Master's Thesis
석사 학위논문

Iterative MIMO Detection Based on Dimension Reduction Soft Demodulation

Sang-Sik Shin (신 상 식 辛 相 植)

Department of Information and Communication Engineering
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Advisor : Professor Ji-Woong Choi

Co-advisor : Professor Hongsoo Choi

By

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A thesis submitted to the faculty of DGIST in partial fulfillment of the requirements for the degree of Master of Science in the Department of Information and Communication Engineering. The study was conducted in accordance with Code of Research Ethics[1]

12. 5. 2012

Approved by

Professor Ji-Woong Choi (Signature)
(Advisor)

Professor Hongsoo Choi (Signature)
(Co-Advisor)

[1] Declaration of Ethical Conduct in Research: I, as a graduate student of DGIST, hereby declare that I have not committed any acts that may damage the credibility of my research. These include, but are not limited to: falsification, thesis written by someone else, distortion of research findings or plagiarism. I affirm that my thesis contains honest conclusions based on my own careful research under the guidance of my thesis advisor.

Iterative MIMO Detection Based on Dimension Reduction Soft Demodulation

Sang-Sik Shin

Accepted in partial fulfillment of the requirements for the degree of Master of Science.

12. 5. 2012

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ABSTRACT

Spatial multiplexing (SM) multi-input multi-output (MIMO) technology is considered as core advanced communication technology to achieve more capacity. Although it guarantees more capacity, it gives huge burden on the receiver side to detect each stream which is transmitted from each transmit antenna. The main reason is inter-stream interference caused from streams of other antennas.

In this thesis, to reduce inter-stream interference effects we propose dimension reduction soft demodulation (DRSD) with maximum a posteriori (MAP) for iterative detection and decoding (IDD). The DRSD with MAP employs all ordering successive interference cancellation (AOSIC) with slicing MAP criterion for hard detection and also adding one more candidate for AOSIC to improve performance. DRSD can provide low complexity to separate hard streams and soft streams and slicing MAP criterion also provides similar performance to conventional IDD algorithms such as the soft-input soft-output single tree-search based on sphere decoding (SISO-STS-SD) which has better performance than others.

Our proposed algorithm can reduce the complexity of iterative soft MIMO detection and give fixed complexity on the variety of SNR. Moreover, receiver performance of proposed scheme nearly approaches the performance of SISO-STS-SD.

Keywords: Dimension reduction soft demodulation. Iterative detection and decoding. All ordering successive interference cancellation, Slicing MAP criterion.

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Ⅰ. INTRODUCTION

1.1 Overview of this study

The continuous increase in data rate currently caused by mobile devices such as smart phones, portable multimedia devices and tablet PCs cannot be neglected. To meet these explosive needs, advanced technology is required such as MIMO which employs multiple antennas on both sides of the antennas. Specifically, spatial multiplexing (SM) MIMO technology is considered a main technology to provide more capacity and concurrently has been incorporated in many advanced wireless communication standards such as IEEE 802.11n and LTE-Advanced [1]. On the other hand, SM MIMO technology places a huge burden on the receiver side because of inter-stream interference. To detect each symbol or bit, we should deal with inter-stream interference because each receiver antenna gets interferences from other antennas. To reduce the inter-stream interference, many schemes have been developed such as linear equalizers [2] or maximum likelihood detectors, etc. Among these algorithms, although maximum likelihood (ML) detector has optimal performance, it entails significant complexity to determine each stream though the candidates for M^{N_S} where M is the number of complex constellations and N_S is the number of spatial streams.

Moreover, when using channel coding such as convolution coding or block coding or low-density parity-check (LDPC), ML detectors cannot provide optimum performance because channel coding causes correlation between bits. The detector must make a decision jointly on all the blocks using knowledge of the correlations across blocks introduced by the channel code. In the case of a coded system, a soft decision detector, calculation of the log likelihood ratio (LLR) of each bit is required and has better performance instead of a hard decision detector.

However, the soft decision detector is also insufficient to achieve near-capacity bound. Therefore, we consider iterative detection and decoding (IDD) algorithms which, in general, can achieve significantly better performances when using the priori information rather than decoding on hard detection or soft detection only [3]-[7]. When better performance is required, iterative detection is one of best solutions. However, IDD has significant computational tasks compared to the hard detector or soft detector only. Thus, we propose a low complexity solution with better performance for iterative SM MIMO detection.

1.2 Notation

The superscripts ^{T} and ^{H} stand for transpose and conjugate transpose, respectively. The $\mathbf{C}^{M\times N}$ is a set of all complex matrices of size $M\times N$. M_T and M_R are the number of transmitter and receiver antennas respectively. N_s (= $min\{M_R, M_T\}$), is the number of spatial streams. M represents the number of complex constellation points for the modulation. $b_{s,b}$ is the b-th bit of the s-th stream. $\mathrm{P}[s]$ indicates the probability of an event s. The probability density function of an event s is expressed as $\mathrm{p}[s]$.

Ⅱ. MIMO SPATIAL MULTIPLEXING TECHNOLOGIES BACKGROUND

2.1 System model

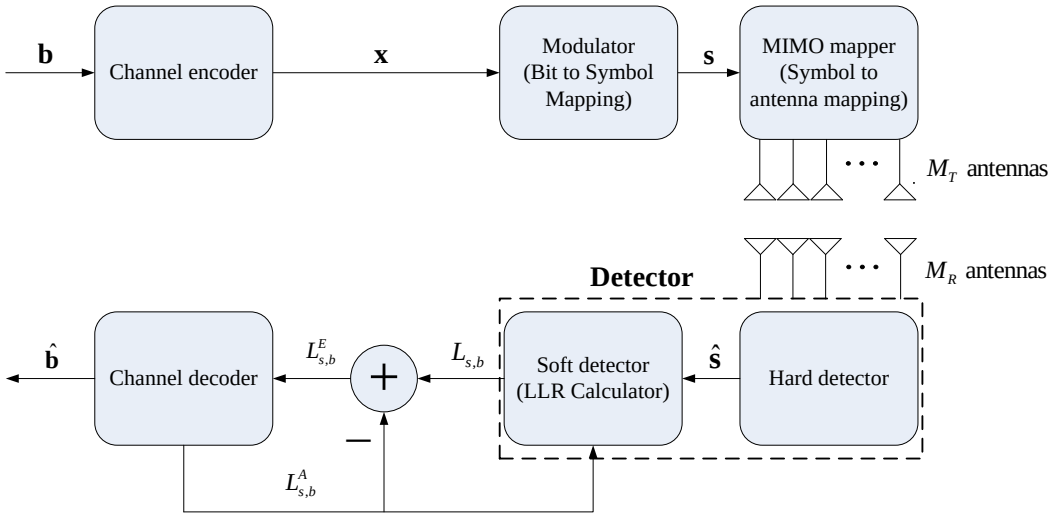

Figure 2.1 Coded SM MIMO transmitter and receiver.

We consider a coded SM MIMO system with M_R and M_T over a flat fading channel as shown in Fig. 2.1 where $\mathbf{b}$ is data bits, $\mathbf{x}$ is coded bits, $\mathbf{s}$ is transmit symbols, $\hat{\mathbf{s}}$ is detected transmit symbols and $\hat{\mathbf{b}}$ is estimated bits. At the transmitter, data bits sequences are encoded by a coding scheme such as block codes, turbo codes, and low density parity check (LDPC) codes. The coded bits are assigned into N bits, which are mapped to a modulation symbol for M-ary modulation with $M = 2^N$. Then, a group of N_s streams are transmitted through multiple transmit antennas. The received signal through a channel can be represented as

$$\mathbf{y}=\mathbf{Hs}+\mathbf{z}, \tag{1}$$

where $\mathbf{y} = [\mathrm{y}_1 ... \mathrm{y}_{M_R}]^T$ is an $(M_R \times 1)$ receiver signal vector, $\mathbf{H} = [\mathbf{h}_1 ... \mathbf{h}_{M_T}]$ is a $(M_R \times M_T)$ effective channel matrix with $\mathbf{h}_m$ representing an $(M_R \times 1)$ channel gain vector from the m-th stream to all receive antennas, and $\mathbf{s}$ is a vector of transmit symbol such as $\mathbf{s} = [\mathrm{s}_1 ... \mathrm{s}_{N_S}]$.

We assume the channel $\mathbf{H}$ and the noise variance σ^2 are perfectly known at the receiver. In addition, the probability density function (pdf) of the noise vector $\mathbf{z}$ is expressed as

$$p(\mathbf{z}) = \frac{1}{(\pi\sigma^2)^{N_R}} \exp(-\frac{1}{\sigma^2}\|\mathbf{z}\|^2). \tag{2}$$

2.2 SM detection and decoding

MIMO technology provides two main advantages; diversity gain and SM gain [2]. Diversity gain is connected to reliability which is related to how error probability can be reduced. On the other hand, SM represents that how many data rates can be transmitted. In this thesis, we consider only SM as a method of capacity improvement.

SM of MIMO technology basically loads each data stream on each antenna as shown in Fig. 2.1 assuming $M_R \geq M_T$. Although the transmitters load the data stream on each antenna, the receiver cannot detect the stream of each antenna correctly because of inter-stream interference from other antennas. To reduce the effect of inter-stream interference, a variety of SM detection algorithms are presented such as linear equalizer or decision feedback equalizer. Among algorithms, vertical Bell Lab layerd space-time (V-BLAST) [8] which removes interference between inter-streams and successively detects each stream is a popular detection because of good performance and easy implementation.

Then, SM detection algorithms are combined with channel coding schemes to achieve near channel capacity. In Fig. 2.1, SM detection and the channel decoding block are independently operated to estimate each bit correctly. The bit information delivered to the decoder from the detector is measured as the ratio of bit probabilities and is called the maximum a posteriori (MAP) or a posteriori probability (APP). There are two ways to exchange information between SM detection and decoder such as non-iterative detection decoder (Non-IDD) and iterative detection and decoder (IDD). In non-IDD, an output of the detector is passed to the channel decoder for bit decision without any feedback where the detector can employ hard or soft detection. Hard-detection is to determine each symbol independently using a symbol by symbol detector such as linear detector and non-linear detector. Soft-detector is expressed as the log likelihood ratio (LLR) called L-values [9]. The large absolute value of LLRs means that the detected or decoded bit information is reliable. By contrast, near zero value of LLRs indicates that the estimated bit is unreliable. On the other hand, in IDD, priori information between the

detector and decoder is exchanged in an iterative operation until desired performance is achieved or maximum numbers of iterations are performed. The IDD achieves near optimum performance with MAP or APP unlike non-IDD. More details are described below.

2.3. Non-iterative detection and decoding

Non-IDD assumes that all transmitted messages are of equal probability. Then, priori information is not considered in this algorithm. There are mainly two receivers in non-iterative detection and decoding such as hard-detection receivers and soft-detection receivers. The details are presented below.

2.3.1 Hard-detection receivers

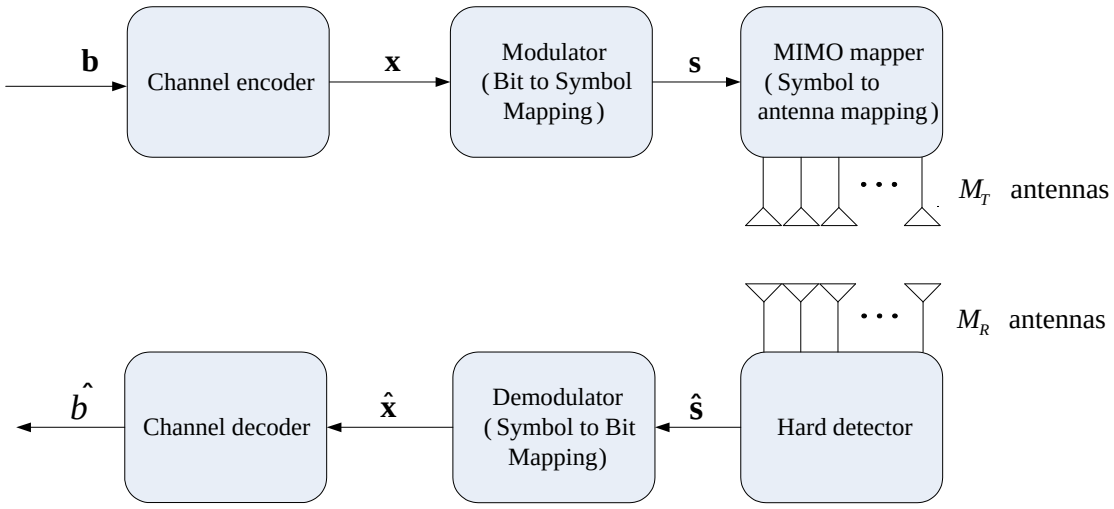

Figure 2.2 A MIMO receiver model with hard detection receivers

Hard SM detection as a symbol by symbol detector determines the transmitted streams without any other information from the decoder such as feedback and can provide estimated bits from demodulator to decoder. These are the main characteristics from my points of view. Fig. 2.2 shows a MIMO receiver model with hard detection receivers.

The SM MIMO hard detector detects a transmit symbol vector from the signal vector received at the receive antennas. Each element of the transmit symbol vector is demapped to the candidate symbol on the constellation used at the transmitter, which in turn estimates the coded bits transmitted. The estimated coded bit is used by the hard

decoder to generate the data bit. An uncoded system can be viewed as a special case of this hard decoding, where there exists no encoder at the transmitter and no decoder at the receiver. Thus, the same MIMO hard detection can be applied to the uncoded system.

One of the most complex parts for designing a MIMO receiver with hard decoding is the MIMO hard detector, which detects a transmit symbol vector from a receive signal vector $\mathbf{y}$. ML detection output of the transmit symbol vector assuming that all transmitted messages are of equal probability is given by

$$\hat{\mathbf{s}} = \underset{\mathbf{s}\in\mathbf{S}}{\operatorname{argmax}}\ \mathrm{p}(\mathbf{y}\,|\,\mathbf{s}), \tag{3}$$

where $\mathbf{S}$ is a set of all possible M^{N_S} transmit symbol vectors, and

$$\mathrm{p}(\mathbf{y}|\mathbf{s}) = \frac{1}{(\pi\sigma^2)^{M_R}} \exp\left(-\frac{1}{\sigma^2}\|\mathbf{y}-\mathbf{H}\mathbf{s}\|^2\right) \tag{4}$$

which shows that the ML detector is equivalent to the minimum distance detector.

The straightforward implementation of the ML hard detector (3) is calculating the Euclidean distance (ED) for all and then finding $\hat{\mathbf{s}}$ which minimizes the minimum ED and the corresponding $\hat{\mathbf{s}}$. However, to avoid exhaustive search such as M^{N_S} more efficient algorithms exist that do not require the calculation of EDs for all possible transmit symbol vectors. One such example is a sphere decoder with an infinite initial sphere size [10, 11]. Furthermore, near-ML hard detectors also exist that further reduces the number of ED calculations [3, 12, 13].

2.3.2 Soft-detection receivers

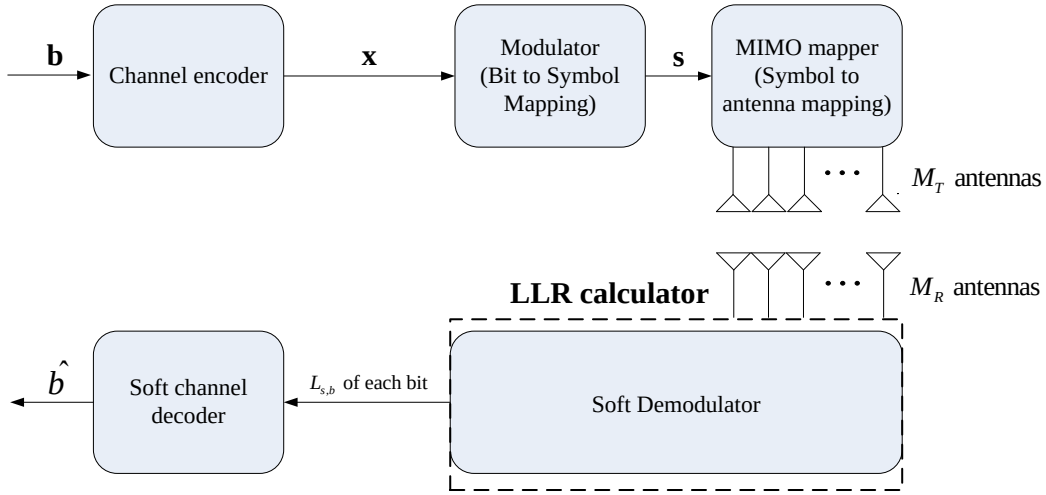

Figure 2.3 A MIMO receiver model with soft detection

For channel coding systems, soft detection receivers can provide the log likelihood ratio (LLR) of each coded bit unlike the hard detection receivers. This LLR information of each bit can be used for soft decoding. Then the soft decoding can give better performance than hard detection which does not pass LLR of each coded bit to decoder. Fig. 2.3 shows a MIMO receiver model with soft detection. In contrast to a receiver with hard detection, the LLRs of coded bits are directly calculated from the received signal vectors. The LLR becomes an input to a soft decoder to generate the data bit estimates. The LLR for the b-th bit of the s-th stream, $b_{s,b}$, is

$$L_{s,b} \triangleq \log\left(\frac{\mathrm{P}[\mathrm{b}_{s,b}=+1\,|\,\mathbf{y}]}{\mathrm{P}[\mathrm{b}_{s,b}=-1\,|\,\mathbf{y}]}\right). \tag{5}$$

Using the conditional pdf in (4), the LLR can be represented assuming that all transmitted messages are of equal probability as

$$L_{s,b}=\log\left(\sum_{\mathbf{s}\in\mathbf{S}_{s,b}^{+1}}\exp(-\frac{1}{\sigma^2}\|\mathbf{y}-\mathbf{Hs}\|^2)\right)-\log\left(\sum_{\mathbf{s}\in\mathbf{S}_{s,b}^{-1}}\exp(-\frac{1}{\sigma^2}\|\mathbf{y}-\mathbf{Hs}\|^2)\right) \tag{6}$$

where $\mathbf{S}_{s,b}^{+1}$ and $\mathbf{S}_{s,b}^{-1}$ are the sets of symbol vectors that have the bit corresponding to +1 and -1 bit at a b-th bit of s-th stream respectively. For example, $\mathbf{S}_{1,1}^{+1}$ is the sets of symbol vectors which has +1 bit at the first bit of the first stream.

The LLR can be calculated in a straightforward way by literally evaluating (6) using EDs for all possible transmit vectors. However, the complexity is too high to implement using state-of-the-art technology. Thus, a so-called max-log approximation [8, 9-13] is commonly employed in practice, where the logarithm of the sum of multiple exponentials is approximated as the maximum among the arguments of the exponentials. With the max-log approximation, the following approximate LLR can be calculated as

$$L_{s,b} = \min_{s \in \mathbf{S}_{s,b}^{-1}} \frac{1}{\sigma^2} \|\mathbf{y} - \mathbf{Hs}\|^2 - \min_{s \in \mathbf{S}_{s,b}^{+1}} \frac{1}{\sigma^2} \|\mathbf{y} - \mathbf{Hs}\|^2 \tag{7}$$

However, the complexity of this approximate LLR calculation is still quite high, and even further approximation is often taken in practice [3, 13-16].

2.4 Iterative detection and decoding (IDD).

IDD assumes that all transmitted messages are not of equal probability and can exchange the prior information between the SM detector and the channel decoder in an iterative fashion unlike non-IDD.

We consider an iterative soft MIMO decoder as shown in Fig. 2.1. The iterative MIMO detector calculates the log-likelihood ratio (LLR) of $L_{s,b}$ according to [17] as (5). Using Bayes's theorem, we can rewrite (5) because all transmitted messages are not of equal probability as

$$\begin{aligned} L_{s,b} &= \log\left(\frac{\mathrm{p}(\mathbf{y} \mid \mathrm{b}_{s,b} = +1)\mathrm{P}(\mathrm{b}_{s,b} = +1) / \mathrm{p}(\mathbf{y})}{\mathrm{p}(\mathbf{y} \mid \mathrm{b}_{s,b} = -1)\mathrm{P}(\mathrm{b}_{s,b} = -1) / \mathrm{p}(\mathbf{y})}\right) \\ &= \underbrace{\log\frac{\mathrm{P}[\mathrm{b}_{s,b} = +1]}{\mathrm{P}[\mathrm{b}_{s,b} = -1]}}_{\text{a priori information}} + \underbrace{\log\left(\frac{\mathrm{p}(\mathbf{y} \mid \mathrm{b}_{s,b} = +1)}{\mathrm{p}(\mathbf{y} \mid \mathrm{b}_{s,b} = -1)}\right)}_{\text{an extrinsic information}}. \end{aligned} \tag{8}$$

Extrinsic information can be represented using the expectation as

$$\begin{aligned} L_{s,b} &= \log\frac{\mathrm{P}[\mathrm{b}_{s,b}=+1]}{\mathrm{P}[\mathrm{b}_{s,b}=-1]} + \log\left(\frac{\sum_{\mathbf{s}\in\mathbf{S}_{s,b}^{+1}} \mathrm{p}(\mathbf{y}\,|\,\mathbf{s})\mathrm{P}(\mathbf{s}\,|\,\mathrm{b}_{s,b}=+1)}{\sum_{\mathbf{s}\in\mathbf{S}_{s,b}^{-1}} \mathrm{p}(\mathbf{y}\,|\,\mathbf{s})\mathrm{P}(\mathbf{s}\,|\,\mathrm{b}_{s,b}=+1)}\right) \\ &= L_{s,b}^{A} + L_{s,b}^{E} \end{aligned} \tag{9}$$

for all symbols s=1, ... , N_s and all bits b=1, ... , N .

The conditional pdf of a received signal vector $\mathbf{y}$ given a transmit symbol vector $\mathbf{s}$ is as (4). Then, the MIMO detector computes the extrinsic LLRs

$$L_{s,b}^{E} = L_{s,b} - L_{s,b}^{A},\ \forall \mathrm{s}, \mathrm{b}, \tag{10}$$

that are conveyed to a channel decoder. Instead of calculating extrinsic information directly, we consider maximizing a posteriori probability for simple calculation. We then remove the priori information to provide extrinsic information to the channel decoder such as $L_{s,b}^{E} = L_{s,b} - L_{s,b}^{A}$. To find the LLRs for each bits, we require the computation of M^{N_s} Euclidean distances per LLR value, which invokes massive computational complexity to the detector. Max-log approximation and QR-decomposing are commonly deployed to solve the problem [13], where approximate LLR can be defined as

$$\begin{aligned} L_{s,b} &= \log\left(\sum_{\mathbf{s}\in\mathbf{S}_{s,b}^{+1}} \exp(-\frac{1}{\sigma^2}\|\mathbf{y}-\mathbf{Hs}\|^2)\mathrm{P}[\mathbf{s}]\right) - \log\left(\sum_{\mathbf{s}\in\mathbf{S}_{s,b}^{-1}} \exp(-\frac{1}{\sigma^2}\|\mathbf{y}-\mathbf{Hs}\|^2)\mathrm{P}[\mathbf{s}]\right) \\ &\approx \min_{\mathbf{s}\in\mathbf{S}_{s,b}^{-1}}\left(\frac{1}{\sigma^2}\|\tilde{\mathbf{y}}-\mathbf{Rs}\|^2 - \log\mathrm{P}[\mathrm{s}]\right) - \min_{\mathbf{s}\in\mathbf{S}_{s,b}^{+1}}\left(\frac{1}{\sigma^2}\|\tilde{\mathbf{y}}-\mathbf{Rs}\|^2 - \log\mathrm{P}[\mathrm{s}]\right) \end{aligned} \tag{11}$$

where $\mathbf{H}=\mathbf{QR}$, $\tilde{\mathbf{y}}=\mathbf{Q}^H\mathbf{y}$, $\mathbf{Q}$ and $\mathbf{R}$ are an $N_R \times N_R$ unitary matrix and an $N_R \times N_S$ upper triangular matrix respectively, and $\log\mathrm{P}[\mathbf{s}]$ is the priori information term as [18]

$$
\begin{aligned}
\log \mathrm{P}[\mathbf{s}] &= \log\left(\prod \mathrm{P}[b_{s,b}]\right) \\
&= \sum \log\left(\frac{\exp(0.5\mathrm{b}_{s,b}L_{s,b}^{A})}{\exp(0.5L_{s,b}^{A})+\exp(-0.5L_{s,b}^{A})}\right) \\
&= \sum 0.5b_{s,b}L_{s,b}^{A} - \log(\exp(0.5L_{s,b}^{A})+\exp(-0.5L_{s,b}^{A}))\} \\
&\approx \sum (0.5b_{s,b}L_{s,b}^{A} - 0.5\left|L_{s,b}^{A}\right|),\ \text{for}\left|L_{s,b}^{A}\right| > 2.
\end{aligned}
\tag{12}
$$

Although (11) can achieve better performance than non-IDD, it also requires significant computational complexity calculations. To reduce this massive complexity, we consider all ordering successive interference cancellation (AOSIC) [19] with MAP criterion for the hard-detection and dimension reduction soft demodulator (DRSD) [20] for the soft-detection iteratively.

Ⅲ. PROPOSED SCHEMES

3.1 DRSD with MAP

DRSD with MAP are extended to IDD algorithm because DRSD in [20] is based on non-IDD algorithm. Then, to calculate the LLR value of (11), an iterative dimension reduction soft demodulator is employed. The dimension reduction reduces the number of streams whose transmit symbol candidates are required to be calculated exhaustively for soft detection. The iterative DRSD considers only part of the streams for soft detection and employs a hard detector to find the best transmit symbol subvector for the remaining streams iteratively.

First of all, the calculation of the LLRs for the N_S^{so} streams among the total N_S stream is focused. Accordingly, N_S^{ha} ($= N_S - N_S^{so}$) is the number of remaining streams out of the total N_S streams. The transmit symbol vector corresponding to soft detection streams as s^{so} and the transmit symbol vector corresponding to the remaining hard detection streams as s^{ha} are represented. Then, a transmit symbol vector can be divided as

$$\mathbf{s} = \begin{bmatrix} \mathbf{s}^{ha} \\ \mathbf{s}^{so} \end{bmatrix}. \tag{13}$$

The channel matrix corresponding to each soft stream and hard streams are also divided into two submatices as

$$\mathbf{R} = \left[\mathbf{R}^{ha} \, \mathbf{R}^{so} \right], \tag{14}$$

where $\mathbf{R}^{ha} \in \mathbf{C}^{N_R \times N_S^{ha}}$ and $\mathbf{R}^{so} \in \mathbf{C}^{N_R \times N^{so}}$ represent the channel matrices for s^{so} and s^{ha} , respectively. The received signal is represented as

$$\tilde{\mathbf{y}} = \mathbf{R}^{ha}\mathbf{s}^{ha} + \mathbf{R}^{so}\mathbf{s}^{so} + \tilde{\mathbf{z}}. \tag{15}$$

The LLR of (11) for the b-th bit of the s-th stream is

$$
\begin{aligned}
L_{s,b} \quad &= \min_{\mathbf{s}^{so} \in \mathbf{S}_{\mathbf{s,b}}^{so(-1)}, \mathbf{s}^{ha} \in \mathbf{S}^{ha}} \{ \frac{1}{\sigma^2} \left\| \tilde{\mathbf{y}} - \mathbf{R}^{ha}\mathbf{s}^{ha} - \mathbf{R}^{so}\mathbf{s}^{so} \right\|^2 \\
&\qquad - \log \mathrm{P}[\mathbf{s}] \} \\
&- \min_{\mathbf{s}^{so} \in \mathbf{S}_{\mathbf{s,b}}^{so(+1)}, \mathbf{s}^{ha} \in \mathbf{S}^{ha}} \{ \frac{1}{\sigma^2} \left\| \tilde{\mathbf{y}} - \mathbf{R}^{ha}\mathbf{s}^{ha} - \mathbf{R}^{so}\mathbf{s}^{so} \right\|^2 \\
&\qquad - \log \mathrm{P}[\mathbf{s}] \}
\end{aligned} \tag{16}
$$

where $\mathbf{S}_{\mathbf{s,b}}^{\mathbf{so(b)}}$ is the set of soft detection transmit symbol subvectors $\mathbf{s}^{so}$ with $b_{s,b} = b$, and $\mathbf{S}^{ha}$ is the set of all hard detection transmit symbol subvectors $\mathbf{s}^{ha}$ with $b_{s,b} = b$.

Calculating the LLR values over the sets $\mathbf{S}_{\mathbf{s,b}}^{\mathbf{so(b)}}$ and $\mathbf{S}^{\mathbf{ha}}$ can be operated in 3 three steps: 1) instead of extrinsic information, find the minimum ED over the set $\mathbf{S}^{\mathbf{ha}}$ for each $\mathbf{s}^{\mathbf{so}}$ with the priori information $\log \mathrm{P}[\mathbf{s}^{\mathbf{ha}}]$, 2) calculate the minimum ED of each $\mathbf{s}^{so}$ with the priori information $\log \mathrm{P}[\mathbf{s}^{so}]$, and 3) subtract a priori information of the b-th bit of the s-th stream as (10) to pass extrinsic LLRs to a channel decoder as

$$
\begin{aligned}
L_{s,b} = &\min_{\mathbf{s}^{so} \in b_{s,b}^{so(-1)}} \{ \min_{\mathbf{s}^{ha} \in \mathbf{S}^{ha}} \left(\frac{1}{\sigma^2} \left\| \tilde{\mathbf{y}}(\mathbf{s}^{so}) - \mathbf{R}^{ha}\mathbf{s}^{ha} \right\|^2 - \log \mathrm{P}[\mathbf{s}^{ha}] \right) - \log \mathrm{P}[\mathbf{s}^{so}] \} \\
&- \min_{\mathbf{s}^{so} \in b_{s,b}^{so(1)}} \{ \min_{\mathbf{s}^{ha} \in \mathbf{S}^{ha}} \left(\frac{1}{\sigma^2} \left\| \tilde{\mathbf{y}}(\mathbf{s}^{so}) - \mathbf{R}^{ha}\mathbf{s}^{ha} \right\|^2 - \log \mathrm{P}[\mathbf{s}^{ha}] \right) - \log \mathrm{P}[\mathbf{s}^{so}] \},
\end{aligned} \tag{17}
$$

where

$$
\tilde{\mathbf{y}}(\mathrm{s}^{so}) \triangleq \tilde{\mathbf{y}} - \mathbf{R}^{so}\mathbf{s}^{so} = \mathbf{R}^{ha}\mathbf{s}^{ha} + \tilde{\mathbf{z}}, \tag{18}
$$

$$
\log \mathrm{P}[\mathbf{s}] = \log \mathrm{P}[\mathbf{s}^{ha}] + \log \mathrm{P}[\mathbf{s}^{so}], \tag{19}
$$

which is formed by subtracting the transmit symbol subvector $\mathbf{S}^{so}$ for DRSD detection. $\mathrm{P}[\mathbf{s}^{ha}]$ and $\mathrm{P}[\mathbf{s}^{so}]$ are independent.

The MAP hard detector calculates the minimum Euclidean distance (ED) for each $\mathbf{s}^{so}$ with the priori information as

$$
C(\mathbf{s}^{so}) \triangleq \{ \frac{1}{\sigma^2} \left\| \tilde{\mathbf{y}}(\mathbf{s}^{so}) - \mathbf{R}^{ha}\hat{\mathbf{s}}^{ha}(\mathbf{s}^{so}) \right\|^2 - \log \mathrm{P}[\hat{\mathbf{s}}^{ha}] \} - \log \mathrm{P}[\mathbf{s}^{so}]. \tag{20}
$$

where

$$\hat{\mathbf{s}}^{ha} = \arg\min_{\mathbf{s}^{ha} \in \mathbf{S}^{ha}} \left(\frac{1}{\sigma^2} \left\| \tilde{\mathbf{y}}(\mathbf{s}^{so}) - \mathbf{R}^{ha}\mathbf{s}^{ha} \right\|^2 - \log \mathrm{P}[\mathbf{s}^{ha}] \right) \tag{21}$$

Finally, the LLR can be calculated by

$$L_{s,b} = \min_{\mathbf{s}^{so} \in b_{s,b}^{so(-1)}} \mathrm{C}(\mathbf{s}^{so}) - \min_{\mathbf{s}^{so} \in b_{s,b}^{so(+1)}} \mathrm{C}(\mathbf{s}^{so}) \tag{22}$$

Then, based on (10), the extrinsic LLR for the channel decoder is denoted as

$$L_{s,b}^{E} = \{ \min_{\mathbf{s}^{so} \in \mathbf{S}_{s,b}^{so(-1)}} \mathrm{C}(\mathbf{s}^{so}) - \min_{\mathbf{s}^{so} \in \mathbf{S}_{s,b}^{so(+1)}} \mathrm{C}(\mathbf{s}^{so}) \} - L_{s,b}^{A} \tag{23}$$

where $L_{s,b}^{\mathrm{A}}$ is the data bit and the a priori information of the b-th bit of the s-th streams. To have full LLR values for iteration soft decoding, the DRSD operation should be done multiple times. The LLR calculation for the remaining streams can be calculated by rearranging the transmit symbol vector. For example, when (N_S, N_S^{so}) = (3, 1), first of all, the iterative DRSD can be performed with $\tilde{\mathbf{s}} = [s_1\, s_2\, s_3]$ and $\mathbf{H}=[\mathbf{h}_1\, \mathbf{h}_2\, \mathbf{h}_3]$, for the soft detection of streams 3. Then, the DRSD can be repeated with $\tilde{\mathbf{s}} = [s_1\, s_3\, s_2]$ and $\mathbf{H}=[\mathbf{h}_3\, \mathbf{h}_1\, \mathbf{h}_2]$, for the soft detection of stream 2. With this repetition of calculation, the iterative soft decoder can have the full LLR values, estimating the bit and provide iteratively the priori information of each bit to the iterative soft decoder

3.1.1 AOSIC with slicing MAP criterion

For each $\mathbf{s}^{so}$, all ordering successive interference cancellation (AOSIC) with MAP criterion can directly find vectors $\mathbf{s}^{\mathbf{ha}}$ from the received signal as follows [19]

Initialization: $\mathbf{G}_1 = \mathrm{R}^{+} = [\mathbf{R}^H\mathbf{R} + \sigma^2\mathbf{I}]^{-1}\mathbf{R}^H$ - Find pseudo inverse (24a)

$i = 1$

$\mathrm{Ns!}$ - Find all stream orders to detect

j - The next detected symbol order from $\mathrm{Ns!}$ ordering

Recursion:

$$\mathbf{w}_j = (\mathbf{G}_i)_j \quad \text{- Find nulling matrix} \tag{24b}$$

$$\hat{s}_j^{ha} = \mathbf{w}_j \tilde{\mathbf{y}}_i \quad \text{- Interference nulling} \tag{24c}$$

$$\bar{s}_j^{ha} = \mathrm{dec}(\hat{s}_j^{ha}) \quad \text{- Slicing} \tag{24d}$$

$$\tilde{y}_{i+1} = \tilde{\mathrm{y}}_i - \bar{s}_j^{ha} (\mathbf{R})_j \quad \text{- Cancelling} \tag{24e}$$

$$\mathbf{G}_{i+1} = (\mathbf{R}_j^-)^+ \quad \text{- Update pseudo inverse} \tag{24f}$$

$$i = i + 1$$

Finalizing:

$$\hat{\mathbf{s}}^{ha}(\mathbf{s}^{so}) = \underset{\bar{\mathbf{s}}^{ha} \in \mathbf{\Phi}}{\arg\min} \left(\frac{1}{\sigma^2} \left\| \tilde{\mathbf{y}}(\mathbf{s}^{so}) - \mathbf{R}^{ha} \bar{\mathbf{s}}^{ha} \right\|^2 - \log \mathrm{P}[\mathbf{s}^{ha}] \right), \tag{24g}$$
$$\Phi = \{\bar{\mathbf{s}}_1^{ha}, \bar{\mathbf{s}}_2^{ha}, \cdots, \bar{\mathbf{s}}_{N_S!}^{ha}\}$$

where $(\mathrm{A})_j$ is j-th row of A and H_i^- is H with rows of $k_{1,} \cdots, k_{i,}$ removed and $\bar{s}_j^{ha}$ is output from the AOSIC with the j-th ordering for hard detection.

However, this AOSIC with MAP criterion is not enough to have better performance because the iteration does not affect AOSIC procedure. Then, we propose AOSIC slicing MAP criterion which extends MAP detector by using a priori probabilities. Conventional slicer is to determine one constellation point which is nearest constellation point as (24c) and (24d). On the other hand, AOSIC slicing MAP criterion is used as

$$\begin{aligned}
\bar{\mathbf{s}}^{ha} &= \underset{\mathbf{s}^{ha} \in \mathbf{S}^{ha}}{\mathrm{argmin}} \left(\frac{1}{\sigma^2} \left\| \mathbf{w}^{-1} \mathbf{w} \{ \tilde{\mathbf{y}}(\mathbf{s}^{so}) - \mathbf{R}^{ha} \mathbf{s}^{ha} \} \right\|^2 - \log \mathrm{P}[\mathbf{s}^{ha}] \right) \\
\bar{\mathbf{s}}^{ha} &= \underset{\mathbf{s}^{ha} \in \mathbf{S}^{ha}}{\mathrm{argmin}} \left(\frac{1}{\sigma^2} \left\| \mathbf{w}^{-1} \{ \mathbf{s}^{ha} + \mathbf{w}\mathbf{z} - \mathbf{s}^{ha} \} \right\|^2 - \log \mathrm{P}[\mathbf{s}^{ha}] \right) \\
\bar{\mathbf{s}}^{ha} &= \underset{\mathbf{s}^{ha} \in \mathbf{S}^{ha}}{\mathrm{argmin}} \left(\frac{1}{\sigma^2} \left\| \mathbf{z} \right\|^2 - \log \mathrm{P}[\mathbf{s}^{ha}] \right) \\
\bar{\mathbf{s}}_j^{ha} &= \underset{\mathbf{z}_j \in \mathbf{Z}}{\mathrm{argmin}} \left(\frac{1}{\sigma^2} \left| \mathbf{z}_j \right|^2 - \log \mathrm{P}[\mathbf{s}_j^{ha}] \right) \\
\bar{\mathbf{s}}_j^{ha} &\approx \underset{\mathbf{s}_j^{ha} \in \mathbf{C}}{\mathrm{argmin}} \left(\frac{1}{\sigma^2} \left| \mathbf{s}_j^{ha} - \hat{s}_j^{ha} \right|^2 - \log \mathrm{P}[\mathbf{s}_j^{ha}] \right)
\end{aligned} \tag{25}$$

,where $\mathbf{C}$ is constellation points, instead of using slicing as (24d). For each bit of $\mathbf{s}$-

th stream, the constellation points can be divided into two groups such as +1 group and -1 group. Fig. 3.1 shows a couple of groups of each bit. With this partition, each bit can be easily decided by calculating the distance with the priori information. For exam

ple, we assume the priori information of each stream is given. Then, the AOSIC slicing MAP criterion is applied for QPSK with 2 transmit and 2 receive antennas for hard detections as

$$\begin{aligned} \mathrm{d}_1 - \log[\mathbf{s}_2^{ha}] \geq \bar{\mathrm{d}}_1 + \log[\mathbf{s}_2^{ha}] \Leftrightarrow \mathrm{b}_{s,1} = -1 \\ \mathrm{d}_2 - \log[\mathbf{s}_2^{ha}] \geq \bar{\mathrm{d}}_2 + \log[\mathbf{s}_2^{ha}] \Leftrightarrow \mathrm{b}_{s,2} = -1 \end{aligned} \tag{26}$$

where d_1 is the distance between image value of upper constellation points and image value of estimate $\hat{s}_2$ $(d_1 = \left(\sqrt{\frac{1}{\sqrt{2}} - \Im(\hat{s}_2)}\right)^2)$, $\bar{\mathrm{d}}_1$ is the distance between image value of lower constellation points and image value of estimate $\hat{s}_2$ $(\bar{d}_1 = \left(\sqrt{\frac{-1}{\sqrt{2}} - \Im(\hat{s}_2)}\right)^2)$, d_2 is the distance between real value of right constellation points and real value of estimate $\hat{s}_2$ $(d_2 = \left(\sqrt{\frac{1}{\sqrt{2}} - \Re(\hat{s}_2)}\right)^2)$ and $\bar{\mathrm{d}}_2$ is the distance between real value of left constellation points and real value of estimate $\hat{s}_2$ $(\bar{d}_2 = \left(\sqrt{\frac{-1}{\sqrt{2}} - \Re(\hat{s}_2)}\right)^2)$. $\log[\mathbf{s}_2^{ha}]$ is the priori information of second stream. Impact slicing MAP criterion is as

$$\begin{aligned} \left(\sqrt{\frac{1}{\sqrt{2}} - \Im(\hat{s}_2)}\right)^2 - 0.5L_{s_2,1}^A \geq \left(\sqrt{\frac{-1}{\sqrt{2}} - \Im(\hat{s}_2)}\right)^2 + 0.5L_{s_2,1}^A \quad \Leftrightarrow b_{s,1} = -1 \\ \Im(\hat{s}_2) \leq -\frac{\sqrt{6}}{4} L_{s_2,1}^{\mathrm{A}} \Leftrightarrow b_{s,1} = -1 \\ \left(\sqrt{\frac{1}{\sqrt{2}} - \Re(\hat{s}_2)}\right)^2 - 0.5L_{s_2,2}^A \geq \left(\sqrt{\frac{-1}{\sqrt{2}} - \Re(\hat{s}_2)}\right)^2 + 0.5L_{s_2,2}^A \quad \Leftrightarrow b_{s,2} = -1 \\ \Re(\hat{s}_2) \leq -\frac{\sqrt{6}}{4} L_{s_2,2}^{\mathrm{A}} \Leftrightarrow b_{s,2} = -1 \end{aligned} \tag{27}$$

where $b_{s,1}$ and $b_{s,2}$ are the first and second bit of the second stream respectively and

$L^{A}_{s_2,1}$ and $L^{A}_{s_2,2}$ are a priori LLR value of the first bit and a priori LLR value of the second bit of second stream respectively. With impact slicing MAP criterion, calculation of Euclidean distance is not necessary just like conventional slicing. Then, without more complexity, AOSIC with slicing MAP criterion can provide iteration improvement performance.

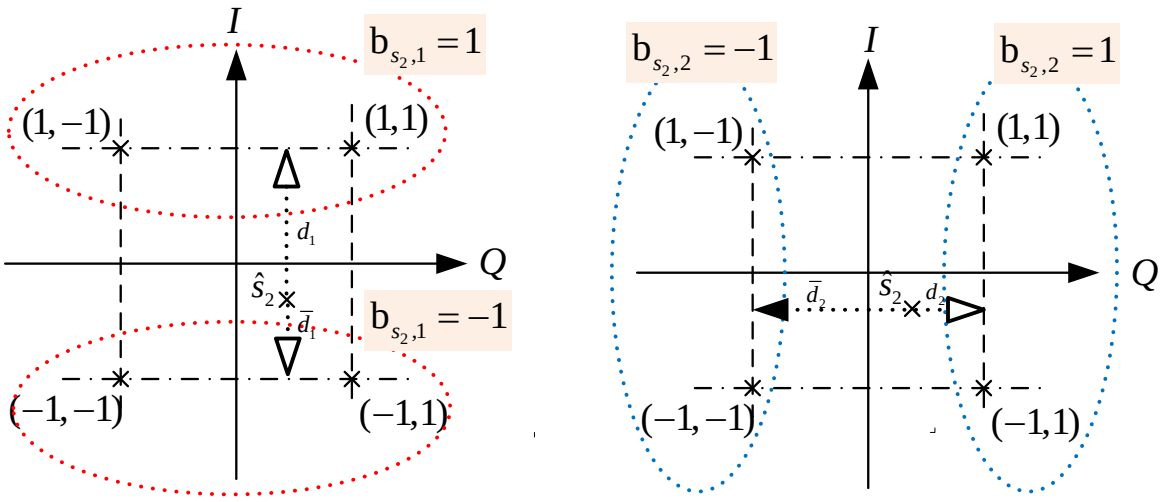

Figure 3.1 Bit partition example of the QPSK constellation

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3.1.2 Adding one more candidate

The more candidates of symbol for hard detection we add, the more complexity arises. Therefore, to find more exact each symbol or stream for hard detection are critical factor to maintain low computation complexity because AOSIC with slicing MAP criterion is not enough to achieve performance of MAP detection.

One minor approach is to use the DRSD with MAP property which has each estimated hard stream for each soft stream because to find minimal ED of each soft stream, a detector should detect the hard streams. Then, hard streams with minimal ED that are detected by AOSIC with slicing MAP criterion can be used to find the minimum distance for other calculation of ED. After deciding the hard streams for minimum distance, double checking of each distance with fixed hard streams for other soft stream can provide improved performance because AOSIC algorithm has limited candidates' numbers and are sensitive on noise effects.

If the fixed hard streams are not included as candidates in other soft AOSIC detector, then one more candidate such as estimated hard streams is included to check

the minimum distance. The AOSIC with slicing criterion (24g) can be modified as

$$\hat{\mathbf{s}}^{ha}(\mathbf{s}^{so}) = \underset{\bar{\mathbf{s}}^{ha}\in\mathbf{\Phi}}{\arg\min}\frac{1}{\sigma^2}\left\|\tilde{\mathbf{y}}(\mathbf{s}^{so}) - \mathbf{R}^{ha}\bar{\mathbf{s}}^{ha}\right\|^2 - \log \mathrm{P}[\mathbf{s}^{ha}],$$
$$\Phi = \{\bar{\mathbf{s}}_1, \bar{\mathbf{s}}_2, \cdots, \bar{\mathbf{s}}_{N_S!,}\bar{\mathbf{s}}_{A,}\}, \tag{28}$$

where $\tilde{\mathbf{s}}_A$ is estimated as hard streams previously.

For example, hard streams $\mathbf{s}^{ha}$ are two with QPSK constellation and soft stream $\mathbf{s}^{so}$ is one $(N_S, N_S^{ha}, N_S^{so})$ = (3, 2, 1). AOSIC with slicing MAP criterion provides each estimated hard stream for each soft stream as (24g). Then, minimal estimated streams $\hat{\mathbf{s}}$ are determined as

$$\hat{\mathbf{s}} = \min\left((\mathbf{s}_{1+j,}^{so}\ \hat{\mathbf{s}}_{2,1}^{ha},\ \hat{\mathbf{s}}_{3,1}^{ha}),(\mathbf{s}_{1-j,}^{so}\ \hat{\mathbf{s}}_{2,2}^{ha},\ \hat{\mathbf{s}}_{3,2}^{ha}),(\mathbf{s}_{-1+j,}^{so}\ \hat{\mathbf{s}}_{2,3}^{ha},\ \hat{\mathbf{s}}_{3,3}^{ha}),(\mathbf{s}_{-1-j,}^{so}\ \hat{\mathbf{s}}_{2,4}^{ha},\ \hat{\mathbf{s}}_{3,4}^{ha})\right) \tag{29}$$

where $\mathbf{s}_c^{so}$ is soft stream with each constellation point of such as QPSK has four constellation points and $\hat{\mathbf{s}}_{stream,\,candidate}^{ha}$ is estimated hard streams. When $\hat{\mathbf{s}}$ is determined as $(\mathbf{s}_{1+j,}^{so}\ \hat{\mathbf{s}}_{2,1}^{ha},\ \hat{\mathbf{s}}_{3,1}^{ha})$, $\hat{\mathbf{s}}_{2,1}^{ha}$ and $\hat{\mathbf{s}}_{3,1}^{ha}$ (= $\bar{\mathbf{s}}_A$) become fixed hard stream which has minimal ED. Then, other soft streams check $\hat{\mathbf{s}}_{2,1}^{ha}$ and $\hat{\mathbf{s}}_{3,1}^{ha}$ candidates included to calculate minimum distance. If they already include these candidates $\bar{\mathbf{s}}_A$, $\bar{\mathbf{s}}_A$ does not included. If they does not include these candidates, $\bar{\mathbf{s}}_A$ should be included as (28).

Ⅳ. COMPLEXITY and PERFORMACNE EVALUATION

4.1 Complexity Evaluation

The complexity evaluation of the iterative DRSD detector is compared with iterative MAP soft detections. To calculate the Euclidean distance for each LLR value, tree searching should be considered. Then, the number of visited constellation points (same as nodes in tree searching representation) is chosen as the complexity measure reference because the complexity associated with each node of a tree is approximately the same regardless of the node location. In this paper, only the complexity for the Euclidean distance calculation is considered because the calculation of priori information is not a tree search scheme and priori information is commonly computed by most iterative detectors.

With conventional MAP computation, the number of visited nodes is

$$C_{MAP}(N_S) = \sum_{i=1}^{N_S} M^i = \frac{M^{N_S+1} - M}{M-1}, \tag{30}$$

since a conventional search visits all the nodes of the tree which has M^i nodes in layer i for i = 1, 2,..., N_S.

On the other hand, based on the DRSD, the number of visited nodes for the soft detection of N_S^{so} streams is

$$C_{DRSD,part}(N_S, N_S^{so}) = \frac{M^{N_S^{so}+1} - M}{M-1} + \mathrm{M}^{N_S^{so}} C_{AOSIC+MAP}(N_S^{ha} = N_S - N_S^{so}), \tag{31}$$

where $C_{\mathrm{AOSIC+MAP}}(N_S^{ha})$ is the number of visited nodes of the considered AOSIC detector with MAP criterion. With the repeated use of the same partial DRSD $[N_S / N_S^{so}]$ times for full LLR values, the total number if visited nodes for the demodulation of all N_S streams is

$$C_{DRSD,tot}(N_S, N_S^{so}) = [\frac{N_S}{N_S^{so}}] C_{DRSD,part}(N_S, N_S^{so}). \tag{32}$$

The AOSIC with MAP reduces the candidates of the tree searching as (16). To calculate the complexity of the hard detectors, we calculate the number of visiting nodes based on AOSIC with MAP as

$$C_{\text{AOSIC+MAP}}(N_S - N_S^{so}) \approx (N_S - N_S^{so})!(N_S - N_S^{so}). \tag{33}$$

Finally, the complexity of the iterative DRSD with AOSIC is

$$C_{DRSD,tot}(N_S, N_S^{so}) \approx [\frac{N_S}{N_S^{so}}]\{\frac{M^{N_S^{so}-1} - M}{M-1} + \mathrm{M}^{N_S^{so}}(N_S - N_S^{so})!(N_S - N_S^{so})\}. \tag{34}$$

To compare with complexity and performance, we introduce soft-input soft-output single tree-search based on sphere decoding (SISO STS-SD) which uses tightening of the tree-pruning criterion [4]. To the best knowledge of authors, SISO STS-SD is considered as one of best algorithms by using LLR correction method with low complexity. However, unlike our algorithm, the complexity of SISO STS-SD has unfixed characteristics because sphere decoding is changed by SNR. Then, the average visiting nodes from our simulation are represented as complexity for SISO STS-SD. Fig. 3 compares the complexity of DRSD with the exhaustive MAP and SISO STS-SD. As you can see, our algorithm has better and fixed complexity on a variety of SNR.

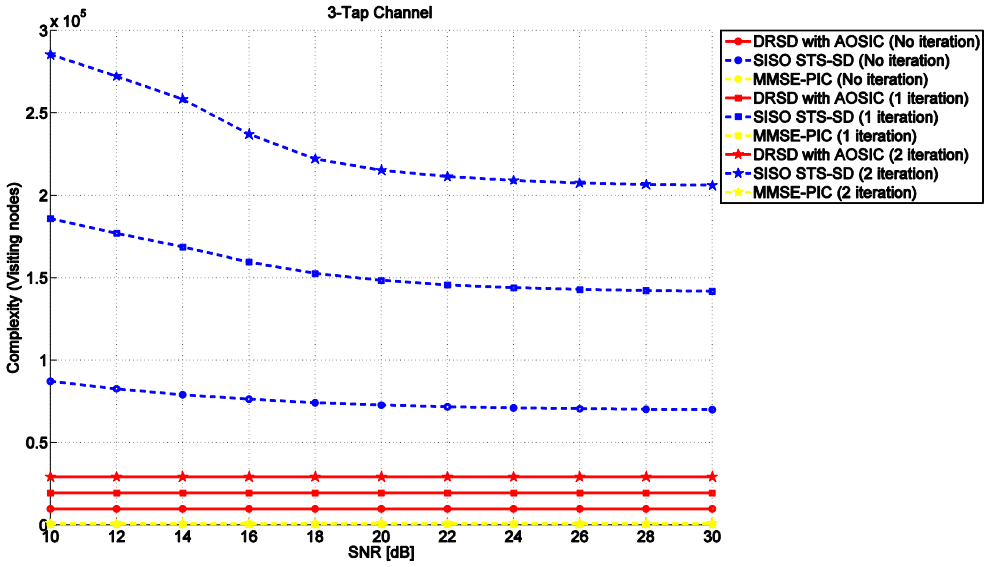

Figure 4.1 Complexity comparasion for 16QAM with 3 transmit and 3 receive antennas.

4.2 Performance evaluation

We tested our algorithm with the MIMO-OFDM simulator for QPSK and 16QAM constellations using Gray code respectively. The simulation results are based on a convolution encoder (rate R = 5/6, constraint lengths K = 7, polynomials [133 171]) and by implementing BCJR channel decoder [21] based on the min-sum algorithm and considering the three tap channel which is generated randomly. One packet consists of 4 OFDM symbols and 128 subcarriers are used for simulation. We assume that bits are statistically independent. If one of the bits in the frame has an error, the frame is considered to be in error. Because of the simulation time limitation, up to three iterations is performed. In this section, besides SISO STS-SD scheme, we introduce another scheme such as minimum mean-squared error (MMSE) based parallel interference cancellation (MMSE-PIC) algorithm which initially is proposed by Wang and Poor in 1999 for multi-user detection [22].

Fig.4 shows the packet error rate (PER) curves for QPSK with 3 transmit and 3 receive antennas. Three streams are transmitted (N_S=3) and the number of soft demodulation streams is chosen as 1 (N_S^{so}=1) for the DRSD. The DRSD with MAP performs better than the SISO STS-SD algorithm, where MMSE-PIC has a large degradation of performance.

Fig.5 shows PER curves for 16QAM with 3 transmit and 3 receive antennas. Three streams are transmitted (N_S=3) and the number of soft demodulation streams is chosen as 1 (N_S^{so}=1) for the DRSD. The DRSD with M-AOSIC performs the almost similar as the SISO-STS-SD, where MMSE-PIC has a large degradation of performance.

Lastly, Fig.6 shows the packet error rate (PER) curves for 16QAM with 4 transmit and 4 receive antennas. Three streams are transmitted (N_S=3), and the number of soft demodulation streams is chosen as 1 (N_S^{so}=1) for the DRSD. The DRSD with M-AOSIC has performance degradation compared to SISO-STS-SD because of the performance degradation of AOSIC with slicing criterion.

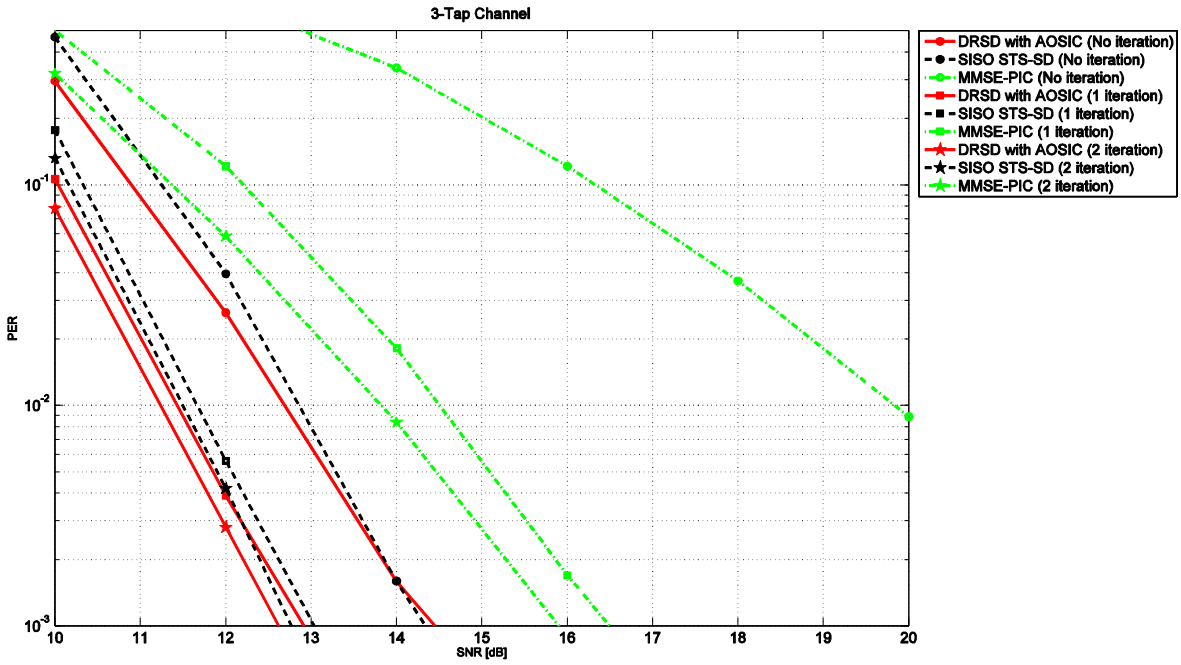

Figure 4.2 PER curves for QPSK with 3 transmit and 3 receive antennas.

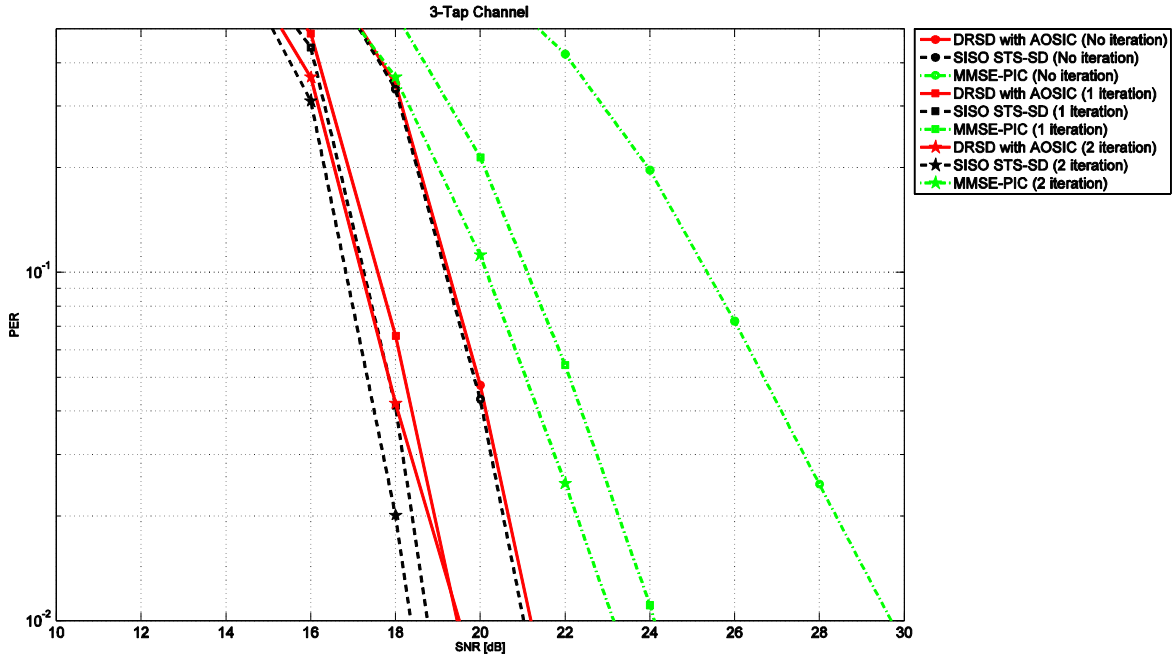

Figure 4.3 PER curves for 16QAM with 3 tranmit and 3 receive antennas.

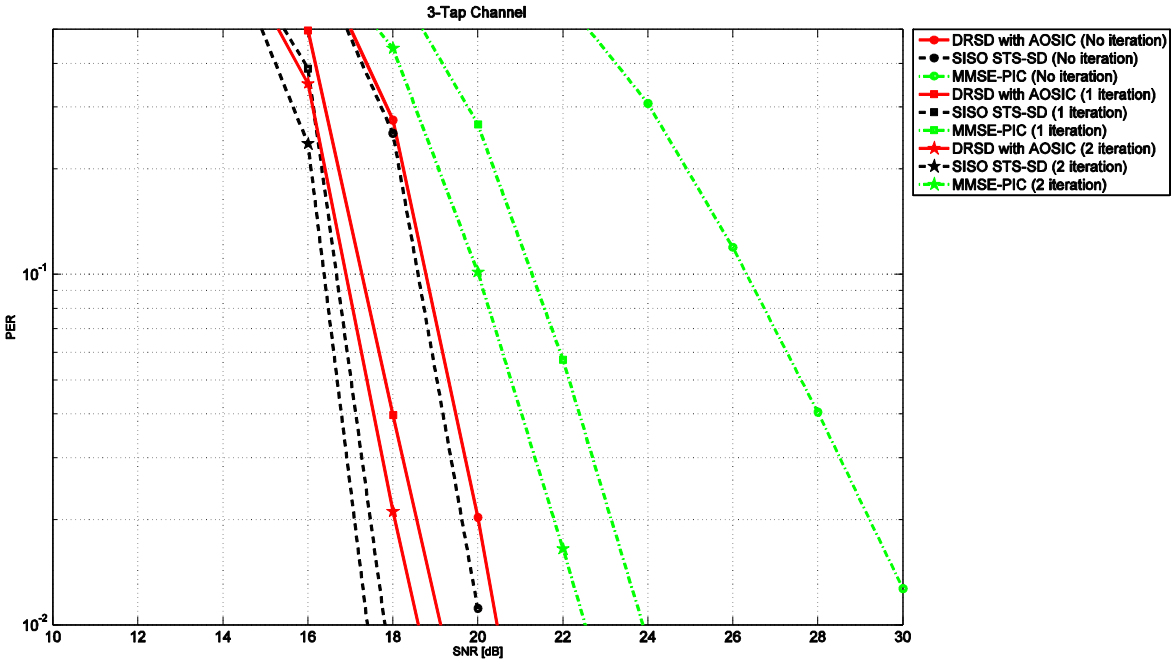

Figure 4.4 PER curves for 16QAM with 4 transmit and 4 receive antennas.

Ⅴ. SUMMARY and FUTURE WORK

5.1 Summary

SM MIMO transmission has attracted attention to approach near capacity bound which provides more data rate. One severe problem is that receiver side has massive burden of computational complexity to detect each stream or symbol because of inter-stream interference. To reduce this problem, non-IDD and IDD algorithm are introduced as background knowledge. IDD algorithm of SM MIMO transmission is mainly considered as main technology in this thesis.

In this thesis, we have proposed DRSD with MAP that employ AOSIC with slicing MAP criterion and adding the one more candidate. DRSD basically separates soft-streams and hard-streams to give complexity burden to hard detector. Then, slicing MAP criterion used for hard detector provides improving performance. In addition, adding one more candidate which is best hard streams through the DRSD with MAP improves performance.

The use of the proposed IDD algorithm can provide similar performance with lower fixed complexity on SNR variation compared to other IDD algorithm such as SISO-STS-SD.

5.2 Future work

We simulated 4 transmit and 4 receiver antennas with 16QAM. In the simulation results, although our algorithm has less complexity, our algorithm cannot have better performance than the SISO-STS-SD algorithm. In terms of high order antennas such as 8x8 antennas, it is expected that performance of the proposal scheme becomes worse than the SISO-STS-SD algorithm. To add more candidates, a new algorithm or new types of criterion is required with low complexity for high order antennas implementation.

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요 약 문

차원감소 소프트복조 기반의 다중 안테나 반복검출 기법

공간다중 다중안테나 검출기법은 높은 데이터 율을 얻기 위해서 꼭 필요한 기술이지만 실제 적용에 있어서 문제를 가지고 있다. 특히 공간다중 다중안테나 검출기법 중 반복검출복호기법의 경우 확실한 수신 성능의 개선이 있지만 수신 단에 많은 계산양의 부담을 주어서 실제 적용하기가 어렵다.

이에 본 논문은 이 문제를 해결하기 위해서 최대사후확률을 사용한 차원감소 소프트복조기법을 제안한다. 차원감소 소프트복조기법의 하드검출을 위해서 모든 순서순차간섭삭제기법을 슬라이싱 최대사후확률 기준을 가지고 개선하며 추가 성능 향상을 위해서 모든 순서순차간섭삭제기법에 하나의 스트림 리스트를 추가하는 기법을 제안한다. 하드 검출과 소프트 검출로 스트림을 분리하여 복잡도를 낮추었으며 특히 슬라이싱 최대사후확률 기준을 가지고 반복검출복호기법의 충분한 성능을 보인다.

제안한 기법은 반복검출복혹기법의 기존의 기법에 비해 낮은 계산량과 신호 및 잡음비에 무관한 고정 계산량을 제공하며 기존 기법의 성능에 근접한 성능을 보인다.

핵심어: 반복 검출, 모든순서순차삭제기법, 낮은차수검출기법, 최대사후확률, 최대우도

감사의 글

회사를 약 5 년 넘게 다니다 다시 학문을 하기 위해서 두려움 반 기대반의 설렘을 안고 대학원 생활을 시작한지 2 년이 되어서 이제 짧지만 소중한 시간을 정리하게 되었습니다. 개인적인 사정으로 학문의 길을 계속 이어가지는 못하지만 짧은 기간 배운 대학원 학문이 제가 살아가는데 등불 같이 앞날을 비추어 주리라 믿어 의심치 않습니다.

우선 대학원 입학에 대해서 부정적으로 생각하고 있을 때 저를 이 길로 이끌어 주시고 들어오게 해주신 지도 교수님에게 감사의 마음을 전하고 싶습니다. 저의 많은 부족한 점을 채워주시고 인생의 살아가는 방법을 가르쳐 주신 것에 대해서 무한한 감사를 드립니다.

대학원에 입학하여 2 년 동안 연구실 생활을 하여 함께 지낸 정보통신융합공학전공 대학원 동기들과 통신 및 신호처리 연구실 동기 및 후배들에게 깊은 감사 드립니다. 하나밖에 없는 랩 동기 인호님, 같은 랩 사람은 아니지만 항상 기혼자의 마음을 알아주신 류성근 박사님, 처음 학교가 시작할 때부터 알아온 손성화 동기님, 톡톡 튀는 성격으로 생활에 활력을 준 송효찬 동기님, 한 학기 늦게 들어왔지만 동기처럼 잘 지낸 윤솔님, 저의 성격을 다 받아주며 1 년을 보낸 조재욱 후배, 1 학기 늦게 들어왔지만 마지막에 저의 충고를 많이 받은 김경수 후배, 목소리가 너무 커서 어디에 있는지 무슨 생각을 하는지 바로 알 수 있는 신재섭 후배, 말은 잘 안 듣고 자기 마음대로 하지만 자기 소신이 뚜렷해서 좋은 한성민 후배 등 동기들 및 후배들에게 감사의 말을 전하고 싶습니다.

끝으로, 참으로 셀 수조차 없는 긴 시간을 학업에 매달리느라 집을 비운 시간을 묵묵히 내조해 준 아내 유진이에게 이 작은 기쁨을 바칩니다. 그리고 언제나 내 꿈의 언저리에서 맴도는 눈에 넣어도 아프지 않을, 사랑스런 내 인생의 보배 세영이와 세아의 앞날에 아버지라는 이름의 작은 등불이 되길 간절한 마음으로 기원합니다.

마지막으로 지면으로 통해서 일일이 언급을 하지 못했지만 그 동안 저를 아끼고 사랑해주신 모든 분들께 다시 한 번 진심으로 감사 드립니다.

Curriculum Vitae

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Education

2011-2013 M.S. in Information and Communication Engineering, DGIST, Daegu, Korea

1998-2006 B.S. in Electronics Engineering, Dong-A, Pusan, Korea

Work Experience

2010-2011 Research Assistant, Daegu Technopark, Daegu, Korea

- Assisted local IT companies about IT technology

2005-2010 Research Assistant, Samsung Electronic Inc, Gu-mi, Korea

- Developed GSM cell phone for Europe Market
- Electric circuit design, optimization, and testing for baseband
- Field test of GSM cell phone in Poland, German, Italy

Honors and Awards

Award of excellence research topic

during the Summer DGIST ICE Student Workshop 2011