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碩 士 論 文

應用於多天線偵測之可變可重疊之叢集演算法

The Study of Variable and Overlapped Cluster-based MIMO Detection

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應用於多天線偵測之可變可重疊之叢集演算法

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摘要

在這篇論文裡，我們推薦一個具有高輸出率、固定複雜度的硬性輸出球體解碼器，並支援高維度 64QAM、256QAM 調變的 4T4R 和 8T8R 多輸入多輸出通訊系統。

本論文提出一基於可變可重疊之叢集的 MIMO 偵測方法(Variable and Overlapped Cluster-based MIMO Detection Algorithm)，在 PER 在 0.08 下與最大相似算法誤差在 0.5dB 以內，較 K best 球體解碼器演算法低複雜度，可硬體實作的演算法。

本演算法是在偵測前，以基礎等化器找出的可能落點為依據，決策出該每個天線維度上可能候選星群，並以寬度優先搜尋的分支分界的方法，結合 MMSE-SQRD 解碼的系統架構來解碼，而本叢集分群法為以下兩種：

重疊叢集法(Overlap cluster)，為一減少複雜度並維持偵測效能之方法，在叢集的決策上，為了減少在邊界情況(Boundary condition)下的決策失誤，兩個不同的群可能會有相同的候選星群，藉此在叢集上有更高的準確性。

可變叢集法(Dynamic cluster)，為適應不同天線的通道衰減效應，而改進的叢集法。在決策的候選星群時，利用排序 QR 分解(Sorted QR Decomposition)演算法之通道路徑的範數(norm)資訊，使低通道衰減之天線有低數量之候選星群，高通道衰減天線維度擁有較多數量之候選星群候選星群，而此法符合實際天線陣列在真實情況下的傳輸環境。

實作於 IEEE 802.11n 的通訊平台上，提供 4T4R 和 8T8R 在高維度 64QAM、256QAM 調變，在符合 TGN-E 所規範的通道模型中進行模擬。模擬結果指出此演算法與傳統 K-best 球體解碼器，若維持 PER 在 0.08 的誤差 0.5dB 之內，以較低的複雜度完成相同的系統效能；若維持約略相同複雜度之下，具有較佳的系統效能表現。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。

The Study of Variable and Overlapped Cluster-based MIMO Detection

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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, the ZFD, the MMSED, V-BLAST, the maximum likelihood detection (MLD) as well as the Sphere Decode detection (SD).

We propose the Variable and Overlapped Cluster-based MIMO Detection algorithm by partitioning the transmitted MIMO signal vectors into vary clusters with estimated symbol in each dimension in 64-QAM/256-QAM and finding out the result signal by comparing the received signal with all the candidates above. And the proposed method, step A) as well as B), are demonstrating in the following.

In A), we demonstrate overlap clustering algorithm that the estimated signal got by linear detectors, as ZFD or MMSED, and then pick out the possible constellation points falling on each antenna according to the range which the estimated signal is in.

After overlap clustering algorithm in step A, we enlarge/narrow the possible constellations points according to the column norm of H included channel gain information.

Moving on B), we have all the candidates signals compare with the received signal, and then apply BFS with best K candidates in the searching space of MMSE SQRD. Eventually, the detection signal with the least accumulative square Euclidean distance is delivered.

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.

誌謝

論文止筆於此，代表求學的生涯將在此落幕了，遙想當時在找指導教授時，和金毛碰巧路過許騰尹老師的辦公室，因之前沒有上過許老師的課，帶點陌生與膽怯的心而敲了門，沒想到在短短兩小時的生動對話中，就被老師的年輕風趣所吸引，不顧學長姊們口中的傳聞，硬體很操喔、那間實驗室很精實、很恐怖不要問，就下定決心跟許騰尹了。

如今能順利將本論文如期完成，在研究這條路上給予我無限的發展自由，最重要的要感謝指導教授許騰尹老師，在這兩年多來的如師如友的照顧，尤以在我對通訊和硬體完全沒有概念時，婉如大海中的一條迷船，看不到未來在哪裡，且常會誤入暴風雨與漩渦中，老師會適時的點出大方向，引導走向對的航道，並且因材施教地指導我們該如何做，才有機會在未來的職場上生存下來。除此之外，經驗豐富的學長 Jason，在討論時常會一語道破徵結點，並且在我不懂的時候能夠不厭其煩的教導我，更常是在晚上邊帶小孩子時跟我分析實驗數據。Panda 學長、具啟發性的 A 伏龍，幽默風趣的小賢大哥，在我突發其想時，會給我最有力的協助。學長姊鴻偉、建安、蘇蘇、于萱、卉萱、貴英、阿德，在帶 DLab 時陪著我和金毛渡過了開心的一年半，那段打打鬧鬧聊天的時光真的很開心。現今實驗室也多了些有趣的生力軍，包子和建亞身為實驗室的活寶，讓我們在研究苦悶無力時可以適度放鬆心情、輕鬆一下。還有包括了 Kent、魯魯米、柏良、金毛、老翁、小王子、大師、姚哥、色魔、PASS、流川、阿古、培宇、彭彭，這兩年騎單車、架網站、看煙火、衝蜂炮、打球、對抗 IC 競賽、跑步跳繩、打三國紀錄連贏五十六場、吃大餐、游泳重訓、一起努力畢業，蕭博文、甄、maud 學姊，無拘無束地聊天共享心事。這兩年，能有大家的陪伴，過得開心與踏實。

最後此篇論文，要對我的家人致上最後的謝意，為了從小體弱多病又鼻過敏的的我，家人耐心地帶我處處尋醫吃藥；在求學這段日子，家人的關心處處可見，每週回家都看得到的補品或愛吃的菜餚，阿嬤也都會特地煮拿手菜給我吃，讓我不胖也不行。

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Chapter 1

Introduction

Recently, orthogonal frequency division multiplexing (OFDM), which simplifies the receiver design, has become a widely used technique for broadband wireless systems. Multiple-input multiple-output (MIMO) channels offer improved capacity and potential for improved reliability compared to single input single-output (SISO) channels. The MIMO technique in combination with OFDM (MIMO-OFDM) has been identified as a promising approach for high spectral efficiency in wideband systems. For high data rate is the tendency of the wireless communication system, the MIMO-OFDM technique has been a spotlight for its ability to increase data rate. Many new systems such as 802.11n, TGac, 3GPP LTE and WiMax adopt the technique to increase data throughput and system performance.

To exploit the spectrum efficiency, large number of antennas and high order QAM constellations are often employed, which leads a challenge to design the MIMO detection with acceptable complexity and sub-optimal performance.

There are several conventional signal detection approaches for MIMO-OFDM SDM system [1]. The linear detections, such as the ZFD and the MMSED, uses the inverse of estimated channel response to extract the desired signals. Both of these two approaches are easy to implementation, but enlarge performance degradation with the enhancing channel noise. Another category is the nonlinear approaches such as V-BLAST and the maximum likelihood detection (MLD). The V-BLAST algorithm uses ordered successive interference cancellation with QR decomposition [2]. The MLD algorithm reaches the optimal performance mathematically with the unacceptable computation complexity [3][4].

Sphere decoding (SD) [5] algorithm can reduce the unacceptable computation complexity by confining the number of constellation points to be searched, Fincke-Pohst [6] and Schnorr-Euchner [7] are two of the most common computationally efficient search strategies for realizing the ML detection.

Some methods [8]-[10] reduce the search set by employing the multilevel structure of the N-QAM constellations. The multilevel structure decomposes N-QAM demodulation into a sequence of sub-demodulations with a hierarchical order, which has been widely investigated for complexity reduction purpose [11]. Also, the original K-best sphere decoder (K-best SD) [12], whose complexity is proportional to the number of transmit antennas, gives us the basis of our proposal algorithm.

In this paper, we propose the Variable and Overlapped Cluster-based (VACO) MIMO Detection by partitioning the transmitted MIMO signal vectors into vary clusters with estimated symbol in each dimension in N-QAM and finding out the result signal by comparing the received signal. The overlap clustering algorithm pick out the possible constellation points according to the estimated signal got by linear detectors, as ZFD or MMSED. And then we enlarge/narrow the set of the possible constellations points according to the channel gain information. Hence, we have all the candidates signals compare with the received signal, and then apply breadth-first searching with best K candidates in the searching space of SQRD. Eventually, the detection signal with the least accumulative square Euclidean distance is delivered.

The remainder of this paper is organized as follows. The system assumptions with problem statement are addressed in Chapter 2. The proposed Variable and Overlapped Cluster-based MIMO Detection algorithm is described on example in Chapter 3. Performance and complexity are evaluated and compared with different approaches in Chapter 4. Finally, Chapter 5 gives conclusions.

Chapter 2

System Assumptions

2.1 MIMO System Description

MIMO system consists of multiple transmitter antennas and receiver antennas. Signals are mixed from each transmitter antenna and received by multiply receiver antennas. In this section, the system architecture used in this thesis will be described. The research is designed for a coded MIMO system. The MIMO system has N_t transmitter antennas and N_r receiver antennas and is denoted as $N_t \times N_r$. The MIMO technique is spatial multiplexing, which means independent data streams are transmitted from each transmitter antenna, and a MIMO detector is in the receiver and decodes the mixed signal. The data bit symbols are modulated to N_t-dimensional data symbol vector $\boldsymbol{x} = \left[x_1, x_2, ..., x_{N_T}\right]^T$ ($[*]^T$ means transpose), whose entries x_i is mapped in the complex constellation. Each data symbol is transmitted by one of the N_t transmitter antennas, respectively. The rich-scattering environment additive white Gaussian noise (AWGN) is assumed here. Assuming perfect timing and frequency synchronization, the received baseband signal for $N_T \times N_R$ MIMO system is modeled as following:

$$\boldsymbol{y} = H\boldsymbol{x} + \boldsymbol{n} \tag{2.1}$$

where $\boldsymbol{x} = \left[x_1, x_2, ..., x_{N_T}\right]^T$, x_i is the transmitted signal modulated with N-QAM constellation in the i-th transmitted antenna in the transmitted signal space;

$\boldsymbol{y} = \left[y_1, y_2, \ldots, y_{N_R} \right]^T$ denote the received symbol vector in the received signal space, and $\boldsymbol{n} = \left[n_1, n_2, \ldots, n_{N_R} \right]^T$ 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 [13] is represented by the $N_R \times N_T$ channel matrix H, which can be express as:

$$\boldsymbol{H} = \begin{pmatrix} h_{11} & \cdots & h_{1Nt} \\ \vdots & \ddots & \vdots \\ h_{Nr1} & \cdots & h_{NrNt} \end{pmatrix} \qquad (2.2)$$

where $h_{i,j}$ represents the complex transfer function and the channel state information (CSI) from j th transmitter antenna to i th receiver antenna. The mathematical equation shows that the received signals are linear combination of transmitter signal. We assume that the receiver knows the channel matrix perfectly, and that N_R=N_T in this paper. Fig. 2.1 illustrates an example diagram of 2 x 2 MIMO system.

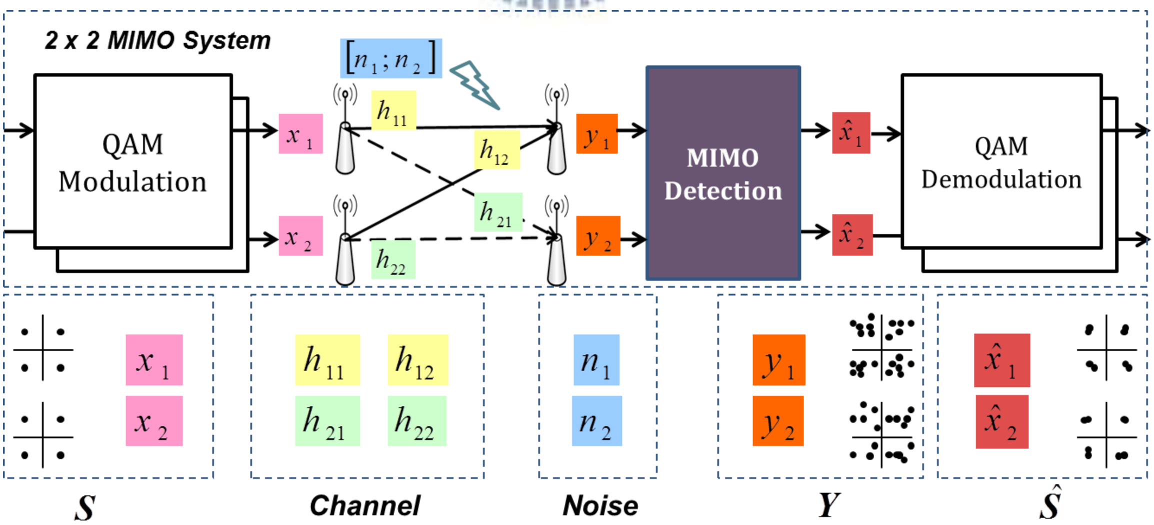

Figure 2.1 2 x 2 MIMO system

2.2 Motivation and Problem Statement

While employing large number of antennas and high order QAM constellations in MIMO-OFDM systems, it leads a challenge to design the MIMO detection with acceptable complexity and sub-optimal performance. Especially occurred in the maximum-likelihood detector (MLD) [3], it requires unacceptable computation to exhausted search the all combinations of each likelihood symbols.

To overcome the complexity problem, the Variable and Overlapped Cluster-based MIMO algorithm tries to restrict the extending constellation points according to the pre-estimated signal of the N-QAM constellations, and then keeps the shorted K paths of the likelihood candidates which can reduce the search space and computation complexity significantly.

In this thesis, we make a comparison in complexity and performance between our proposal algorithm and the well-known K-best SD. The K-best SD is the most attractive one of the MIMO Detection algorithms in recently researches, because of its optimal performance as well as its complexity which is proportional to the number of transmit antennas and is lower than the optimal maximum-likelihood detector.

The aim of the Variable and Overlapped Cluster-based method is to design an MIMO Detection algorithm with nearly ML performance and low complexity cost in large number of antennas and high order QAM constellations.

Chapter 3

Variable and Overlapped Cluster-based MIMO Detection

3.1 Introduction

In the beginning, we describe the basic idea of cluster-based MIMO Detection algorithm, which employed standard detectors, ZFD or MMSED, to estimate the N transmitted symbol, and then pick out possible constellation points falling on each antenna. After pruning the search space, we only need to detect correct transmitted signal vector by computing the candidates left in the corresponding clusters.

One of the cluster-based methods is called multilevel cluster-based MIMO detection algorithm by partitioning the transmitted MIMO signal vectors into clusters with the multilevel N-QAM structures in each dimension.

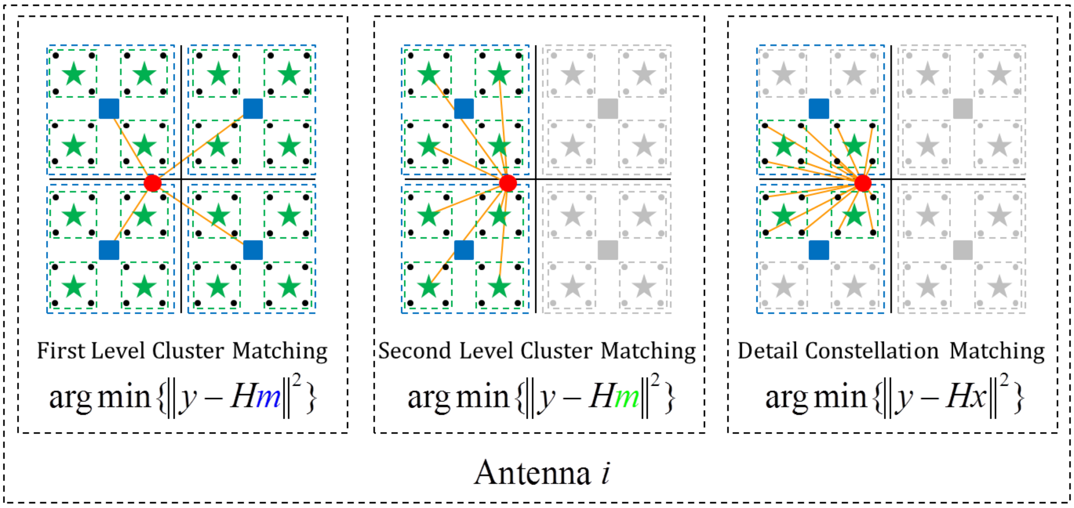

Figure 3.1 The multilevel cluster-based MIMO detection algorithm

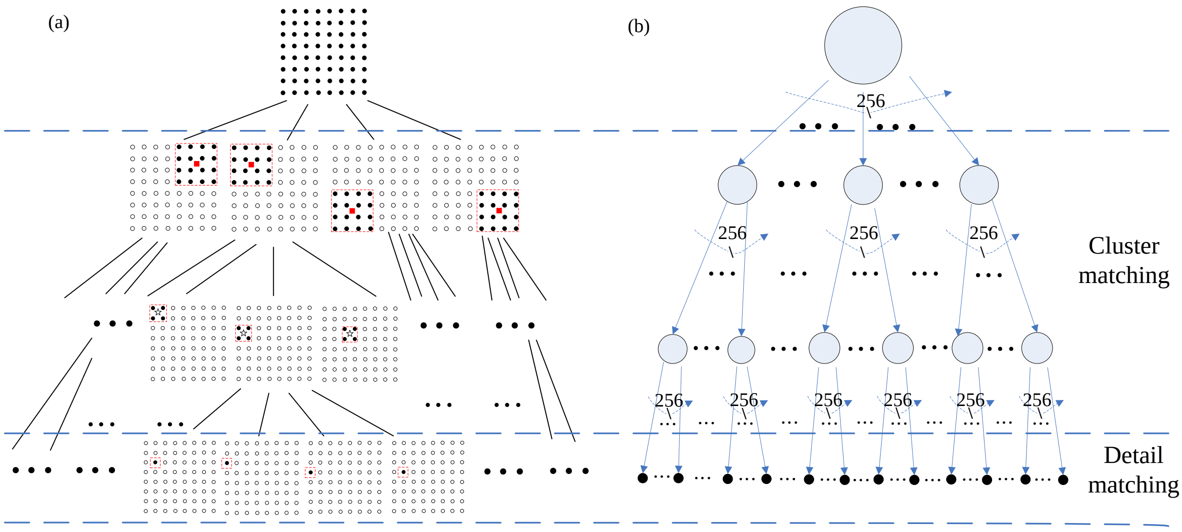

Figure 3.2 (a) Example of multilevel partitions with mean symbols in 64-QAM constellation. (b) Example of multilevel cluster tree in 64-QAM constellation.

The non-repeated candidates picked between each clusters and the fixed size of candidate number in each clusters make SNR loss significant in some environment, such as low channel gain, which should need more candidates. Also, the algorithm persists in square type cluster and hierarchical clustering that aren't a clever way because it increases the possibility choosing the wrong cluster while the pre-estimate I/Q falls on the boundary of two nearby clusters.

To overcome this problem, we draft a flexible clustering method by removing the unitary of clusters by allowing that more than one clusters possess the same candidate constellation points. The simplest example is shown in the Fig. 3.3(a) & (b), we increase the cluster diversity by adding one more cluster in the center of the original 4 clusters.

In this thesis, we break the square type of cluster and increase the cluster diversity substantially. It's given an introduction to our Variable and Overlapped Cluster-based MIMO Detection algorithm.

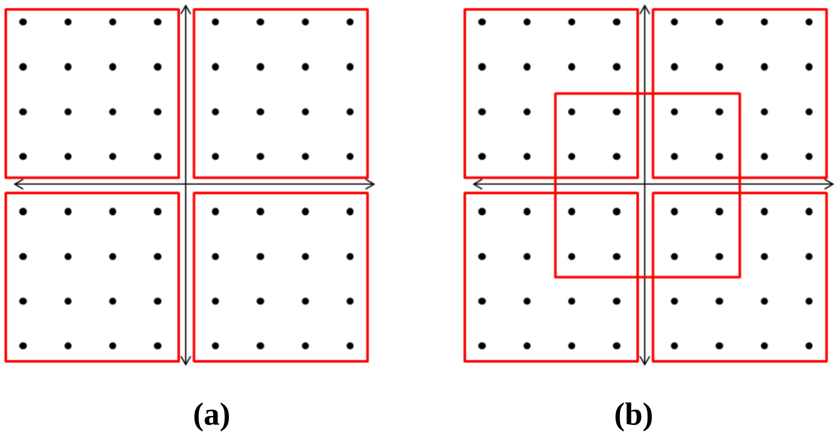

Figure 3.3 (a) Example of 4 clusters in 16-QAM constellation. (b) Example of 5 overlapped clusters in 16-QAM constellation.

3.2 Variable and Overlapped Cluster-based MIMO Detection

3.2.1 Steps of the Variable and Overlapped Cluster-based MIMO Detection

We propose the Variable and Overlapped Cluster-based MIMO Detection algorithm by partitioning the transmitted MIMO signal vectors into vary clusters with estimated symbol in each dimension in 64-QAM/256-QAM and finding out the result signal by comparing the received signal with all the candidates above. And the proposed method, step A), B) as well as C), are demonstrating in the following.

Above all in step A), we have two pre-processing blocks for our proposal algorithm. One is Sorted QR decomposition for computing the unitary matrix Q and the upper-triangular matrix R for the latter use of SD algorithm. And the other one is linear detectors, such as ZFD or MMSED, to get pre-estimating signals.

In B) **step1**, we demonstrate **Overlap Clustering Algorithm** that the estimated signal got by linear detectors, as ZFD or MMSED, and then pick out the possible constellation points falling on each antenna according to the range which the estimated signal is in.

After Overlap Clustering Algorithm in B) **step 1,** we enlarge/narrow the possible constellations points according to the column norm of H included channel gain information which is called **Dynamic Cluster Algorithm**.

Moving on C), we have all the candidates signals compare with the received signal, and then apply breadth-first Sphere Decoder with best K candidates in the searching space of MMSE SQRD. Eventually, the detection signal with the least accumulative square Euclidean distance is delivered.

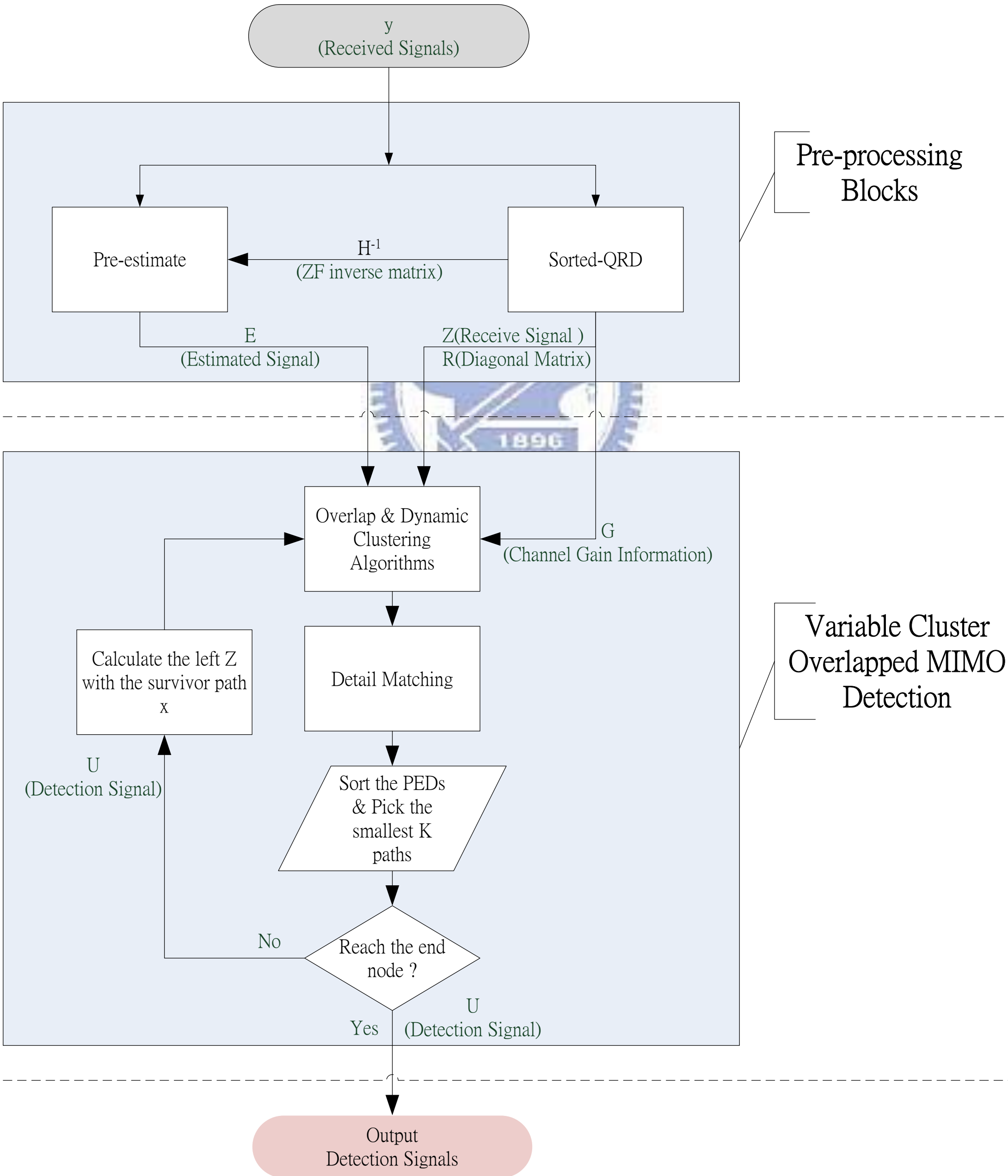

Figure 3.4 The workflow of the Variable and Overlapped Cluster-based MIMO Detection

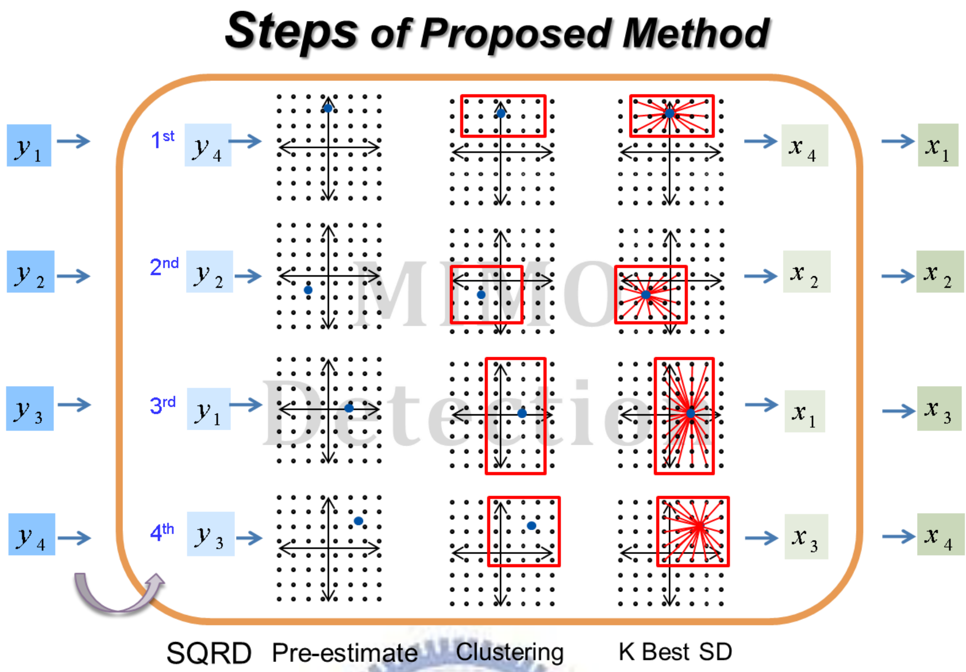

Figure 3.5 The graphic representation of the Variable and Overlapped Cluster-based MIMO Detection

3.2.2 Sorted QR Decomposition

The QR decomposition for computing the unitary matrix Q and the upper-triangular matrix R is often called preprocess in the SD algorithm.

In order to reduce the complexity in the SD algorithm, a common preprocessing approach to prune of the search tree is obtained by performing sorting such that stronger streams in terms of effective SNR correspond to levels closer to the root. This will be known as sorted QR decomposition algorithm (SQRD) in the following that is basically an extension to the modified Gram-Schmidt procedure by reordering the column norm of the channel matrix H iteratively into ascending order prior to each orthogonalization step. That is, SQRD let the diagonal elements $\boldsymbol{R}_{ii}$ as greater as possible at higher level and therefore reduces visited nodes in tree traversal.

In the sequel, we used an adapted version of this heuristic algorithm for MMSE detection (MMSE-SQRD) in both K-best algorithm and proposal algorithm.

3.2.3 Pre-estimating

A Pre-estimating method is also a preprocessing block which is needed to estimate the transmitted signal vector, the calculation of Pre-estimating 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.

3.2.4 Overlap Clustering Algorithm

The Overlap Clustering Algorithm employs the standard detectors, ZFD or MMSED, to estimate the N transmitted symbol, and then pick out possible constellation points $\{C_i^1, C_i^2, \ldots C_i^k\}$ falling on each antenna.

To increase the cluster diversity, we take the real/imaginary part of pre-estimate I/Q as reference value $x^{'}$, and then confine range of the spanning candidates $\{C_i^1, C_i^2, \ldots C_i^k\}$ according to the boundary values $x_1 < x^{'} < x_2$ given in following (3.1) and Fig. 3.5. That's said, we first separate the I/Q to real and imaginary parts and then compute the distance individually with the confine range of the spanning candidates.

$$\omega = \{\underbrace{C_i^1, C_i^2, \ldots C_i^k}_{\text{Total } N_i \text{ candidates}} \mid x_1 < x^{'} < x_2\} \tag{3.1}$$

$x^{'}$ is the estimated signal and $x_1 \ldots x_n$ are boundary values

The more obviously the characteristic is, the more the candidate size is. Therefore, the feature of Overlap Clustering Algorithm owning vary clusters with flexible size of spanning candidates is reasonable to deploy in practical communication environment.

For example, the candidate I/Qs are (+5,+5), (+5,+7), (+7,+5) and (+7,+7) while the real and imaginary values of estimated I/Q are both larger than 6.5. The candidate I/Qs are(+5,-3) ,(+5,-1), (+5,+1), (+5,+3),(+5,+5),(+5,-3) ,(+7,-1), (+7,+1), (+7,+3) and (+7,+5) while the real value is greater than 6.5 as well as the imaginary one is between 0 and 3.5.

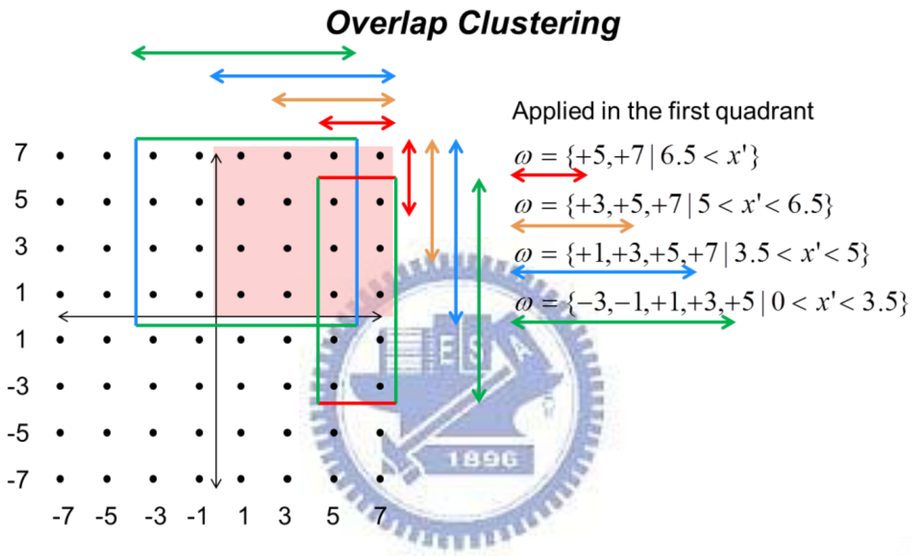

Figure 3.6 (a) Illustration of Overlap Clustering Algorithm applying in first quadrant in 64QAM

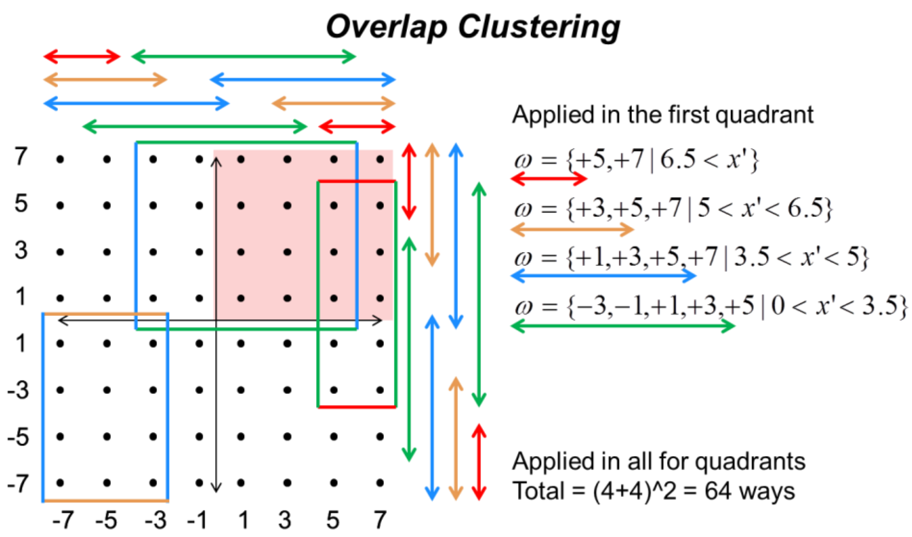

Figure 3.6 (b) Illustration of Overlap Clustering Algorithm in 64QAM

In the Fig. 3.5, it just represents the Overlap clustering Algorithm applying in first quadrant where the reference values are positive. While joining with the left ones, we will have a complete Overlap clustering Algorithm and the whole picture is shown in Fig. 3.6.

3.2.5 Dynamic Clustering Algorithm

To perform efficiently in the changing wireless environment, we deliver Dynamic Clustering Algorithm to enhance our Overlap Clustering Algorithm described previously. While employing Overlap Clustering Algorithm, we enlarge/narrow the possible constellations points $\{C_i^1, C_i^2, \ldots C_i^k\}$ according to the column norm $h^{'}$ of H which is included channel gain information at the same time.

$$\begin{aligned} &\omega = \{C_i^1, C_i^2, \ldots C_i^k \mid 0 < h^{'} < h_1\} \\ &\omega = \{C_i^1, C_i^2, \ldots C_i^{k-1} \mid h_1 < h^{'} < h_2\} \\ &\qquad \ldots \end{aligned} \tag{3.2}$$

$h^{'}$ is the column norm of H and $h_1 \ldots h_n$ are boundary valus

For instance, the original candidate I/Qs are (+7,+7), (+7,+5), (+7,+3), (+7,+1), (+5,+7), (+5,+5), (+5,+3), (+5,+1), (+3,+7), (+3,+5), (+3,+3), (+3,+1), (+1,+7), (+1,+5), (+1,+3) and (+1,+1) will be narrow down to (+3,+3), (+3,+5), (+5,+3) and (+5,+5) while the column norm $h^{'}$ is greater than 25.

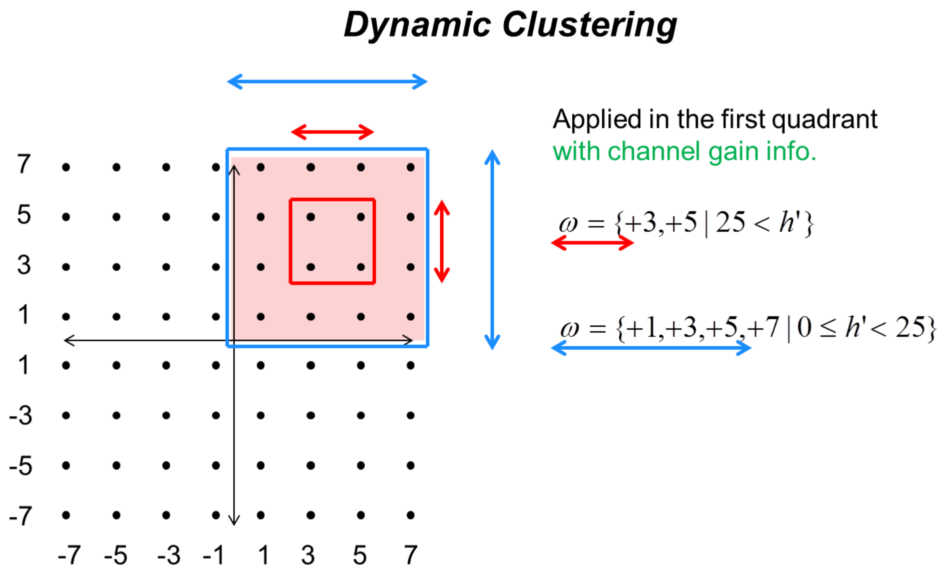

Figure 3.7 Illustration of Dynamic Clustering Algorithm in 64QAM

3.2.6 Detail Matching

The technique Detail Matching used here is one of the well-known SD algorithms named K-best algorithm. It is a breadth-first algorithm based on a tree decoding structure only searching in the forward direction, but the best K candidates are kept at each level. We make a distinct change in the origin K-best algorithm by eliminating the search space of the extending child nodes remarkably, and the principle of Detail Matching is outlined as below.

1) At the root node, initialize all paths with PED (Partial Euclidean Distance) zero.
2) Apply Variable and Overlapped Cluster-based Algorithm to prune the search space of the extending child nodes.
3) Extend each survivor path, retained from the previous node, to contender paths, and then update the accumulated PEDs for each path.
4) Sort the contender paths according to their accumulated PEDs, and select the shortest K-best paths.
5) Update the path history for each retained path, and discard the other paths.
6) If the iteration arrives at the end node, stop the algorithm. Otherwise, go to 2).

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

Meanwhile, a strict K-best algorithm should keep as large as possible without compromising on the optimality, compared with the exhaustive-search ML algorithm. However, limitation can reduce the complexity of the breadth-first algorithm. Therefore, there is a tradeoff between complexity and performance in to select a proper K value.

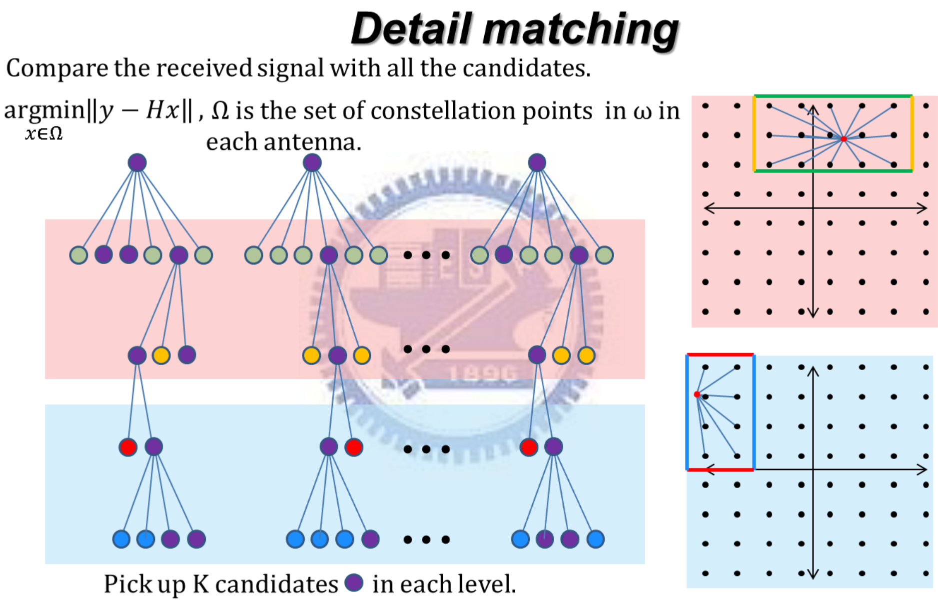

Figure 3.8 Illustration of Detail Matching in 64QAM

Chapter 4

Simulation Results

This section compares performance and complexity between K-best SD and the Variable and Overlapped Cluster-based Algorithm in MIMO detection. Note that the performance comparison is considered under packet error rate (PER) 0.08 and normalizes to the ML detection methods.

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 4.1.

Environment Description	
Parameter	***Value***
Simulation Platform	IEEE 802.11n
Signal Bandwidth	40 MHz
Number of subcarries	108 subcarriers
FFT size	128 points
Number of antenna	4 Tx 4 Rx / 8 Tx 8 Rx
Forward Error Correction	Convolution and Viterbi (Coding Rate 2/3)
Packet size	1024 Bytes per Tx antenna
Channel Model	TGN-E with AWGN
RMS delay spread	100 ns
Subcarrier modulation	64QAM/256QAM
Preprocessing Block	SQRD、ZFD
Signal Detection	K-best SD Algorithm Variable and Overlapped Cluster-based

Table 4.1 Simulation parameters

4.1 Performance Evaluation

Since K-best sphere decoder was accepted in practical implementation, the goal of our Variable and Overlapped Cluster-based algorithm is complexity reduction and remains performance at the same time. To compare with the K-best sphere decoder, we tune K-best parameter: k and cluster parameter: Spanning Cluster Candidate & Boundary to have nearly the same performance in different methods.

For the purpose of performance comparison, Fig. 4.1 and Fig. 4.2 present the PER with ML, the Variable and Overlapped Cluster-based algorithm as well as K-best sphere decoders for 4 x 4 and 8 x 8 MIMO-OFDM systems. The methods such as the proposed Variable and Overlapped Cluster-based method and K-best sphere decoder maintain SNR degradation within 0.57dB in the Fig. 4.2 and 0.58dB to 1.02dB in the Fig. 4.3.

The table 4.2 summarizes the performance of Fig. 4.1 normalized to ML detection method and the complexity compared with the K-best SD algorithm. The proposed Variable and Overlapped Cluster-based algorithm can maintain performance within 0.57dB such that the method is suitable for practical system. And the algorithm complexity can reduce to 27.29% ~ 56.25% in average case and 39.06% ~ 57.25% in worst case which means the hardware cost in practical implementation.

For 8 x 8 MIMO-OFDM systems in the table 4.3, the proposed method maintains performance within 1.02dB. Still, the algorithm complexity can reduce to 35% ~ 56.25% in average case and 57.25% in worst case .

It's clear to see that, there is better performance in 4 x 4 MIMO-OFDM system rather than 8 x 8 one. However, while it comes to higher antenna number, it becomes a critical issue that the complexity grows remarkably. Hence, Variable and Overlapped Cluster-based method will be acceptable in practical.

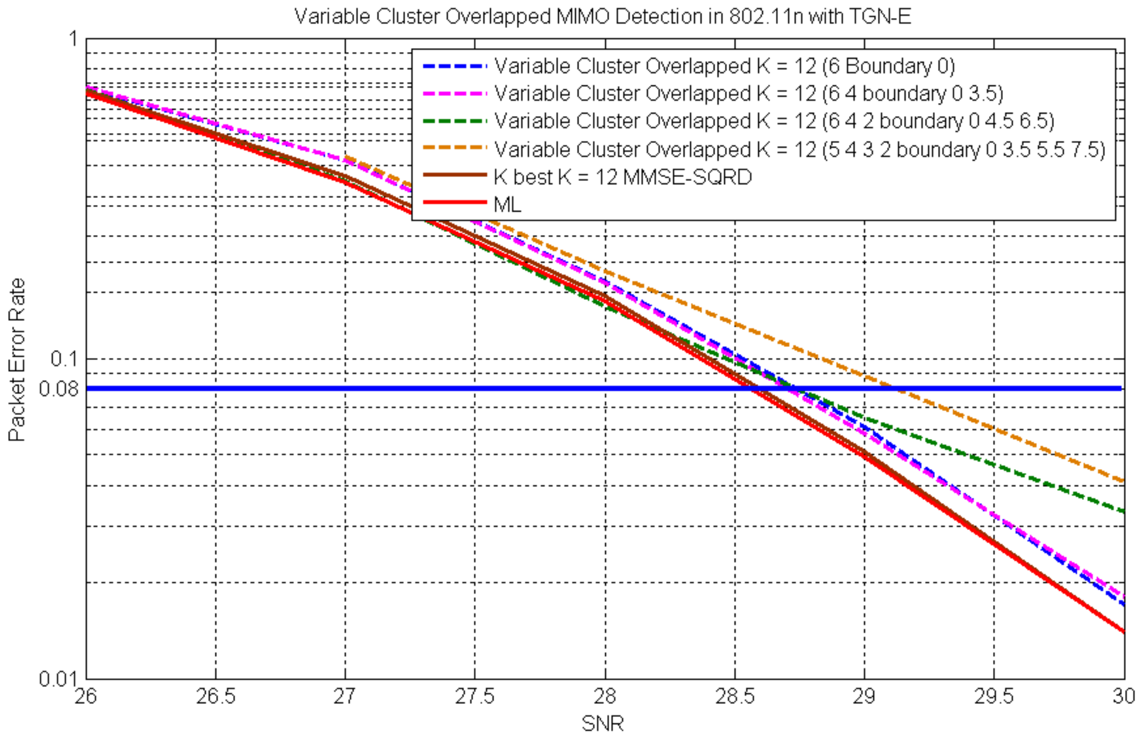

Figure 4.1 Performance in the VACO, 4T4R 64QAM

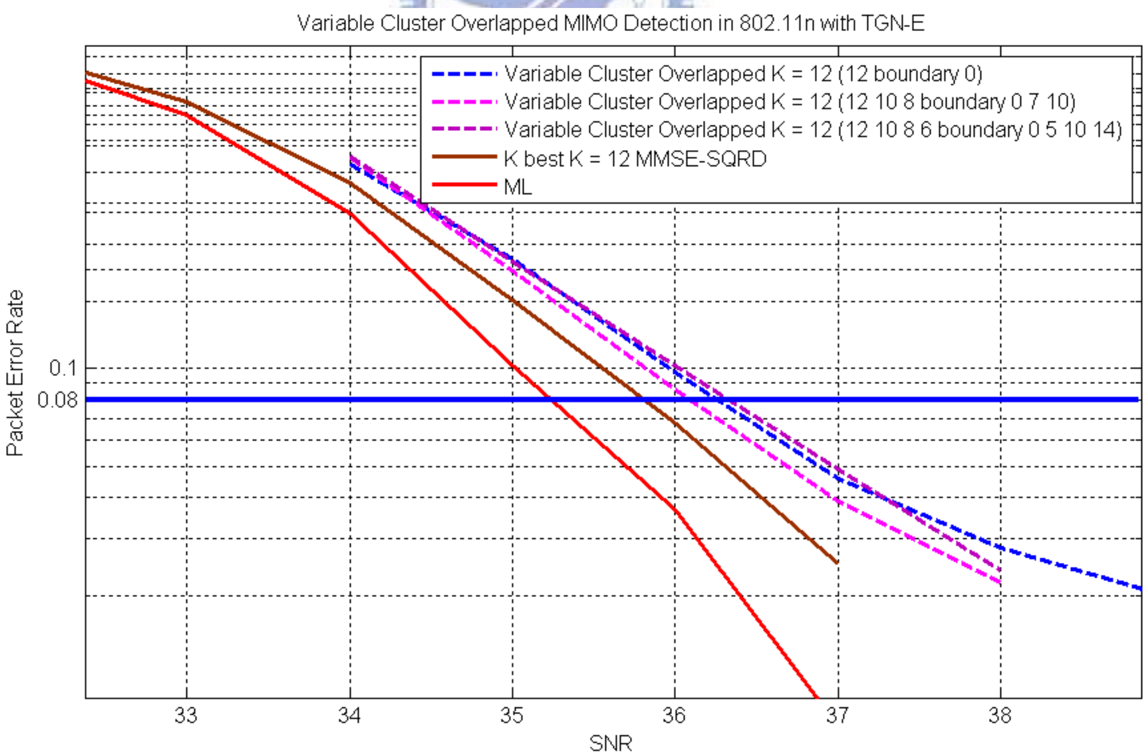

Figure 4.2 Performance in the VACO, 8T8R 256QAM

4 x 4 MIMO-OFDM system 64 QAM						
Method	ML	K-best SD MMSE-SQRD	Variable and Overlapped Cluster-based			
	×	K=12	K=12			
Spanning Cluster Candidate	8	8	6	6,4	6,4,2	5,4,3,2
Boundary	×	×	0	0,3.5	0,4.5,6.5	0,3.5,5.5,7.5
SNR in PER 0.08	28.55	28.62	28.74	28.70	28.77	29.13
SNR-Loss	0	0.07	0.19	0.15	0.22	0.57
Average Case						
Candidate Number Reduction	×	100%	56.25%	38.25%	38.17%	27.29%
Multiplication	×	36864	20736	14100	14071	10059
Addition	×	35008	19692	13390	13362	9553
Worst Case						
Candidate Number Reduction	×	100%	56.25%	56.25%	56.25%	39.06%
Multiplication	×	36864	20736	20736	20736	14400
Addition	×	35008	19692	19692	19692	13675

Table 4.2 Performance & complexity reduction table, 4T4R 64QAM

8 x 8 MIMO-OFDM system 256 QAM					
Method	ML	K-best SD MMSE-SQRD	Variable and Overlapped Cluster-based		
		K=12	K=12		
Spanning Cluster Candidate	16	16	12	12,10,8	12,10,8,6
Boundary			0	0,7,10	0,5,10,14
SNR in PER 0.08	35.23	35.81	36.25	36.15	36.15
SNR-Loss	0	0.58	1.02	0.92	0.92
Average Case					
Candidate Number Reduction		100%	56.25%	39.94%	35%
Multiplication		294,912	165,888	117,798	102,407
Addition		289,536	162,864	115,651	100,540
Worst Case					
Candidate Number Reduction		100%	56.25%	56.25%	56.25%
Multiplication		36,864	165,888	165,888	165,888
Addition		35,008	162,864	162,864	162,864

Table 4.3 Performance & complexity reduction table, 8T8R 256QAM

4.2 Complexity Evaluation

Discussed in the section 4.1 previously, we compare the complexity between the Variable and Overlapped Cluster-based algorithm and K-best SD with nearly the same performance. Differently in this section, we do a comparison of the performance between them with nearly the same complexity.

By observing the Fig. 4.3, it's very clearly to see that the Variable and Overlapped Cluster-based algorithm has better performance than K-best SD. Meanwhile, it also maintains performance within 0.5dB that the method is suitable for practical system.

While it comes to the same complexity in both methods above, detail statistics are shown in table 4.4. Our proposal method is 0.25dB better compared to K-best SD.

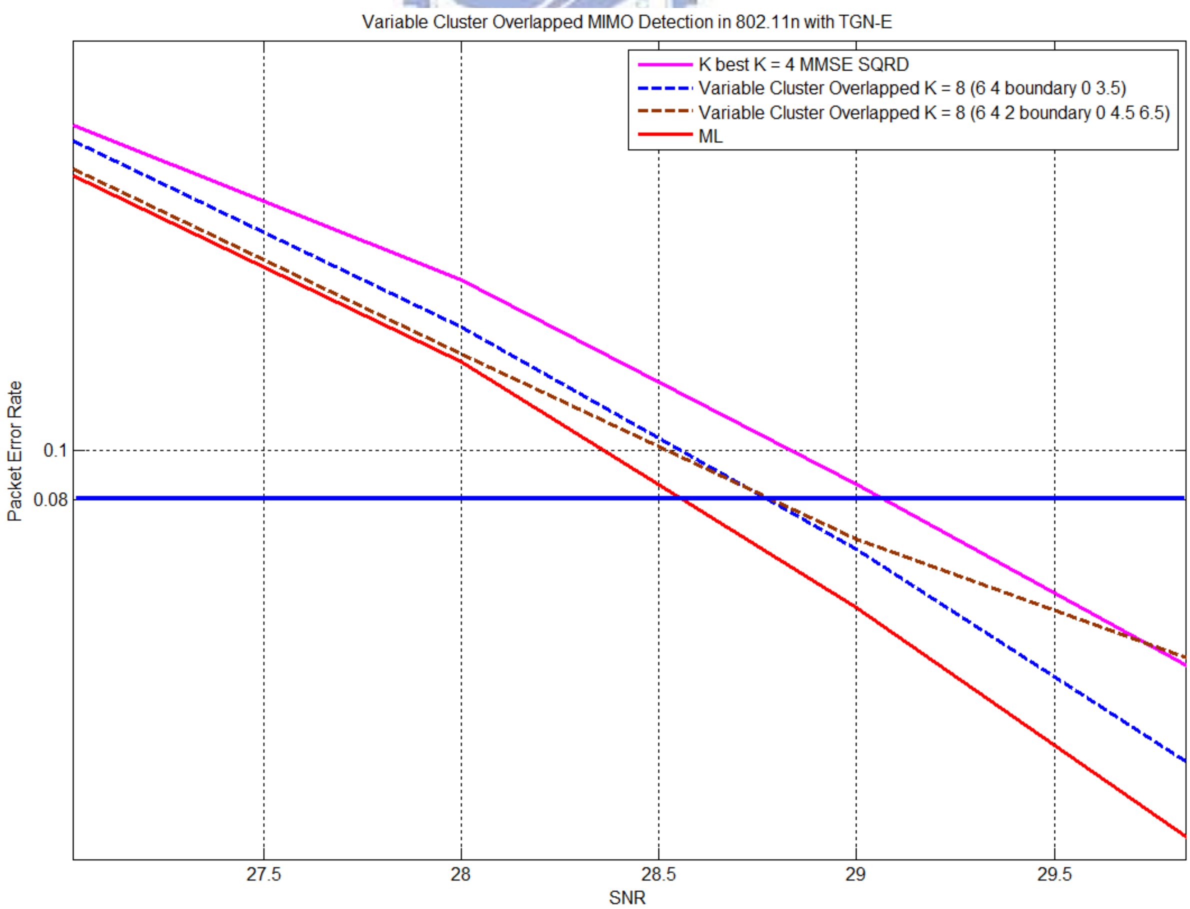

Figure 4.3 Performance in the VACO with the same complexity, 4T4R 64QAM

<table>
<tr><th colspan="5">4 x 4 MIMO-OFDM system 64 QAM</th></tr>
<tr><td rowspan="2">Method</td><td>ML</td><td>K-best SD
MMSE-SQRD</td><td colspan="2">Variable and Overlapped Cluster-based</td></tr>
<tr><td></td><td>K=4</td><td colspan="2">K=8</td></tr>
<tr><td>Spanning Cluster Candidate</td><td>8</td><td>8</td><td>6,4</td><td>6,4,2</td></tr>
<tr><td>Boundary</td><td></td><td></td><td>0,3.5</td><td>0,4.5,6.5</td></tr>
<tr><td>SNR in PER 0.08</td><td>28.55</td><td>29.08</td><td>28.78</td><td>28.79</td></tr>
<tr><td>SNR-Loss</td><td>0</td><td>0.53</td><td>0.23</td><td>0.24</td></tr>
<tr><th colspan="5">Average Case</th></tr>
<tr><td>Candidate Number Reduction</td><td></td><td></td><td>38.25%</td><td>38.17%</td></tr>
<tr><td>Multiplication</td><td></td><td>24,576</td><td>18,800</td><td>18,761</td></tr>
<tr><td>Addition</td><td></td><td>24,768</td><td>18,580</td><td>18,541</td></tr>
<tr><th colspan="5">Worst Case</th></tr>
<tr><td>Candidate Number Reduction</td><td></td><td></td><td>56.25%</td><td>56.25%</td></tr>
<tr><td>Multiplication</td><td></td><td>24,576</td><td>27,648</td><td>27,648</td></tr>
<tr><td>Addition</td><td></td><td>24,768</td><td>27,324</td><td>27,324</td></tr>
</table>

Table 4.4 Performance & complexity table, 4T4R 64QAM

Chapter 5

Hardware Implementation and Measurement

5.1 Introduction

The Variable and Overlapped Cluster-based algorithm is a modified method of K-best SD, thus it inherits the K-best SD advantage so that it is very suitable to parallel and design in pipeline. In this chapter, our proposed hardware architecture is presented.

5.2 Design Flow

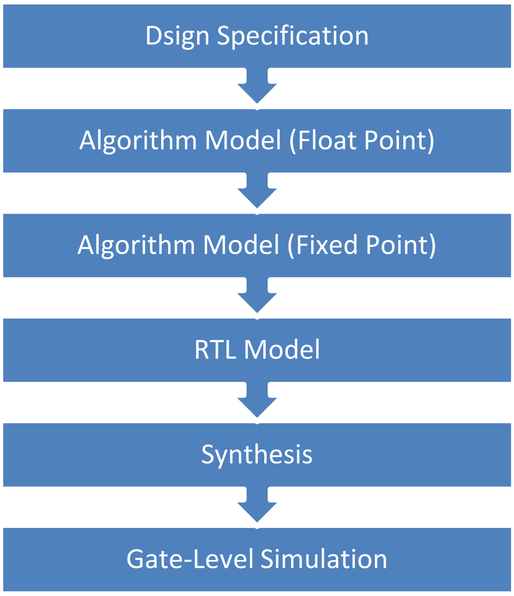

Figure 5.1 The design flow

In the Fig. 5.1 shows the design flow of the hardware architecture for the

Variable and Overlapped Cluster-based algorithm. In the step of algorithm design, Matlab is used to build up and experiment the detecting algorithm. After the algorithm model is determined, the measurement of the bit length and accuracy is applied so that we need to convert the variable from float point to fixed point. Meanwhile, the performance loss is taken carefully and the golden pattern is generated for logic design. After the algorithm simulations, the hardware design is implemented by Register Transfer Level (RTL) with the Verilog. The Verilog tool helps us code in behavior language and confirm the correctness of hardware design. Then, the RTL code will be synthesized by Design Compiler to gate-level netlist. Finally, the gate-level simulation helps us to verify whether the behavior of gate-level is fit in with our requirements.

5.3 Proposed Architecture

Table 5.1 gives the detail specification of the Variable and Overlapped Cluster-based algorithm, where achieving GigaLAN is our goal here.

The Fig. 5.2 illustrates overviews of the VACO. In the top architecture diagram, there is a preprocessing block including common sorted QR decomposition (SQRD). And the MIMO Detection is implemented with the Variable and Overlapped Cluster-based algorithm.

The Fig. 5.3 shows the parallel architecture of the proposed architecture. Due to the reason that there’s not enough time to process the input I/Qs while using only one set of MIMO Detector. (Roughly 4 clock cycle time to process one level I/Qs which is absolutely impossible). With 14 sets of MIMO detector in parallel architecture, there’s is enough time to finish this work. (Up to 56 clock cycle time)

As shown in block diagram of Fig. 5.2, the architecture consists of twelve pipeline stages. Each stage has a processing element (PE), which implements the operations corresponding to step 2)–step 5) of Detail Matching in section 3.2.6. Stage 1 to stage 12 corresponds to the twelfth to the first level of computation in the algorithm. The buffers R, Z, D, U and E between adjacent PEs are correspond to the upper triangular matrix, updated received signal, K-best PEDs, K-best paths and estimated signal in the algorithm, respectively.

Design Specification	
Parameter	***Value***
Simulation Platform	IEEE 802.11n
Signal Bandwidth	50 MHz
Number of subcarriers	108 subcarriers
FFT size	128 points
Number of antenna	6 Tx 6 Rx
Forward Error Correction	Convolution and Viterbi (Coding Rate 3/4)
Packet size	1024 Bytes per Tx antenna
Subcarrier modulation	256QAM
Preprocessing Block	ZFD
Signal Detection	Variable and Overlapped Cluster-based

Table 5.1 The proposed design specification

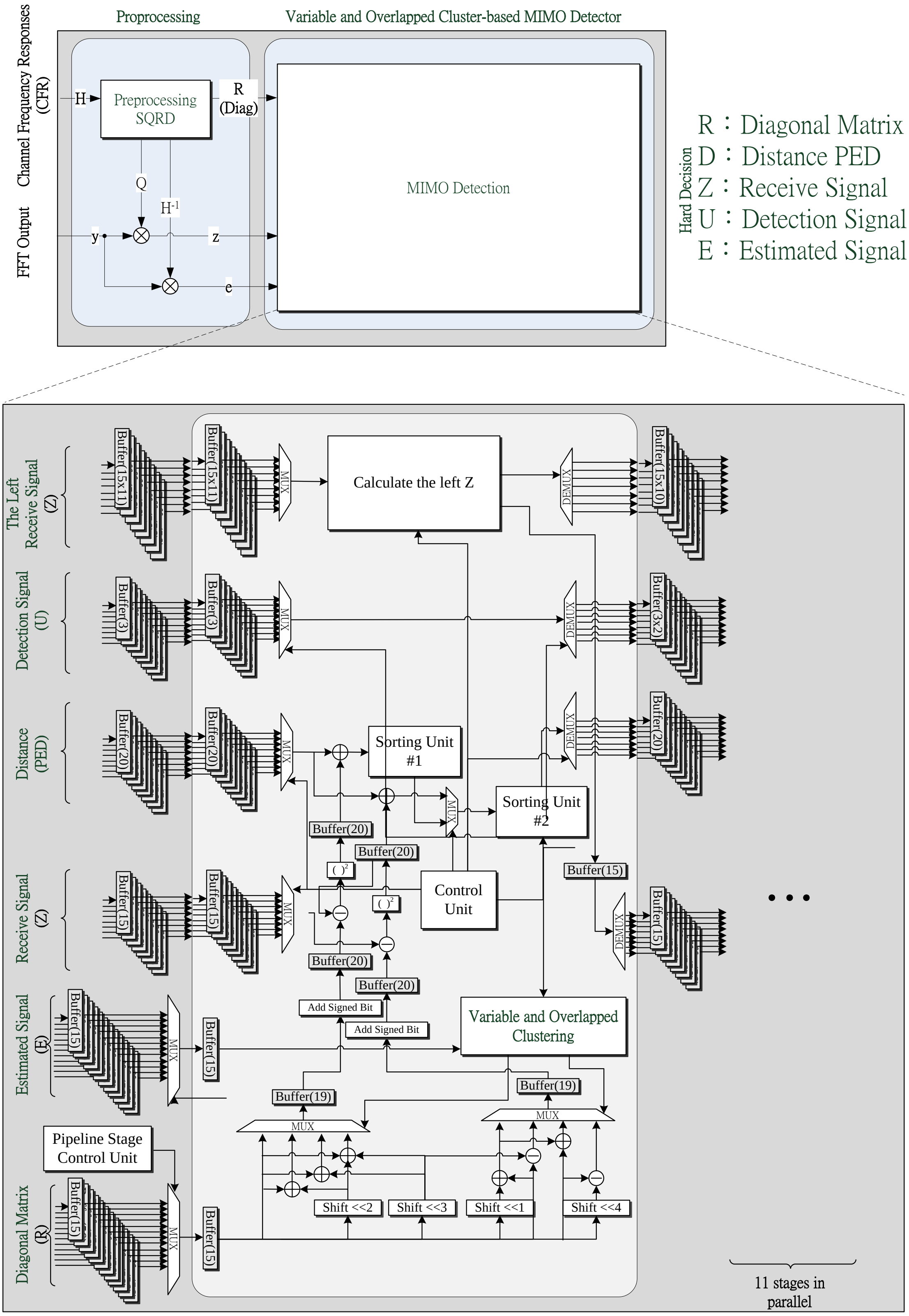

Figure 5.2 VLSI architecture of the VACO for 6T6R 256-QAM MIMO system

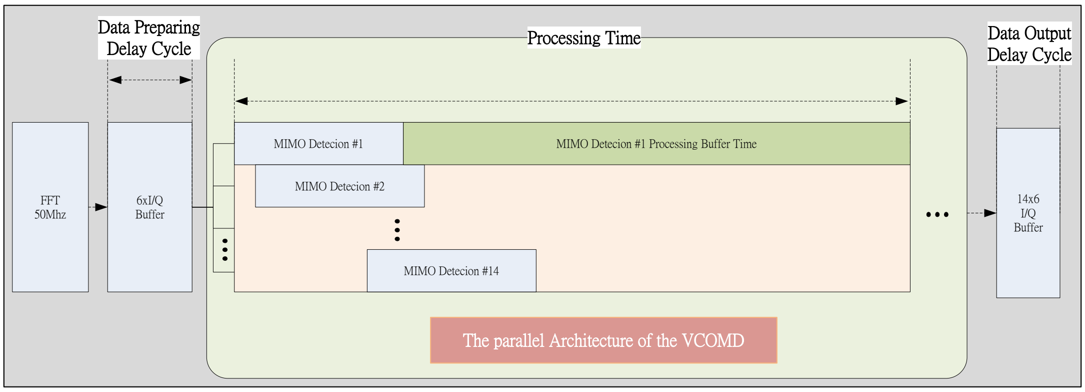

Figure 5.3 The parallel architecture of the VACO

5.3.1 Word-Length Determination

In the mathematical model, all the variable and computations use the floating point number. On the other hand, the practical hardware computations use the fixed point number. To translate the float point model to fixed point model, the simulations of measurement are required. The measurement includes the length (width) and depth (accuracy). The longer word length it has, the higher performance it has. Hence, the tradeoff between the hardware cost and performance is needed. Fig. 5.4 illustrates the signal distribution of variable R, and the word length and the depth of variable R are roughly 15 and 2^{-10}. The value is a rough estimate, and the detail simulations will be taken to get the proper parameter.

Table 5.2 a) gives the number of all buffer needed while table 5.2 b) collates the word-length information of all buffer. In the end, the performance comparison between floating point and fixed point is showed in Fig. 5.5 with 256-QAM 6 x 6 MIMO system. The SNR degradation in word-length determination is less than 0.2 dB.

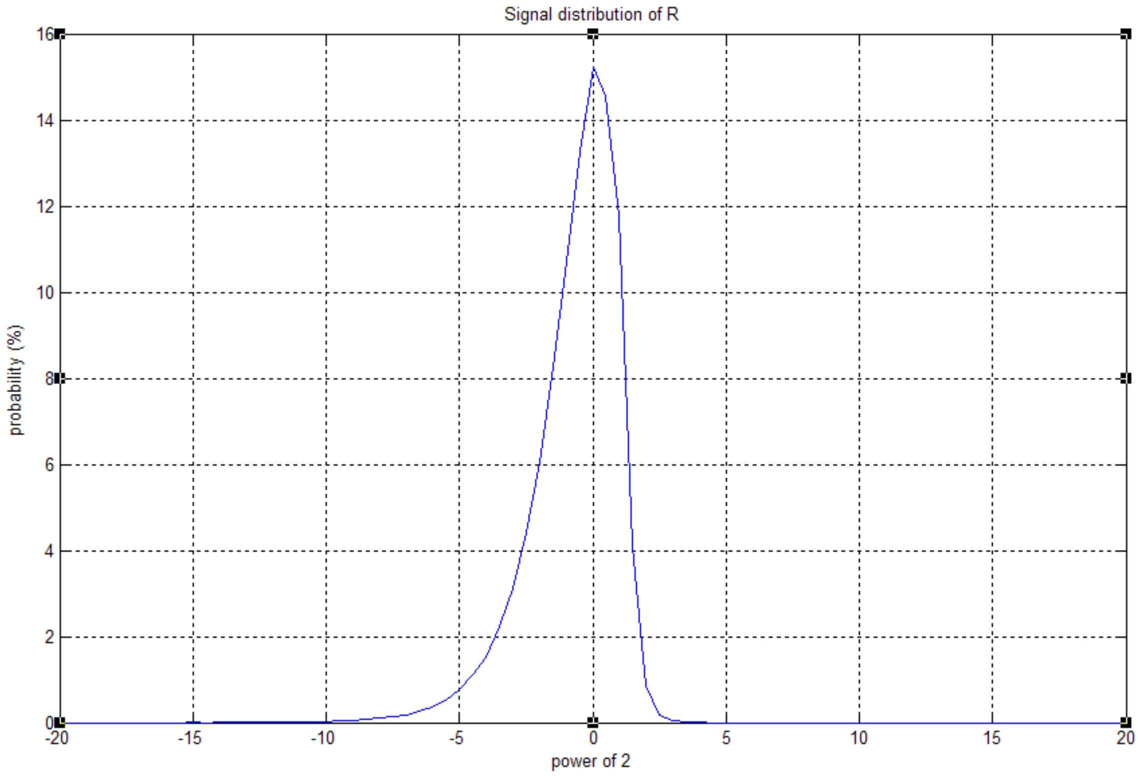

Figure 5.4 The signal distribution of variable R.

Buffer	Stage											
	1	2	3	4	5	6	7	8	9	10	11	12
R	1x12	1x11	1x10	1x9	1x8	1x7	1x6	1x5	1x4	1x3	1x2	1x1
D	8	8	8	8	8	8	8	8	8	8	8	1
Z	8	8	8	8	8	8	8	8	8	8	8	1
U	8x1	8x2	8x3	8x4	8x5	8x6	8x7	8x8	8x9	8x10	8x11	8x12
E	1	1	1	1	1	1	1	1	1	1	1	1

Table 5.2 (a) Buffer number needed in each stage

	Word-Length
R	15
D	20
Z	15
U	3
E	15

Table 5.2 (b) Word-length needed in each buffers

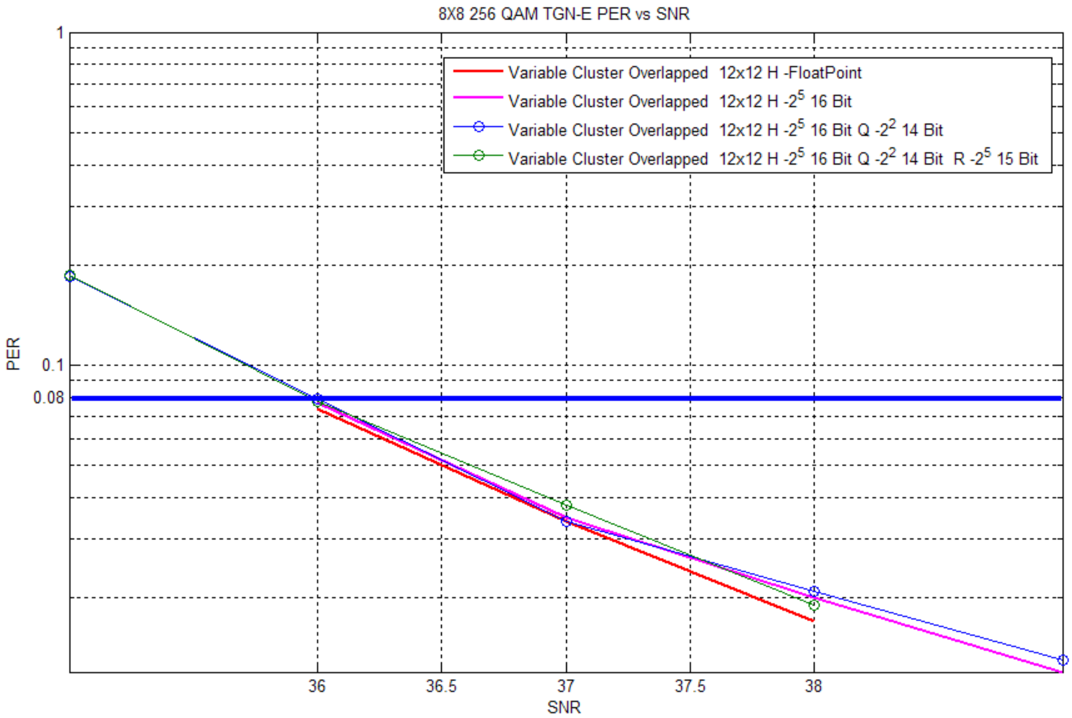

Figure 5.5 Performance comparisons between float point and fixed point

5.3.2 Sorting Design

In each PEs, there are 16 PEDs to sort or 96 PEDs at most. Sorting PEDs is the most time-cost part in the MIMO Detection. This is a critical issue in our VSLI implementation. To overcome the problem of sorting, we deliver 3 sorting designs, which are combined with different number of sorting unit.

The sorting unit shown in Fig. 5.4 employ insertion sort algorithm so that it is able to sort one input data in one cycle time. The first design with one sorting unit in Fig. 5.5 (a), it costs 16 to 96 clock cycles to finish the ordering procedure. And the second one with three sorting units in Fig 5.5 (b), it costs 24 to 64 clock cycles. For the last updated design with two sorting units Fig 5.5 (c), it costs 16 to 56 clock cycles.

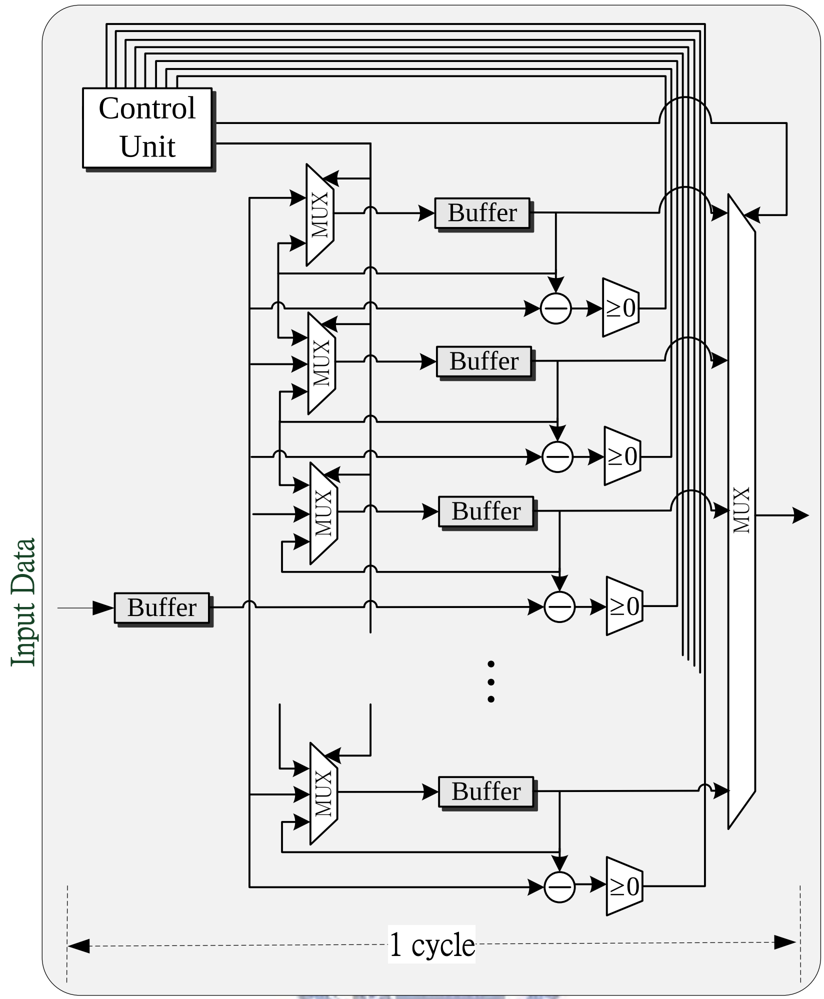

Figure 5.6 VLSI structure of the sorting unit.

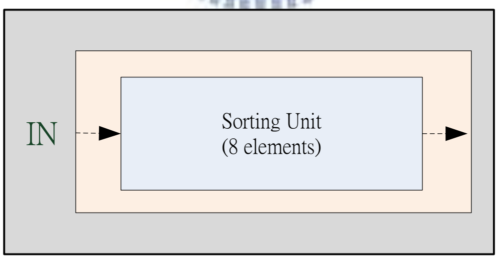

Figure 5.7 (a) The original design of sorting

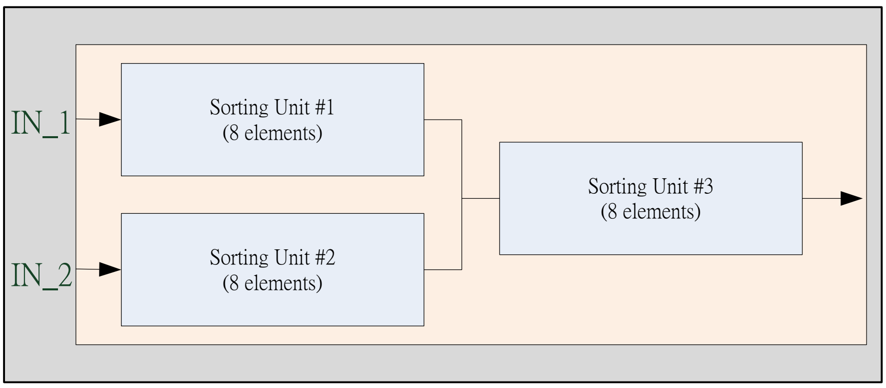

Figure 5.7 (b) The alternative sorting design

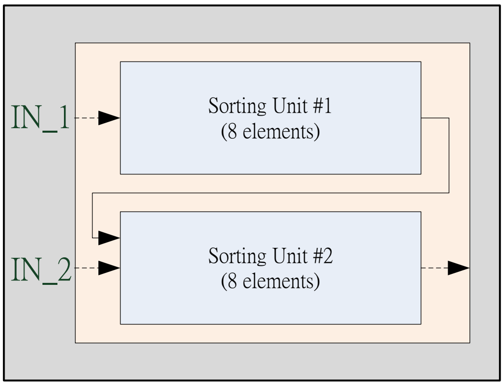

Figure 5.7 (c) The updated sorting design

5.4 Complexity Analysis

In this section, the proposed design is written in Verilog code and sythesised with the library (TSMC 65 nm).

Due to the reason that we want to deliver a RF receiver in 802.11n with GigaLAN spec, there are several critical issues we must face to. The most critical one is that in worst case the tatal cycles taken by a MIMO detection set is 56 cycles (roughly 140 ns), and the Processing Data Rate we have is only 10 ns. To archieve the goal, we have 12 parallel MIMO Detection sets to slow the Processing Data Rate down to 120 ns. Meanwhile with some tricky techniques, I steal some cycles (about 20 ns) in the first and last stages to fit the requirement. On the other hand, the bit length of sorting block is also a key point to reduce the cell area. We remove the LSB of the sorting bit length from 24 bit to 16 bit.

Finally, we deliver a ASIC with roughly 4M gate counts in 6x6 MIMO Detection in 802.11n with GigaLAN criteria.

GigaLAN Spec.	
Signal Bandwidth	50 MHz(256QAM)
Processing Data Rate (Ⅰ)	20 ns /per IQ
Processing Data Rate (Ⅱ)	10 ns
Implementation Issue	
Sorting Type	2 sets
Sorting Bit Length	16 bits
Clock Frequency ('tcbn65gpluswcl‘)	400 MHz (600MHz)
Cycle Period	2.5 ns
Cycles Taken (Worst case)	56 cycles
Processing Data Period (Worst case)	~140 ns
Parallel MIMO Detection Sets Needed (Worst case)	12 sets (120 ns)
Gate Counts of 6x6 256QAM MIMO Detection	
Technology	65 nm
Max. feq	400 Mhz
Parallel MIMO Detection Sets Needed (Worst case)	12
Cell Area	4,303 k
Total Gate Counts (k)	3,984 k

Table 5.3 The summary of systhesis results.

Chapter 6 Future Works and Conclusion

The Variable and Overlapped Cluster-based algorithm presents a near ML performance, low-complexity MIMO detection design, which uses a pre-estimate signal and channel gain information to reduce hardware cost of MIMO-OFDM wireless system. Simulations and measurements indicate that the proposed method can reduce complexity to 27.29% ~56.25% (where the K-best SD is regard as 100%) while still achieving 8% PER with 0.57 dB (4T4R) and 1.02 dB (8T8R) SNR loss compared with MLD in frequency-selective fading of TGN-E channel [10].

Without any specific preamble, pilot format and STBC coding skills, the Variable and Overlapped Cluster-based detection algorithm can provide near ML performance with relatively low complexity especially in higher antenna scheme.

This study is now working in both 802.11n and TGac MIMO-OFDM systems. Nevertheless, this study does not only deliver an efficient solution for OFDM-based MIMO receivers, but is also well-suited method for next-generation wireless LAN discussed in IEEE 802.11 VHT study group.

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