tree, which is mainly composed of two parts of stages: 1) The cluster matching stages. 2) The detail matching stage. The searching begins with root and finds the nearest cluster means from layer *L* to layer 2. For each layer, the searching chooses the nodes which fall inside the sphere with a given radius as candidate nodes, and discards other nodes in future consideration. The candidate nodes are the nodes whose branches are active for further searching. The criteria of candidate node in cluster matching stages is defined as

$$D\left(\boldsymbol{x}^{\ell,\, i}\right) = \left\| y - H\boldsymbol{x}^{\ell,\, i} \right\|^2 < \gamma^{\ell} \tag{4}$$

where γ^{ℓ} is the radius constraint for layer ℓ. Therefore, the set of candidate nodes at layer ℓ can be defined as

$$\Omega^{\ell} : \left\{ \boldsymbol{x}^{\ell,\, i} \;\middle|\; \boldsymbol{x}^{\ell,\, i} \in \Pi^{\ell} \;,\; \left\| \boldsymbol{y} - H\boldsymbol{x}^{\ell,\, i} \right\| < \gamma^{\ell} \right\} \;,\; \Omega^{\ell} \subset \Pi^{\ell} \tag{5}$$

where Π^{ℓ} is the set of all possible nodes extended from the candidate nodes at layer $(\ell+1)$ and all nodes in Ω^{ℓ} can extend their branch to next layer $(\ell-1)$. For layer one, the detail matching performs the ML search to find the nearest transmitted signal vector. The transmitted signal vector can be detected based on ML criteria for detail matching

$$\hat{\boldsymbol{x}} = \underset{\boldsymbol{x}^{1,\, i} \in \Pi^{1}}{\arg\min} \left\| y - H\boldsymbol{x}^{1,\, i} \right\| \tag{6}$$

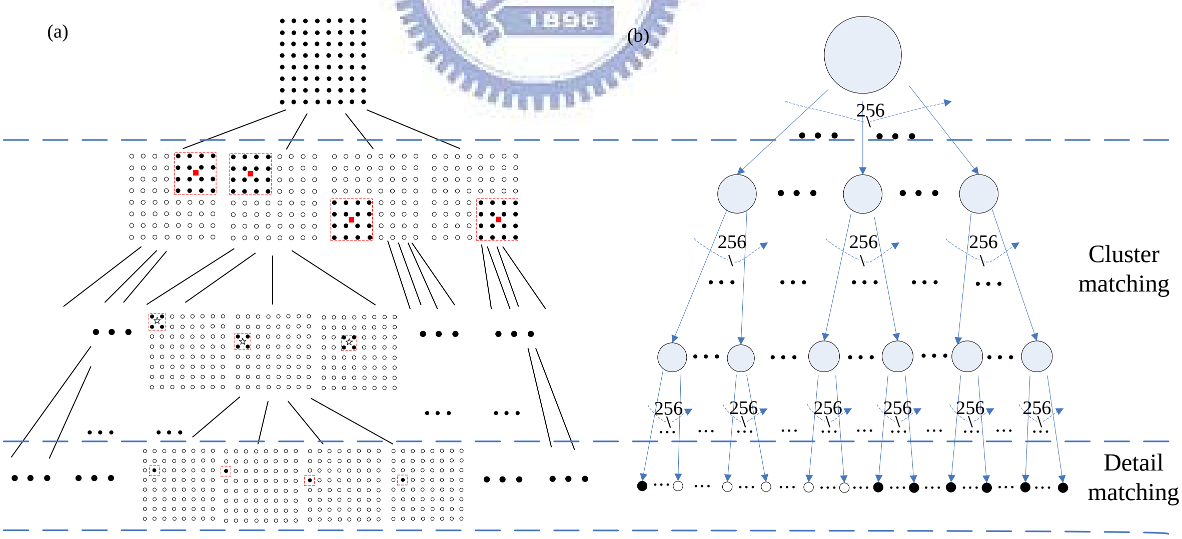

Fig. 1 (a) Example of multilevel partitions with mean symbols in 64-QAM constellation. (b) Example of multilevel cluster tree in 64-QAM constellation.

B. Dynamic Estimation of Radius Constraint

To reduce the search space, the cluster mean outside the radius constraint will be discarded for low-level searching or detail matching. The constraint vector for layer ℓ is defined as $\boldsymbol{v}^{\ell,c} = \left(\boldsymbol{x}^{1,c} - \boldsymbol{x}^{\ell,i}\right)$, where $\boldsymbol{x}^{\ell,i}$ could be any cluster mean at level ℓ and $\boldsymbol{x}^{1,c}$ is a vector of constellation point combination whose vector elements are one of the four corner constellation points in $P^{\ell,i}$. Fig. 2 describes the examples of layer three and layer two for one of the dimensions of $\boldsymbol{x}^{\ell,i}$ in 64-QAM constellation and there are 4^{N_T} possible constraint vectors corresponding to $\boldsymbol{x}^{\ell,i}$. The distance vector between the received signal vector without AWGN effect and $\boldsymbol{x}^{\ell,i}$ can be obtained as

$$\left\|\boldsymbol{y} - H\boldsymbol{x}^{\ell,i}\right\|^2 = \left\|\left(H\boldsymbol{x}^{1,k}\right) - H\boldsymbol{x}^{\ell,i}\right\|^2 = \left\|H\left(\boldsymbol{x}^{1,k} - \boldsymbol{x}^{\ell,i}\right)\right\|^2 \le \left\|H\boldsymbol{v}^{\ell,c}\right\|^2 \tag{7}$$

The length of all possible constraint vectors for $\boldsymbol{x}^{\ell,i}$ is equal in transmitted signal space. However, it is no longer equal in received signal space due to the cross-talk effect in MIMO channel which introduce different channel gain for elements in the constraint vectors. Hence, the maximum length of possible constraint vectors is chosen as the constraint value to include the nearest cluster.

$$d^{\ell} = \max\{\left\|H\vec{\boldsymbol{v}}^{\ell,c}\right\|^2\}, c = 1,\ldots,4^{N_T} \tag{8}$$

The same constraint is applied to other nodes at the same layer because the length of their constraint vectors is the same. To combat with AWGN, the radius is defined as

$$\gamma^{\ell} = \alpha^{\ell} \cdot d^{\ell}, \quad \alpha^{\ell} > 1 \tag{9}$$

where α^{ℓ} is a real value of threshold for layer ℓ. If α^{ℓ} is set too large, more candidates is included which causes more computation complexity. On the other hand, the nearest cluster could not be included when α is not large enough, which causes performance degradation. Fig 3 shows the observation of performance degradation with α setting at different SNR for 4x4 64-QAM MIMO system. The 64-QAM needs two level cluster matching stages where α^{1} and α^{2} are their factors, respectively. The result presents that the influence of α^{1} is less than the influence of α^{2} on performance degradation. The reason is that the distance between cluster mean vectors at higher layer is larger than the distance between cluster mean vectors at lower layer which enhances the noise immunity for higher layer cluster matching.

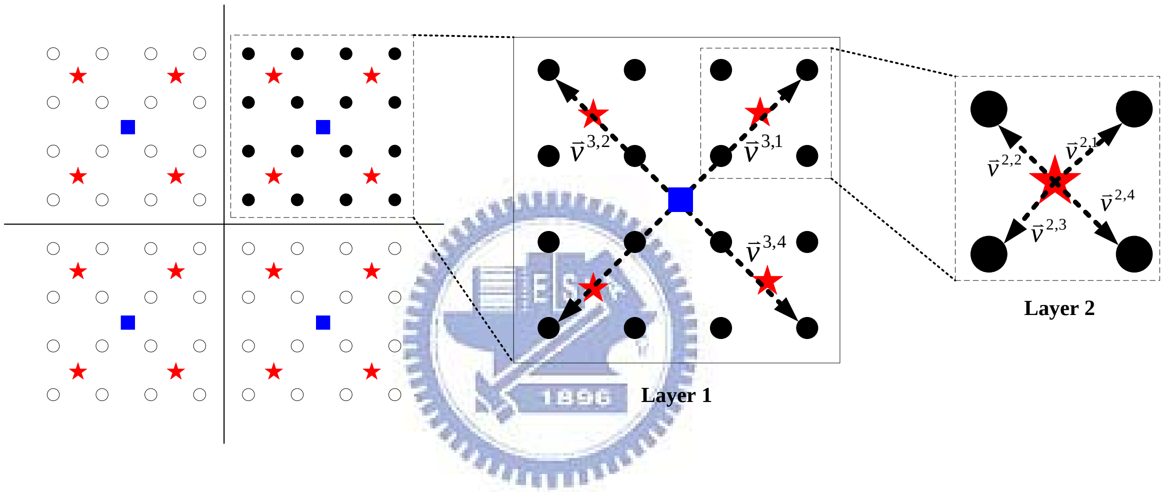

Fig. 2 Constraint vectors of 64-QAM constellation for different layer with one dimension in MIMO symbol vector.

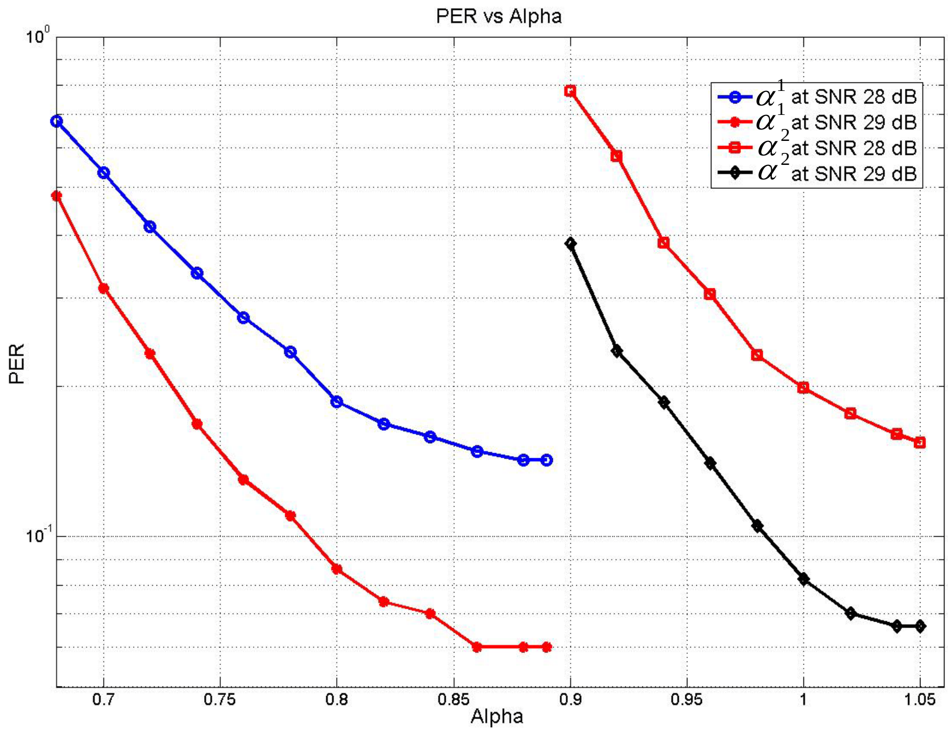

Fig. 3 Alpha vs. PER under fixed SNR for 64-QAM 4 x 4 MIMO-OFDM systems (TGN E channel)

C. Fixed Number of Candidates Selection

Since the number of the candidate nodes which fall within the radius constraint is not a constant, a *M*-algorithm is employed to keep the *M* best candidates at each layer. We first sort the candidate nodes and ranking these nodes with their Euclidean distance metric. The nodes of *M* smallest distance metric are chosen as *M* best candidate nodes. At the cluster matching layers, only the *M* best candidate nodes can expand to next layer and other nodes are discarded to reduce the search. Thus the value of *M* should be large enough, which significantly affects the system performance and computation complexity. The different to a general *M*-algorithm is that each cluster matching layer is applied with different values of *M*. The proper values of *M* are observed through the relation of PER and the value of *M*. Fig. 4 show the example of 4x4 64QAM transmission which has two different values of *M* to apply in two cluster matching layers.

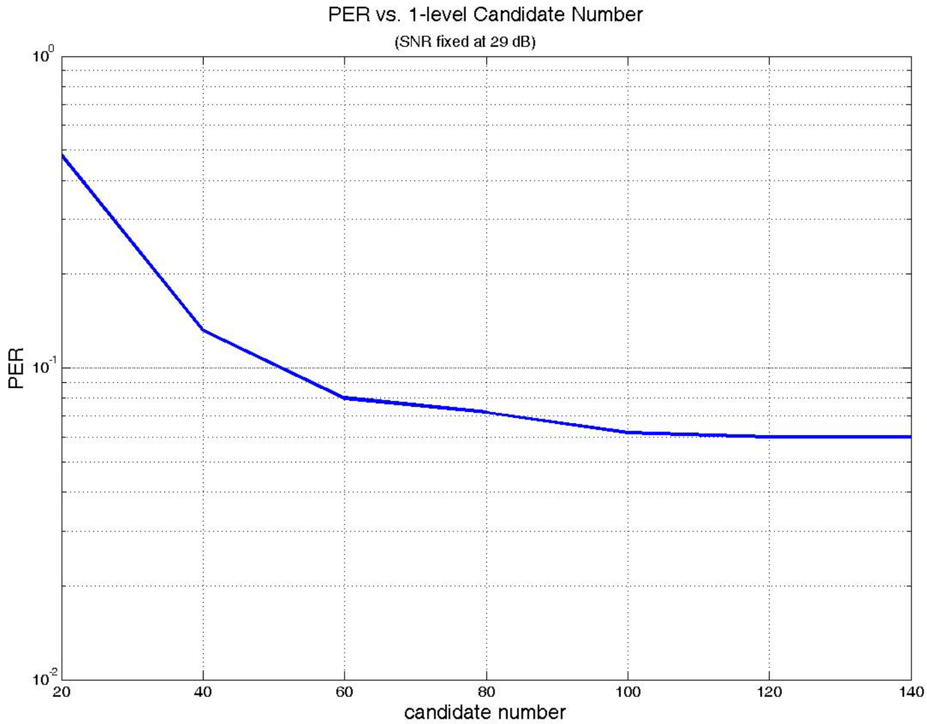

Fig. 4 PER vs. selected candidate number (M-best candidates) under fixed SNR for 64-QAM 4 x 4 MIMO-OFDM systems (TGN E channel)

Chapter 4

Complexity Reduction

A. Fixed Number of Candidates Selection

The BBD method is a general search algorithm, which divides the feasible sets into several subsets and associates each subset to a branch. For each branch, the feasible set is further divided and associated to sub-branches. The algorithm is applied recursively to the sub-problems, forming a BBD tree of sub-problems. The lower-bounding and upper-bounding processes are applied to avoid searching the whole BBD tree to obtain the optimal solution. If the objective cost to a branch (lower bound) exceeds the cost of the best known feasible solution (upper bound), the whole branch is pruned in the BBD tree. Therefore the leaf nodes in the BBD tree represent the feasible solutions of the optimization problem.

Several BBD methods have been employed in wireless communication system for obtaining optimal solution. In multi-user detection, BBD with BFS and BBD with DFS have been used in [10] and [11] to find the minimum distance between different user codes. For the MIMO diction, an iterative list BBD algorithm is investigated in [12]. In our work, we apply BBD to reduce the complexity of measuring full Euclidean distance in Eq. (5) and Eq. (6). To find the candidate nodes form at each layer of the multilevel cluster tree can be treated as the root feasible set in BBD tree. In Eq. (5) and Eq. (6), to obtain the candidate nodes with full dimensional computation of distance metric can be avoided by comparing the partial Euclidean distance with branch and bound search strategy. To apply branch and bound search, we first transform the signal vector and channel matrix to real domain and the Eq. (1)

can be written as

$$\boldsymbol{y}_R = H_R \boldsymbol{x}_R + \boldsymbol{n}_R, \quad \begin{array}{l} \boldsymbol{y}_R \triangleq \begin{bmatrix} real(\boldsymbol{y}) \\ img(\boldsymbol{y}) \end{bmatrix}, \ \boldsymbol{x}_R \triangleq \begin{bmatrix} real(\boldsymbol{x}) \\ img(\boldsymbol{x}) \end{bmatrix}, \\ H_R \triangleq \begin{bmatrix} real(H) & img(H) \\ -img(H) & real(H) \end{bmatrix} \end{array} \tag{10}$$

where *real*(·) and *img*(·) denote the real and image parts of (·), respectively. The *QR* decomposition can be performed on channel matrix.

$$H_R = QR \tag{11}$$

where Q is an $2N_R \times 2N_R$ unitary matrix ($QQ^H = I$) and R is an $2N_T \times 2N_T$ upper triangular matrix .The Eq. (10) can be rewritten as

$$\boldsymbol{y}'_R = R\boldsymbol{x}_R + \boldsymbol{n}'_R \tag{12}$$

where $\boldsymbol{y}'_R$ and $\boldsymbol{n}'_R$ denote the vectors including the first $2N_T$ rows of $Q \cdot \boldsymbol{y}_R$ and $Q \cdot \boldsymbol{n}_R$, respectively. Hence, the distance vector $\boldsymbol{z} = \left[z_1, z_2, \cdots, z_{N_R} \right]^T$ is obtained as

$$\begin{pmatrix} z_1 \\ z_2 \\ \vdots \\ z_{N_R} \end{pmatrix} = \begin{pmatrix} y'_1 \\ y'_2 \\ \vdots \\ y'_{N_R} \end{pmatrix} - \begin{pmatrix} r_{11} & r_{12} & \cdots & r_{1N_T} \\ 0 & r_{22} & \cdots & r_{2N_T} \\ \vdots & \ddots & \ddots & \vdots \\ 0 & \cdots & 0 & r_{N_R N_T} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_{N_T} \end{pmatrix} \tag{13}$$

The distance metric to find the likelihood candidates is

$$D(\boldsymbol{x}) = \left\| \boldsymbol{y}' - R\boldsymbol{x} \right\|^2 = \sum_{j=1}^{N_R} \left\| z_j \right\|^2 \tag{14}$$

Since $D(\boldsymbol{z})$ is derived form $z_1, z_2 \ldots z_{N_R}$, a BBD tree can be employed to search the minimum distance of Eq. (14). The root of the BBD tree is labeled with $\mathrm{X}^{(0)}$ which means the set of all possible vectors ($\boldsymbol{x}$). Each node at layer (*i*-1) branches β new nodes at next layer *i* and the branch cost of node $X_k^{(i)}$ is defined as

$$D(X^{(i)}) = \sum_{j=0}^{i} \left\| z_{(N_R - j)} \right\|^2 = \left\| z_{(N_R - i + 1)} \right\|^2 + D(X^{(i-1)}) < B \tag{15}$$

where B is the upper bound for BBD strategy. It can be easily seen that the search strategy is breadth-first. The distance cost will quickly accumulate layer by layer because $\left\| z_i \right\|^2 \geq 0$ and most branches can be pruned due to the excess of upper bound. Hence, the proposed BBD can significantly avoid calculating full Euclidean distance for all possible vectors in the searching space. Since the nodes in Π^{ℓ} are dynamical obtained from upper layer in multilevel cluster tree, the depth first search is hard to be applied in the proposed BBD tree because each node does not extent a constant branch. The methods of obtaining the upper bound in BBD search strategy are different between cluster matching stages and detail matching stages in multilevel cluster tree. The upper bounds for each cluster matching stage can directly use the value of its radius constraints ($B = \gamma^{\ell}$). The basic idea of obtaining the upper bounds in detail matching is to select the minimum distance form *W* possible transmitted signal vectors. We randomly chose one of the transmitted signal vectors from each of *W* upper layer cluster whose mean symbol vectors have smallest ranking with Euclidean distance metric. Then the smallest Euclidean distance of these *W* possible transmitted signal vectors can be obtained as the upper bounds. The equation can be formula as

$$B = \min\left(D(\boldsymbol{x}^{1,\,1}), D(\boldsymbol{x}^{1,\,2}), \cdots D(\boldsymbol{x}^{1,\,W}) \right), \quad \boldsymbol{x}^{1,\,i} \in C^{1,\,i},\ 1 \leq i \leq W \tag{16}$$

where $C^{1,\,i}$ is one of the *W* cluster whose mean symbol vectors have smallest ranking with Euclidean distance metric. For the ease of understanding, the breadth-first BBD algorithm can be summarized as following steps:

1) Compute QR decomposition matrix on H_R, $H_R = QR$;
2) Pre-compute $\boldsymbol{y}'_R$, $\boldsymbol{y}'_R = Q^H \boldsymbol{y}_R$;
3) Compute the upper bound B ; if the BBD is applied in cluster matching stage, $B = \gamma^{\ell}$, else $B = \min\left(D(\boldsymbol{x}^{1,\,i}), D(\boldsymbol{x}^{1,\,i}), \cdots D(\boldsymbol{x}^{1,\,W}) \right)$;
4) Initialize k=1; activate the root node;
5) Compute $D(X^{(i)}) = \left\| z_{(N_R - i + 1)} \right\|^2 + D(X^{(i-1)})$ for all active nodes;

6) Prune the branches of the nodes whose $D(\mathrm{X}^{(i)})$ is larger than a given upper bound;
7) If the current nodes are leaf nodes, stop; otherwise, move to next layer and goto step 4;

B. First-level Candidate Decision by Phase Detection

For first layer in N-QAM multilevel tree, the number of nodes which need to compute Euclidian distance is $N_T{}^4$. A phase detection method is proposed which only needs to check the phase of each element in estimated signal vector. Although a preprocessing is needed to estimate the transmitted signal vector, the calculation of phase is much less complex than the calculation of the squared Euclidean distance. The transmitted signal vector ($\hat{\boldsymbol{x}}_{MMSE}$) can be estimated through minimum mean-squared error (MMSE) approach ($\hat{\boldsymbol{x}}_{MMSE} = (H^H H + \sigma^2 \boldsymbol{I})^{-1} H^H \boldsymbol{y}$, where σ^2 is a noise variance and I is an identity matrix), which needs very little computation complexity. The function of phase calculation is denoted as $\theta(\hat{x}_j)$ where $\hat{x}_j$ is the element of estimated vector $\hat{\boldsymbol{x}}_{MMSE}$. To decide the elements ($x_j^{L,\,i}$) in each candidate vector ($\boldsymbol{x}^{L,\,i}$) at first layer, the set of possible constellation point can be defined as

$$\Delta_j = \begin{cases} \{s_1^L, s_2^L, s_4^L\}, & if\ \ 0 \le \theta(\hat{x}_j) < \dfrac{\pi}{2} \\ \{s_1^L, s_2^L, s_3^L\}, & if\ \ \dfrac{\pi}{2} \le \theta(\hat{x}_j) < \pi \\ \{s_1^L, s_3^L, s_4^L\}, & if\ \ \dfrac{-\pi}{2} < \theta(\hat{x}_j) \le 0 \\ \{s_2^L, s_3^L, s_4^L\}, & if\ \ \dfrac{-3\pi}{2} \le \theta(\hat{x}_j) < \dfrac{-\pi}{2} \end{cases} \tag{17}$$

where s_1^L, s_2^L, s_3^L and s_4^L is in the upper right section, upper left section, lower left section and lower right section of the I-Q plane respectively. Hence, the set of candidate vectors $\left\{ \boldsymbol{x}^{L,\,i} \right\}$ at first layer can be obtained as $\left\{ \boldsymbol{x}^{L,\,i} \right\} = \left\{ \left[x_1^{L,\,i}, x_2^{L,\,i}, \cdots x_{N_T}^{L,\,i} \right]^T \mid x_j^{L,\,i} \in \Delta_j \right\}$ and the size of the set is 3^{N_T}.

We just apply phase detection at first layer because the distance between each symbol at highest layer is larger than the distance at lower layer. The large symbol distance at first layer reduces the performance loss which is caused by inaccurate estimation of linear approach for $\hat{\boldsymbol{x}}_{MMSE}$. The choice of number of elements in the Δ_j is the trade-off between computation complexity and system performance. Summarily, the complexity reduction of phase detection can be categorized into two ways: 1) The simpler method to obtain the candidates, which reduces the complexity of computing the squared Euclidean distance and sorting for obtain the M-best candidates. 2) The number of candidate decided by phase detection is lesser than the number of candidates decided by the squared Euclidean distance, which also introduce lesser sub-branches in the lower layer. Thus, phase detection method not only uses a simpler metric to searches cluster candidates but also reduces candidate number in multilevel tree.

C. Summary of the Cluster-Based Algorithm with Complexity Reduction Version

We summarize the proposed cluster-based algorithm with complexity reduction version in serial of steps as follows:

1) Compute the MMSE output $\hat{\boldsymbol{x}}_{MMSE}$ and perform phase detection to obtain the candidate nodes in first layer of multilevel tree.
2) For layer $\ell = L-1, \cdots 2$,
   - i) Collect the nodes which extended from the candidate node in upper layer as a search set $\prod^{\ell}$
   - ii) Compute the radius constraint γ^{ℓ} according Eq. (4)
   - iii) Collect the nodes whose $D(\boldsymbol{x}^{\ell, i})$ are less than radius constraint by branch and bound search strategy ($B = \gamma^{\ell}$).
   - iv) Sort the nodes collected by step 2.iii, and select the K^{ℓ} best nodes as candidate nodes.
3) For detail matching ($\ell = 1$),
   - i) Collect the nodes which extended from the candidate node in layer 2 as a search set $\prod^{L}$
   - ii) Find the node which has the smallest distance metric by branch and bound search strategy.

Chapter 5

Simulation Results

A typical MIMO-OFDM system is based on IEEE 802.11n Wireless LANs, TGn Sync Proposal Technical Specification [10] which is used as the reference design platform. The simulation model is mainly based on TGn multipath specification of mode E, which is the multipath fast-fading channel model of 15-taps and 100ns Root Mean Square (RMS) delay. The major simulation parameters are shown in Table 1

Table 1 Simulation parameters

Parameter	***Value***
Number of antennas	3Tx and 3Rx, 4Tx and 4Rx
Signal bandwidth	20 MHz
Number of subcarrier	52
Subcarier modulation	64 QAM
Packet size	1024 (Bytes)
FEC coding rate	2/3
Channel Model	TGn E type
Number of taps	15
RMS delay spread	100 nsec

The proposed cluster-based detection algorithm has two levels in cluster matching and needs to sort cluster candidates in the cluster matching stage. The cluster candidate number is critical for detection complexity and detection precision. Consequently, the approach applies a branch and bound strategy to reduce the number and a sorting strategy to fix cluster candidate number. The fast phase decision method is another way to reduce cluster candidates number. Since the fast phase decision method has fixed candidate number in the first cluster matching stage, it only needs to select cluster candidate in the second stage. However, the phase decision method suffers from signal distortion in large number of antennas. Thus the proposed cluster-based with three phase decision method can mitigate the error detection. This section compares performance and complexity between different detection methods in MIMO detection. Note that the performance comparison is considered under packet error rate 0.08 and normalizes to the ML detection methods.

A. Performance Evaluation

For the purpose of performance comparison, the performance of various MIMO detection methods is considered. Fig. 5 and Fig. 6 present the PER for 3 x 3 and 4 x 4 MIMO-OFDM systems. As can be seen from the figure, there is a large gap between the linear and nonlinear MIMO detection methods. The nonlinear detection methods such as the proposed Cluster-based method and K-best sphere decoder maintain SNR degradation within 0.4dB in the Fig. 5 and 0.2dB to 0.45dB in the Fig. 6

The table 2 summarizes the performance and the performance is normalized to ML detection method. The proposed cluster method can maintain performance within 0.45dB such that the method is suitable for practical system.

Table 2 Summaries performance comparison for various detection methods

Method	***3 x 3 MIMO-OFDM system***					
	ML	**Cluster (33,61)**	K-Best SD (k=8)	VBLAST	MMSE	ZF
SNR in PER 0.08	28.15 dB	**28.55 dB**	28.55 dB	32.20 dB	33.40 dB	34.10 dB
SNR Degradation	0 dB	**0.4 dB**	0.4 dB	4.05 dB	5.25 dB	5.55 dB
Method	***4 x 4 MIMO-OFDM system***					
	ML	**Cluster (100,388)**	K-Best SD (k=12)	VBLAST	MMSE	ZF
SNR in PER 0.08	28.55 dB	**29 dB**	29 dB	33.15 dB	34.60 dB	35.20 dB
SNR Degradation	0 dB	**0.45 dB**	0.45 dB	4.6 dB	6.05 dB	6.65 dB

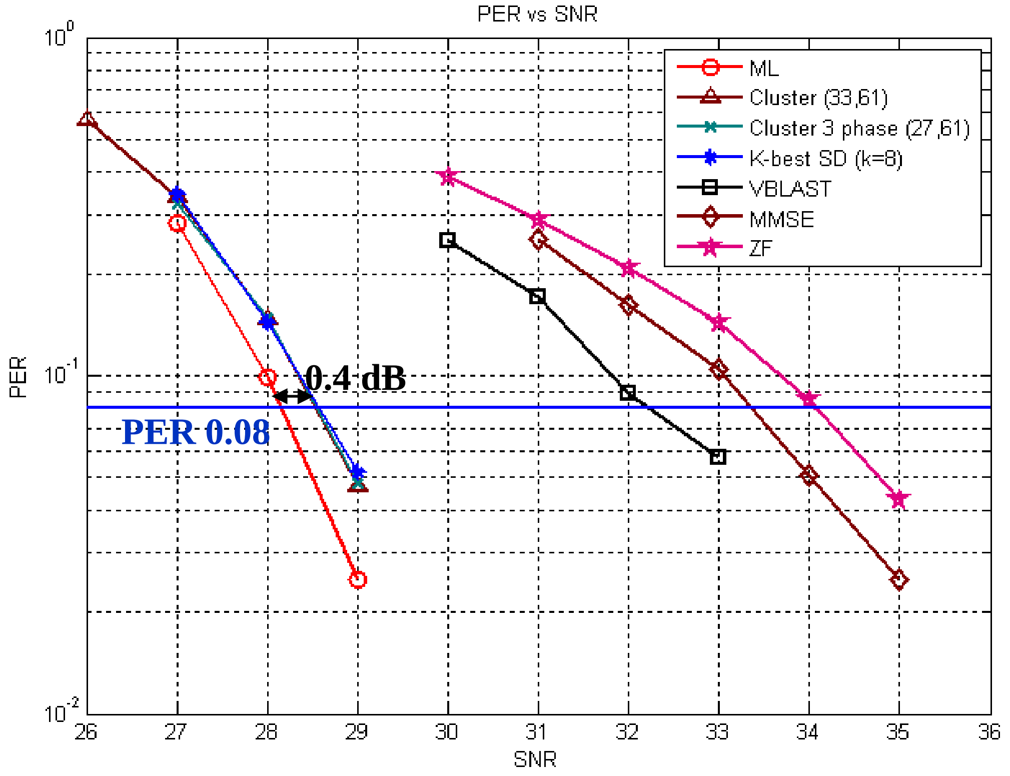

Fig. 5 PER of various detection methods for 64-QAM modulated 3 x 3 MIMO-OFDM systems

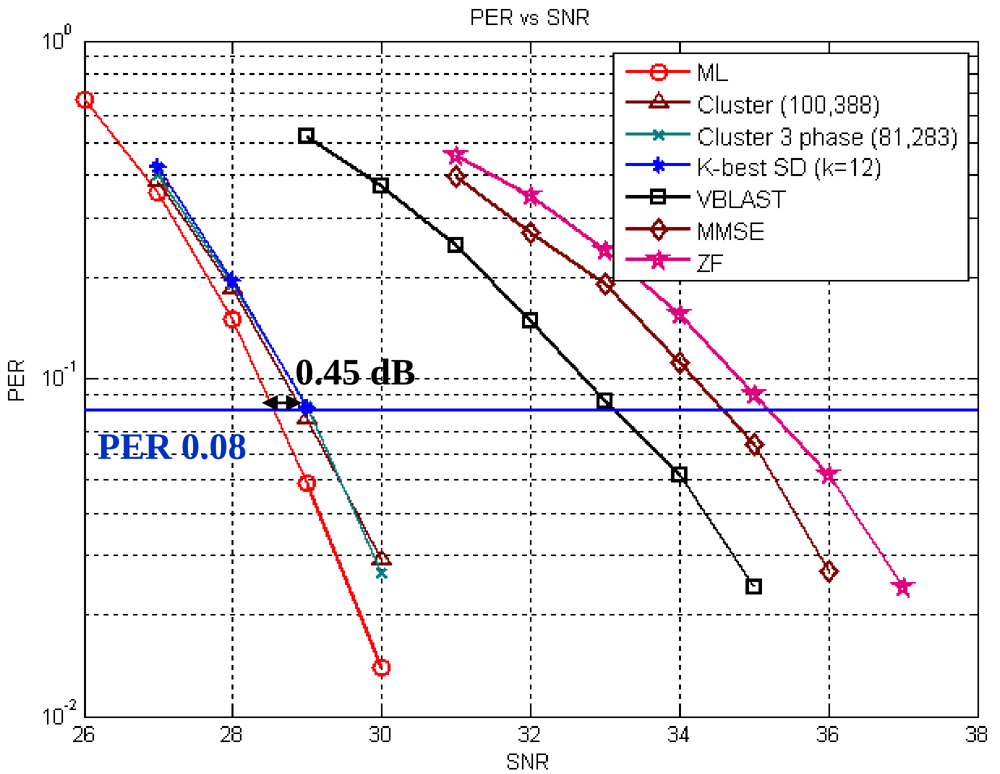

Fig. 6 PER of various detection methods for 64-QAM modulated 4 x 4 MIMO-OFDM systems

Since K-best sphere decoder was accepted as practical, the target of cluster-based detection is complexity reduction and remains performance. For the purpose of complexity comparison between the K-best sphere decoder and the cluster-based methods, we tune K-best parameter: k and cluster parameter: candidate number such that different methods have nearly the same performance.

Fig. 7 and Fig. 8 compare cluster-based detection method and cluster-based phase detection method with K-best sphere decoder.

Observing from the Fig. 7, there is only near 4 dB SNR degradation for cluster-based method, cluster-based with phase decision method and K-best sphere decoding method. To take account of the complexity, the cluster-based with two phase decision method need fewer candidates than the cluster-based with three phase decision method, 8 candidates in phase decision stage and 64 candidates in second level cluster matching stage, to remain the same performance.

Observing from the Fig. 8, cluster-based with two phase decision approach can't remain performance within 0.45 dB. Therefore, cluster-based with three phase detection method is better candidate for 4 x 4 MIMO-OFDY system.

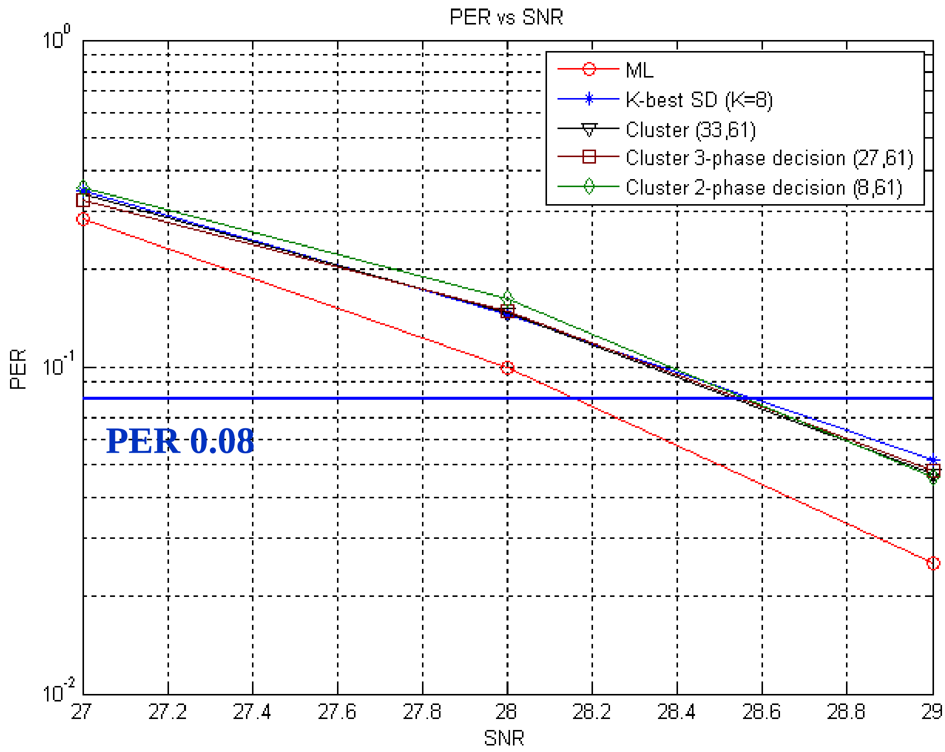

Fig. 7 PER of phase decision methods for 64-QAM modulated 3 x 3 MIMO-OFDM systems

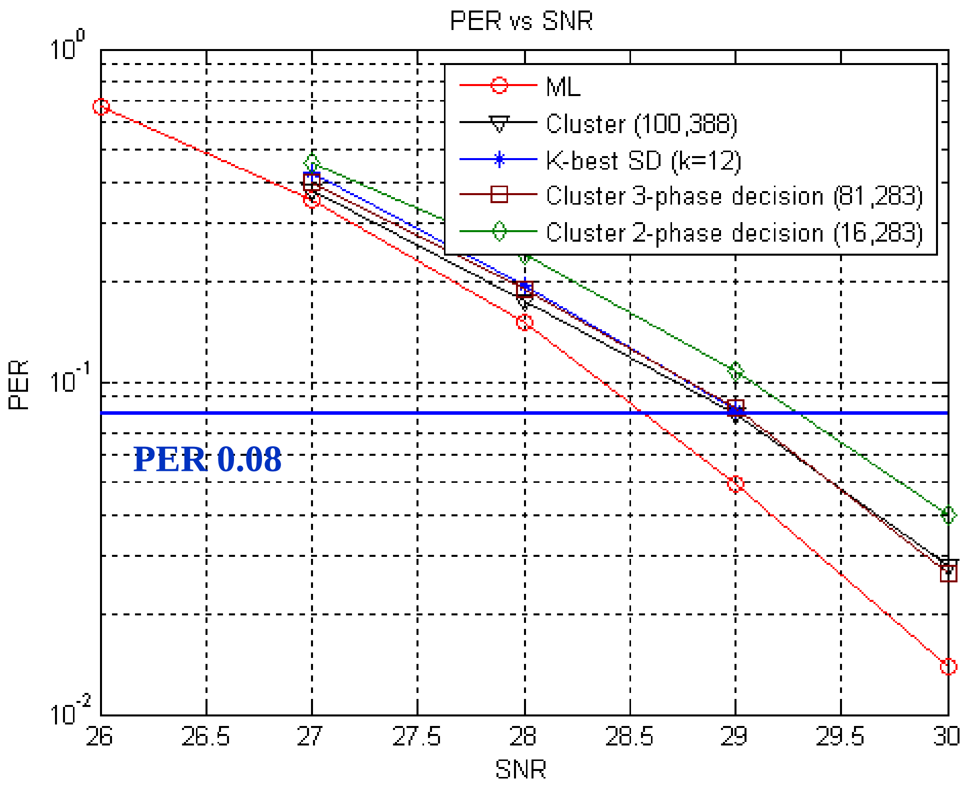

Fig. 8 PER of phase decision methods for 64-QAM modulated 4 x 4 MIMO-OFDM systems

B. Complexity Comparison

The table 3 summarizes the performance and compares sorting operation among these methods. Assume heap sort operation is used and then it needs $N\log_2 N$ sorting operations to sort N element. The table shows that sorting operation in cluster-based methods has complexity reduction ranges from 7.37% to 21.5% in 3 x 3 MIMO-OFDM system and 29.76% to 76.8% in 4 x 4 MIMO-OFDM system.

Table 3 Complexity comparison between K-Best SD, CBD, CBD with 2 phase decision and CBD with 3 phase decision

Method	*3 x 3 MIMO-OFDM system*				
	ML	K-Best SD (k=8)	Cluster Fixed (33,61)	Cluster 2-phase MMSE (8,61)	Cluster 3-phase MMSE (27,61)
SNR in PER 0.08	28.15 dB	28.55 dB	28.55 dB	28.55 dB	28.55 dB
SNR-Loss	0 dB	0.4 dB	0.4 dB	0.4 dB	0.4 dB
Multiplier	3145728 (100%)	2520 (0.08%)	73728 (2.3%)	54528 (1.73%)	69120 (2.19%)
Adder	2883584 (100%)	2342 (0.08%)	67392 (2.3%)	49792 (1.72%)	63168 (2.19%)
Comparator	NA	1560 (100%)	336 (21.5%)	115 (7.37%)	198 (12.69%)

Method	*4 x 4 MIMO-OFDM system*				
	ML	K-Best SD (k=12)	Cluster Fixed (100,388)	Cluster 2-phase MMSE (16,283)	Cluster 3-phase MMSE (81,283)
SNR in PER 0.08	28.55 dB	29.00 dB	29.00 dB	29.3 dB	29.00 dB
SNR-Loss	0 dB	0.45 dB	0.45 dB	0.75 dB	0.45 dB
Multiplier	335544320 (100%)	8096 (0.0024%)	2508800 (0.75%)	1541120 (0.46%)	1873920 (0.55%)
Adder	318767104 (100%)	7930 (0.0024%)	2382336 (0.75%)	1463040 (0.46%)	1779200 (0.56%)
Comparator	NA	3817 (100%)	2934 (76.8%)	1136 (29.76%)	1879 (49.22%)

Chapter 6

Conclusions

This work presents a near ML performance, low-complexity cluster-based MIMO detection design, which use fast phase decision and branch and bound method to reduce the need of system hardware for MIMO-OFDM wireless accesses. Simulations and measurements indicate that the proposed scheme can achieve 8% PER with about 0.45 dB SNR loss compared with MLD in frequency-selective fading of TGn E channel [10]. Without any specific preamble, pilot format and STBC coding, this cluster-based MIMO detection method for 4×4 MIMO-OFDM systems can provide near ML performance with relatively low complexity. This study does not only derive an efficient solution for OFDM-based MIMO receivers, but is also well-suited for next-generation wireless LAN discussed in IEEE 802.11 VHT study group.

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