Editor-in-Chief
Dr. Saif alZahir

SIGNAL PROCESSING (SPIJ)

AN INTERNATIONAL JOURNAL

ISSN : 1985-2339

Volume 9 • Issue 2 • May 2015

Publication Frequency: 6 Issues / Year

CSC PUBLISHERS
http://www.cscjournals.org

SIGNAL PROCESSING: AN INTERNATIONAL JOURNAL (SPIJ)

VOLUME 9, ISSUE 2, 2015

EDITED BY
DR. NABEEL TAHIR

ISSN (Online): 1985-2339

International Journal of Computer Science and Security is published both in traditional paper form and in Internet. This journal is published at the website http://www.cscjournals.org, maintained by Computer Science Journals (CSC Journals), Malaysia.

SPIJ Journal is a part of CSC Publishers

Computer Science Journals

http://www.cscjournals.org

SIGNAL PROCESSING: AN INTERNATIONAL JOURNAL (SPIJ)

Book: Volume 9, Issue 2, May 2015
Publishing Date: 31-05-2015
ISSN (Online): 1985-2339

SPIJ Journal is a part of CSC Publishers
http://www.cscjournals.org

Published in Malaysia

Typesetting: Camera-ready by author, data conversation by CSC Publishing Services – CSC Journals, Malaysia

CSC Publishers, 2015

EDITORIAL PREFACE

This is *Second* Issue of Volume *Nine* of the Signal Processing: An International Journal (SPIJ). SPIJ is an International refereed journal for publication of current research in signal processing technologies. SPIJ publishes research papers dealing primarily with the technological aspects of signal processing (analogue and digital) in new and emerging technologies. Publications of SPIJ are beneficial for researchers, academics, scholars, advanced students, practitioners, and those seeking an update on current experience, state of the art research theories and future prospects in relation to computer science in general but specific to computer security studies. Some important topics covers by SPIJ are Signal Filtering, Signal Processing Systems, Signal Processing Technology and Signal Theory etc.

The initial efforts helped to shape the editorial policy and to sharpen the focus of the journal. Started with Volume 9, 2015, SPIJ appears with more focused issues related to signal processing studies. Besides normal publications, SPIJ intend to organized special issues on more focused topics. Each special issue will have a designated editor (editors) – either member of the editorial board or another recognized specialist in the respective field.

This journal publishes new dissertations and state of the art research to target its readership that not only includes researchers, industrialists and scientist but also advanced students and practitioners. The aim of SPIJ is to publish research which is not only technically proficient, but contains innovation or information for our international readers. In order to position SPIJ as one of the top International journal in signal processing, a group of highly valuable and senior International scholars are serving its Editorial Board who ensures that each issue must publish qualitative research articles from International research communities relevant to signal processing fields.

SPIJ editors understand that how much it is important for authors and researchers to have their work published with a minimum delay after submission of their papers. They also strongly believe that the direct communication between the editors and authors are important for the welfare, quality and wellbeing of the Journal and its readers. Therefore, all activities from paper submission to paper publication are controlled through electronic systems that include electronic submission, editorial panel and review system that ensures rapid decision with least delays in the publication processes.

To build its international reputation, we are disseminating the publication information through Google Books, Google Scholar, Directory of Open Access Journals (DOAJ), Open J Gate, ScientificCommons, Docstoc and many more. Our International Editors are working on establishing ISI listing and a good impact factor for SPIJ. We would like to remind you that the success of our journal depends directly on the number of quality articles submitted for review. Accordingly, we would like to request your participation by submitting quality manuscripts for review and encouraging your colleagues to submit quality manuscripts for review. One of the great benefits we can provide to our prospective authors is the mentoring nature of our review process. SPIJ provides authors with high quality, helpful reviews that are shaped to assist authors in improving their manuscripts.

Editorial Board Members
Signal Processing: An International Journal (SPIJ)

TABLE OF CONTENTS

Volume 9, Issue 2, May 2015

Pages

14 - 24 Fixed Point Realization of Iterative LR-Aided Soft MIMO Decoding Algorithm
Mehnaz Rahman, Gwan S. Choi

Fixed Point Realization of Iterative LR-Aided Soft MIMO Decoding Algorithm

Mehnaz Rahman *mehnaz@tamu.edu*
Department of ECE
Texas A&M University
College Station, Tx- 77840, USA

Gwan S. Choi *gchoi@ece.tamu.edu*
Department of ECE
Texas A&M University
College Station, Tx- 77840, USA

Abstract

Multiple-input multiple-output (MIMO) systems have been widely acclaimed in order to provide high data rates. Recently Lattice Reduction (LR) aided detectors have been proposed to achieve near Maximum Likelihood (ML) performance with low complexity. In this paper, we develop the fixed point design of an iterative soft decision based LR-aided K-best decoder, which reduces the complexity of existing sphere decoder. A simulation based word-length optimization is presented for physical implementation of the K-best decoder. Simulations show that the fixed point result of 16 bit precision can keep bit error rate (BER) degradation within 0.3 dB for 8×8 MIMO systems with different modulation schemes.

Keywords: K-best Algorithm, MIMO, Lattice Reduction, Iterative Soft Decoding.

1. INTRODUCTION

With the evaluation of wireless communication, multiple-input multiple-output (MIMO) systems have been adopted by different wireless standards such as IEEE 802.11n, IEEE 802.16e in order to achieve high data rates. Most of these standards have a specified minimum bit error rate (BER) or packet error rate (PER) to guarantee quality of service (QoS). Such as 10^{-6} is specified as maximum tolerable BER according to IEEE 802.11n standard [1].

The main challenge of MIMO system is to maintain the performance of the receiver with reduced complexity. Several algorithms have been proposed so far to address the issue offering different tradeoffs between performance and power consumption. The maximum likelihood (ML) detector offers optimal performance through exhaustive search, although its complexity increases exponentially with the number of transmitting and receiving antenna and bits in modulation [2, 3]. In contrast, linear detectors (LD) and sub-optimal detectors (zero forcing (ZF), minimum mean square error (MMSE) detectors) have been developed with significant performance loss.

Recently, lattice reduction (LR) has been proposed to achieve high performance with less complexity compared to the conventional K-best decoder [4, 5, 6]. These sub-optimal detectors are based on hard decisions. Hence, soft input-soft output (SISO) decoders are introduced with low density parity check (LDPC) decoder to achieve near Shannon performance with reasonable complexity [7, 8].

When considering practical implementation, fixed point design is a crucial step for hardware implementation in application specific integrated circuits (ASICs) or field programmable gate arrays (FPGAs). This paper presents a fixed point design of iterative soft decision based LR-aided K-best decoder proposed in [9], which exploits the algorithm of on-demand child expansion in iterative soft decoder. For soft decoding, the log likelihood ratio (LLR) values from the K best candidates are first computed for LDPC decoder and then, these are fed to the LLR update unit as inputs to the next iteration. This process of iteration continues until the difference between the last two iterations becomes negligible. After that, the last updated LLR values are used for hard decision.

In this paper, we have conducted a novel study on fixed point realization of iterative LR-aided K-best decoder based on simulation. This process involves 2 steps: first is to select optimized architecture for each sub-module of K-best decoder, and the second is to perform the fixed point conversion. The choice of proper architecture makes the hardware implementation easier, while the fixed point conversion minimizes the bit length of each variable. These objectives lead to the minimization of hardware cost, power, and area as well.

At first, we compare the result of our algorithm with that of a depth first search least sphere decoder (DFS-LSD) in [9] for the 4th iteration. As the benefit gained from 3rd to 4th iteration is limited and negligible for iterations beyond that, all the simulations are performed up to four iterations for iterative decoders [10]. Next, we observe the simulation based optimization of word-length in order to minimize the total bit width of variables while obtaining similar BER. The results demonstrate that the total word length of only 16 bits can keep BER degradation within 0.3 dB for 8×8 MIMO with different modulation schemes. For QPSK modulation, precision of 16 bits results in less than 0.3 dB degradation, while 16 QAM and 64 QAM modulation provide 0.2 dB and 0.3 dB decrease in performance respectively compared to those of the floating bits of MIMO decoder.

The rest of the paper is organized as follow. In Section II we have introduced soft decision based LR-aided MIMO decoding algorithm. Next, in Section III fixed point realization of iterative decoder is proposed. Then, we analyze the results for all of our studied cases in Section IV. Finally, Section V concludes this paper with a brief overview.

2. SYSTEM MODEL

Let us consider a MIMO system operating in M-QAM modulation scheme with $\mathrm{N_T}$ transmit antenna and $\mathrm{N_R}$ receiving antenna. Hence, it can be represented as:

$$\mathrm{y^c = H^c s^c + n^c}, \tag{1}$$

where $\mathrm{s^c = [s_1, s_2, ... s_{N_T}]^T}$ is the $\mathrm{N_T}$ dimensional transmitted complex vector, $\mathrm{H^c}$ is complex channel matrix and $\mathrm{y^c = [y_1, y_2, ... y_{N_R}]^T}$ is the $\mathrm{N_R}$ dimensional received complex vector. Noise $\mathrm{n^c = [n_1, n_2, ... n_{N_R}]^T}$ is a $\mathrm{N_R}$ dimensional circularly symmetric complex zero-mean Gaussian noise vector with variance σ^2. The corresponding real signal mode is:

$$\begin{bmatrix} \Re[\mathrm{y^c}] \\ \Im[\mathrm{y^c}] \end{bmatrix} = \begin{bmatrix} \Re[\mathrm{H^c}] & -\Im[\mathrm{H^c}] \\ \Im[\mathrm{H^c}] & \Re[\mathrm{H^c}] \end{bmatrix} \begin{bmatrix} \Re[\mathrm{s^c}] \\ \Im[\mathrm{s^c}] \end{bmatrix} + \begin{bmatrix} \Re[\mathrm{n^c}] \\ \Im[\mathrm{n^c}] \end{bmatrix}$$

$$\mathrm{y = Hs + n}, \tag{2}$$

where $\mathrm{s = [s_1, s_2, ... s_{2N_T}]^T}$, $\mathrm{y = [y_1, y_2, ... y_{2N_R}]^T}$ and . $\mathrm{n = [n_1, n_2, ... n_{2N_R}]^T}$. $\Re(\cdot)$ and $\Im(\cdot)$ denote the real and imaginary parts of a complex number respectively. ML detector solves for the transmitted signal by performing:

$$\hat{\mathrm{s}} = \arg_{\tilde{\mathrm{s}} \in \mathrm{S}^{2\mathrm{N_T}}} \min \|\mathrm{y} - \mathrm{H}\tilde{\mathrm{s}}\|^2 . \tag{3}$$

Here, $\|.\|$ denotes 2-norm, $\tilde{s}$ is the candidate vector, and $\hat{s}$ represents the estimated transmitted vector. This MIMO detection problem can be represented as the closest point problem in [11], and it performs a search through the set of all possible lattice points. In real signal mode, each antenna provides a search of 2 level: one for real part and the other for imaginary. The search is satisfied by the solutions with minimum error between sent and received signal. ML detector performs a search of all possible branches of the tree. Hence, it can obtain the maximum performance with exponentially increasing hardware complexity. Therefore, LR-aided detection is used to reduce the complexity of the ML detector [12]. Since lattice reduction requires unconstrained boundary, so the following change is made to (3) to obtain a relaxed search:

$$\hat{s} = \arg_{\tilde{s}\in\mathcal{U}^{2N_T}} \min\|y - H\tilde{s}\|^2 , \tag{4}$$

where $\mathcal{U}$ is unconstrained constellation set as $\{\dots, -3, -1, 1, 3, \dots\}$. But $\hat{s}$ may not be a valid constellation point, so a quantization step is applied:

$$\hat{s}^{NLD} = \mathcal{Q}\,(\hat{s}) , \tag{5}$$

where $\mathcal{Q}(.)$ is the symbol wise quantizer to the constellation set S. However, this type of naive lattice reduction (NLD) does not acquire good diversity multiplexing tradeoff (DMT). Hence, MMSE regularization is employed as follows:

$$\overline{H} = \begin{bmatrix} H \\ \sqrt{\frac{N_0}{2\sigma_2^2}}\, I_{2N_T} \end{bmatrix}, \qquad \bar{y} = \begin{bmatrix} y \\ 0_{2N_T\times 1} \end{bmatrix}, \tag{6}$$

where $0_{2N_T\times 1}$ is a $2N_T \times 1$ zero matrix and I_{2N_T} is a $2N_T \times 2N_T$ identity matrix [13, 14]. Eq. (4) can be represented as:

$$\hat{s} = \arg_{\tilde{s}\in\mathcal{U}^{2N_T}} \min\|\bar{y} - \overline{H}\tilde{s}\|^2 . \tag{7}$$

LR- aided detectors apply lattice reduction to the matrix $\overline{H}$ to find a more orthogonal matrix $\widetilde{H} = \overline{H}T$, where T is a unimodular matrix. This reduction effectively finds a better basis for the lattice and reduces the effect of noise and error propagation. After the reduction, the NLD with MMSE becomes

$$\hat{s} = 2T \arg\, \min_{\tilde{z}\in\mathbb{C}^{2N_T}} \left(\left\|\tilde{y} - \widetilde{H}\tilde{z}\right\|^2 + 1_{2N_T\times 1}\right), \tag{8}$$

where $\tilde{y} = (\bar{y} - \overline{H}1_{2N_{T\times 1}})/2$ is the complex received signal vector and $1_{2N_T\times 1}$ is a $2N_T \times 1$ one matrix. After shifting and scaling, (8) became the following one.

$$\hat{s} = 2T\tilde{z} + 1_{2N_T\times 1} . \tag{9}$$

2.1 LR-aided Decoder

LR-aided K-Best decoder belongs to a breath first tree search algorithm. At a high algorithmic point of abstraction, the LR aided K-best search is performed sequentially, solving for the symbol at each antenna. In the beginning, QR decomposition on $\tilde{H} = QR$ is performed, where Q is a $2(N_R + N_T) \times 2N_T$ orthonormal matrix and R is a $2N_T \times 2N_T$ upper triangular matrix. Then (8) is reformulated as

$$\hat{s} = 2T \arg \min_{\tilde{z} \in \mathbb{Z}^{2N_T}} \left(\|\breve{y} - R\tilde{z}\|^2 + 1_{2N_T \times 1} \right), \tag{10}$$

where $\breve{y} = Q^T \tilde{y}$. The error at each step is measured by the partial Euclidean distance (PED), which is an accumulated error at a particular level for a given path through the tree. For each level, the K best nodes are calculated, and passed to the next level for consideration. At the last level, the K paths through the tree are evaluated to find K nodes with minimum PED for hard decision. In our adopted algorithm proposed in [10], the process of node calculation is optimized by on-demand child expansion.

2.2 On-demand Child Expansion

On-demand child expansion employs the principle of Schnorr-Euchner (SE) enumeration [15, 16] in a strictly non-decreasing order. It involves expanding of a node (child) if and only if all of its better siblings have already been expanded and chosen for future candidates [17].

Hence, at an arbitrary level of tree, the number of nodes needs to be expanded is bounded by $K + (K - 1)$ in the worst case scenario. For the entire tree, it becomes $4N_T K - 2N_T$. While considering the conventional K-best algorithm, the number of the expanded nodes is equal to $2N_T Km$, where m is the number of nodes of the modulation scheme. For instance, with list size, K = 4 and N_T = 8, it requires 112 nodes for on-demand and 1024 nodes for conventional K-best algorithm to be expanded considering 16QAM modulation scheme. Therefore, use of on-demand child expansion requires significantly less computation, which reduces hardware complexity as well.

While working with soft decision, each path of chosen K best paths is considered as potential candidate. Hence, these K paths are passed to the soft-input soft-output (SISO) decoder for soft decoding.

2.3 Iterative Soft Decoding

LDPC decoder in [18] calculates approximate LLR from the list of possible candidates using (11).

$$L_E(x_k|Y) \approx \frac{1}{2} \max_{x \in X_{k,+1}} \left\{ -\frac{1}{\sigma^2} \| y - Hs \|^2 + x_{[k]}^T . L_{A,[k]} \right\} - \frac{1}{2} \max_{x \in X_{k,-1}} \left\{ \frac{1}{\sigma^2} \| y - Hs \|^2 + x_{[k]}^T . L_{A,[k]} \right\}, \tag{11}$$

where $\mathbf{x}_{[\mathbf{k}]}^{\mathbf{T}}$ and $\mathbf{L}_{\mathbf{A},[\mathbf{k}]}$ are the candidates values {-1 or 1} and LLR values except k-th candidate respectively. In order to perform the soft decoding, the LLR values are first computed at the last layer of K-best search. Then, the soft values are fed into the iterative decoder for the subsequent iteration. This process is continued till the difference in error levels between the last two iterations becomes negligible. At the end, the last updated values are used for hard decision.

3. FIXED POINT REALIZATION

The system level diagram of adopted iterative LR-aided K-best decoder in [10] is presented in Fig. 1.

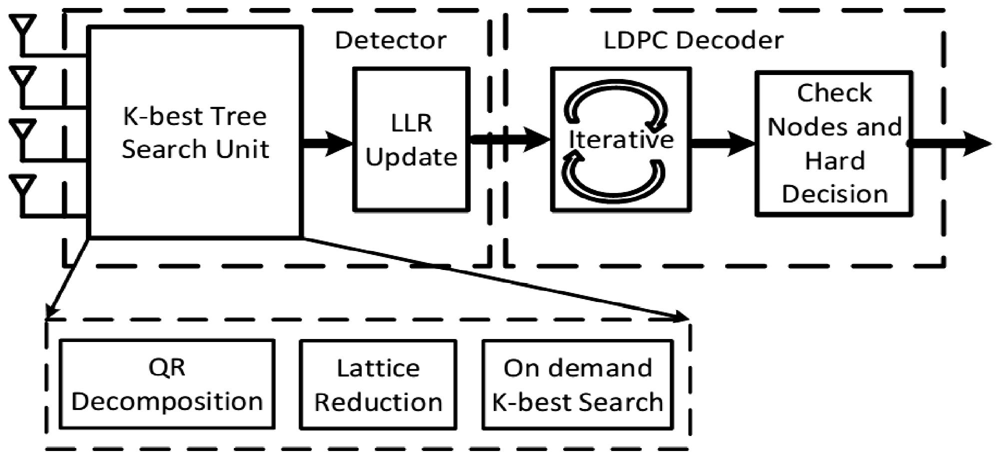


FIGURE 1: System level model of iterative LR-aided K-best decoder.

The fixed point realization of iterative LR-aided decoder involves two steps: First is the architecture selection of each sub-module and the second is the fixed point conversion. The selection of proper architecture makes the hardware implementation easier, and the fixed point conversion minimizes the bit widths of variables. Hence, it can reduce hardware cost including area, power and time delay.

3.1 Architecture Selection of Each Sub-module

3.1.1 QR Decomposition

There are three well known algorithms for QR Decomposition proposed in [19]. Among them, the Givens rotation algorithm implemented by Coordinate Rotation Digital Computer (CORDIC) scheme under Triangular Systolic Array (TSA) in [20, 21] is selected for QR Decomposition. CORDIC is adopted due to its simple shift and operations for hardware implementation with reduced latency and it can be implemented easily exploiting parallel and pipeline architecture.

3.1.2 Lattice Reduction

The Lenstra-Lenstra-Lovasz (LLL) algorithm proposed in [22] is a popular scheme for implementing lattice reduction. It can obtain optimal performance with low complexity. Hence, it is suitable for hardware realization by transforming the complicated division and the inverse root square operation into Newton-Raphson iteration and CORDIC algorithm respectively [23].

3.1.2 LDPC Decoder

The hardware design of LDPC Decoder in [18] consists of separate LLR calculation unit. It takes one of the candidates at a given time and computes the LLR value at each clock cycle. Then, the new LLR is compared to the maximum of previous LLRs. Hence, this unit has to keep track of 2 values for each LLR. One for those whose k-th of the candidate list is 1 (Lambda-ML), and the other for 0 (Lamdba-ML-bar). After that, the LLR values are calculated as the subtraction of Lamdba-ML and Lamdba-ML-bar divided by 2.

3.2 Fixed Point Conversion With Word-length Optimization

In order to perform the fixed point conversion, all floating-point variable and arithmetic operations are converted into fixed point version. It is simulated by MATLAB HDLcoder, which is bit-accurate with verilog source code and mimics the actual operation in hardware.

Each word length is then optimized to determine the minimum bit width for each fixed point variable keeping high performance within tolerated error limit. To choose the length of proper precision bits, first minimum integer word length is calculated under large data simulation. After that, the minimum and maximum value of each variable is calculated through MATLAB profiling.

To estimate precision bits, first minimum and maximum fractional word length are chosen through extensive simulation. Then the bit error rate (BER) performances are evaluated for subsequently decreasing word length from max to selected min. At the end, the word length for which high performance with lower and tolerable error limit can be achieved, is selected as final optimized precision bit length.

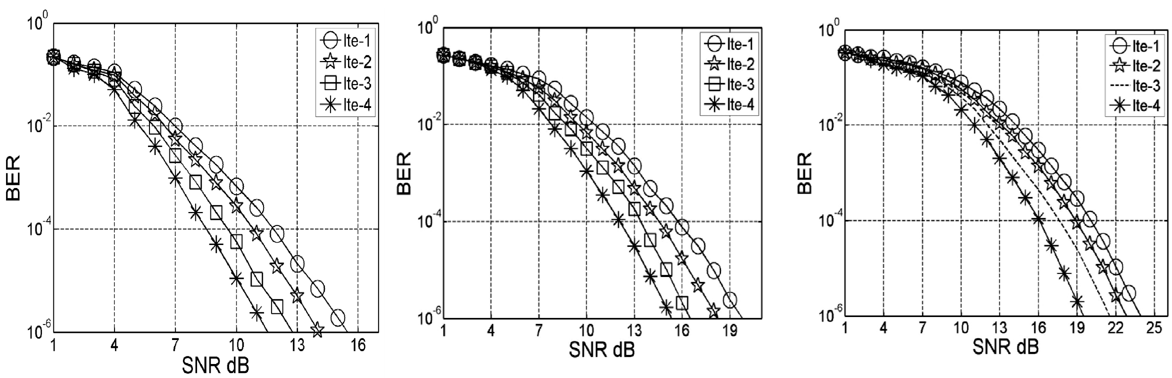
4. SETUP AND RESULTS

This section demonstrates the performance of iterative soft decision based LR-aided K-best decoder in [10] for 8×8 MIMO with different modulation schemes. The signal to noise ratio (SNR) is defined as the ratio of received information bit energy to noise variance.

We first analyze the performance of four iterations of both iterative LR-aided decoder and LSD decoder in [9] with list size of 4 for different modulation schemes. Next, the comparison between LR-aided and LSD decoder is performed for QPSK, 16QAM and 64QAM modulation schemes. We also demonstrate the comparison of performance for floating word length with that of fixed one. For iterative decoder, as shown in [10] the improvement gained from the 3rd to 4th iteration is limited and negligible for iteration beyond that. Hence, we consider BER versus SNR curve of 4th iteration in order to compare among maximum performances. LDPC decoder has been set to continue up to 25 internal iterations, although it would terminate immediately if all the parity check equations are satisfied.

4.1 Simulation and Analysis

The performances of four iterations of 8×8 MIMO for different modulation scheme are presented in Fig. 2.

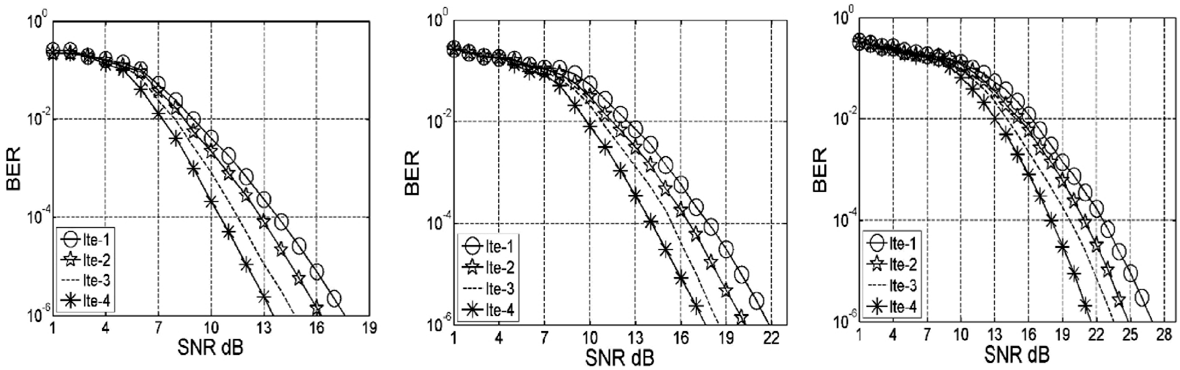


(a) QPSK (b) 16QAM (c) 64QAM

FIGURE 2: BER vs SNR curve of the first 4 iterations of 8 x 8 LR-aided decoder for different modulation schemes with K as 4.

As shown in Fig. 2(a), for QPSK modulation scheme with list size of 4, we observe 1.5 dB improvement in BER due to the 2nd iteration at the BER of 10^{-6}. When we compare the performance of 1st iteration with 3rd and 4th one, the improvement increases to 3.0 and 4.2 dB respectively. Next, the performances of four iterations for 16QAM modulation schemes are given in Fig. 2(b).

As demonstrated in Fig. 2(b), the performance of 2nd iteration is approximately 1.6 dB better than the 1st one with K as 4 for 16QAM modulation scheme. When increasing the iteration, the performance improves by 3.1 dB for the 3rd and 4.2 dB for the 4th iteration compared to the 1st one. For 64QAM modulation scheme having the same K as in 16QAM, the improvement due to the 2nd iteration is 1.5 dB, as shown in Fig. 2(c). If we then compare the 3rd and 4th iteration with respect to the 1st one, the improvements are 3.2 dB and 4.2 dB respectively. Therefore, with iteration number, the performance between i-th and (i+1)-th iteration becomes saturated. Similar curves can be obtained using LSD based decoder for all modulation schemes, as shown in Fig. 3.



(a) QPSK (b) 16QAM (c) 64QAM

FIGURE 3: BER vs SNR curve of the first 4 iterations of 8 x 8 LSD decoder for different modulation schemes with K as 4.

It is evident in Fig. 3(a), the 2nd, 3rd and 4th iteration provide 1.5 dB, 2.8 dB and 4.0 dB improvements respectively comparing with the 1st iteration at the BER of 10^{-6} for QPSK modulated LSD based decoder with K as 4. Again, for 16QAM modulation as shown in Fig. 3(b), the improvements become 1.8 dB for the 2nd iteration and 3.8 dB for the 3rd one with respect to the 1st iteration. When we simulate it further, we get 4.8 dB gain for the 4th iteration.

The performance of LSD decoder for 64QAM modulation is demonstrated in Fig. 3(c). From the curve, we observe 2.5 dB improvement for the 2nd iteration comparing with the 1st one. While considering the 3rd and 4th iteration, the improvements become 4.2 dB and 5.8 dB respectively. Therefore, it is evident that with higher modulation scheme, the performance gain between each iteration of the two methods gets higher. The SNR dB improvements for different iterations using LSD and LR-aided decoder with different modulation schemes are summarized below in Table 1.

Modulation Scheme	**LSD Decoder**			**LR-aided Decoder**		
	1st and 2nd	1st and 3rd	1st and 4th	1st and 2nd	1st and 3rd	1st and 4th
QPSK	1.5	2.8	4.0	1.5	3.0	4.2
16QAM	1.8	3.8	4.8	1.6	3.1	4.2
64QAM	2.5	4.2	5.8	1.5	3.2	4.2

TABLE 1: SNR Improvements (in dB) for both LR-aided and LSD decoder.

4.2 Comparison of Performance

The comparison of performance of between iterative LR-aided decoder and LSD decoder of the 4th iteration for different modulation schemes in presented in Fig. 4. Since the performance becomes saturated after 4th iteration, we have considered the BER vs SNR curves of only 4th iteration to evaluate among maximum performances.

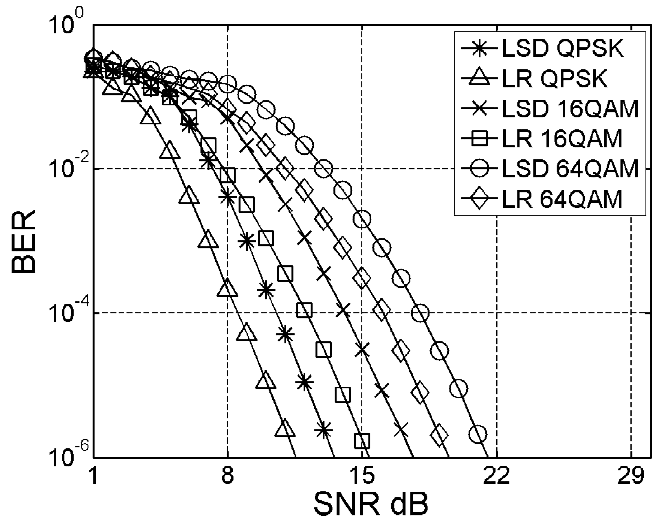


FIGURE 4: BER vs SNR curve of the 4th iteration of iterative LR-aided decoder and LSD decoders for QPSK, 16QAM and 64QAM modulation scheme with list size, K as 4.

As demonstrated in Fig. 4, a 2.5 dB improvements in performance can be obtained using LR-aided decoder for the 4^{th} iteration with QPSK modulation. When considering 16QAM and 64QAM modulation schemes, the performance gain becomes 2.8 dB and 2.5 dB respectively at the BER of 10^{-6}. The gain between LR-aided and LSD decoder for 1^{st} and 4^{th} iteration is summarized in Table 2.

Modulation Scheme	**Gain of LR-aided Decoder Over LSD Decoder**	
	1^{st} and 1st	4th and 4th
QPSK	2.1	2.5
16QAM	2.2	2.8
64QAM	3.0	2.5

TABLE 2: SNR Improvements (in dB) comparing between LR-aided and LSD decoder.

4.3 Optimization of Word-length

The optimization of word length can reduce the total bit width of variables while achieving the similar BER. In Fig. 5, the comparison of performance of iterative LR-aided decoder using floating bit length with that of fixed precision word length is presented for QPSK modulation scheme.

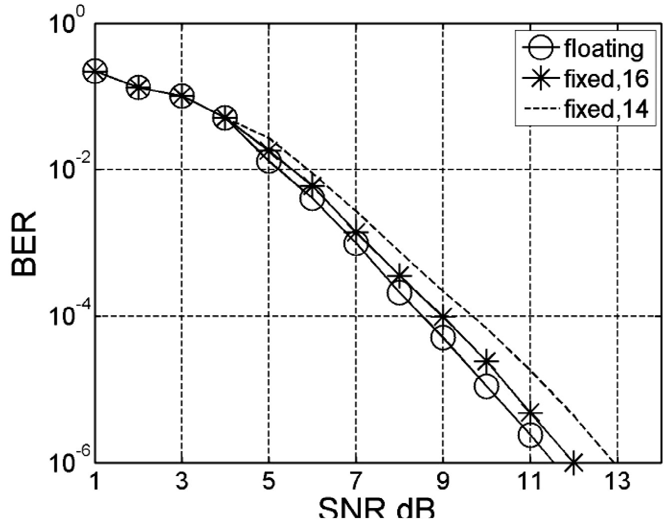
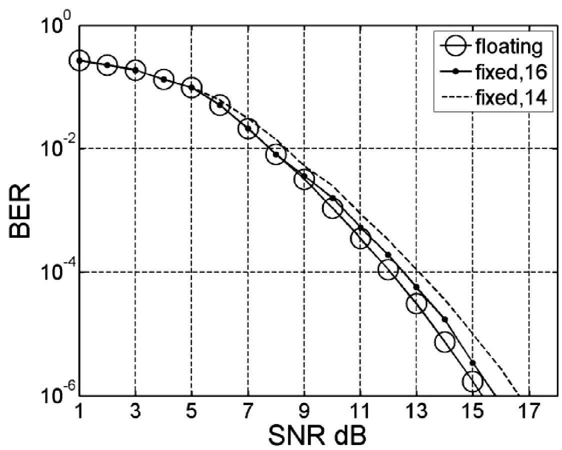
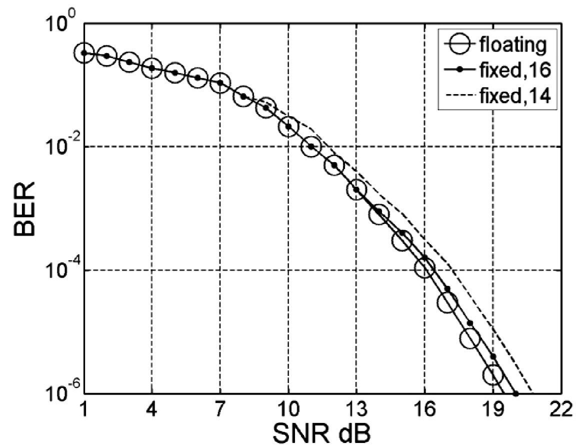


FIGURE 5: BER vs SNR curve of the 4th iteration of 8 x 8 LR-aided decoder for QPSK modulation scheme with floating and fixed word length of 14 and 16 bits.

The simulation is done for 8×8 MIMO system with K equal to 4. We consider only the 4th iteration in order to evaluate comparison among maximum performances. As shown in Fig. 5, when considering bit length of 16 bits, the performance degrades 0.3 dB comparing with the floating one. If we decrease the word length to 14 bits, the performance decreases to 1.3 dB. Hence, 16 bits of fixed word length can limit the performance degradation to 0.3 dB at the BER of 10^{-6}.



(a) 16QAM



(b) 64QAM

FIGURE 6: BER vs SNR curves of the 4th iteration of 8 x 8 LR-aided decoder with floating and fixed word lengths of 14 and 16 bits.

Next, Fig. 6 represents the performance curve of 4th iteration for 16QAM and 64QAM modulation scheme. As demonstrated in Fig. 6(a), for 16 QAM modulation scheme, 16 bit word length decreases the BER performance 0.2 dB at the BER of 10^{-6}. When considering the word length of 14 bit, the performance degrades approximately about 1.3 dB.

While considering the performance of 64QAM, shown in Fig. 6(b), 16 bit precision limits the degradation to 0.3 dB. When evaluating for fixed 14 bits, the performance decreases to more than 1.3 dB. Therefore, 16 bits of fixed word length can keep the BER performance degradation within 0.3 dB for QPSK, 16QAM and 64QAM modulation schemes.

5. CONCLUSION

In this paper, we develop the fixed point design of an iterative soft decision based LR-aided K-best decoder. A simulation based word-length optimization provides feasible solution for hardware implementation with the selection of efficient architectural sub-components. Besides, the fixed point conversion also minimizes the bit width of each variable. Hence, it can reduce hardware cost including area, power and time delay.

Simulation results show that the total word length of only 16 bits can keep BER degradation about 0.3 dB for 8×8 MIMO with different modulation schemes. For QPSK modulation, precision of 16 bits results in less than 0.3 dB degradation, while 16 QAM and 64 QAM modulation provide 0.2 dB and 0.3 dB decrease in performance respectively compared to those of the floating bits of MIMO decoder. Future scope of this proposed work includes but not limited to the hardware implementation of LR-aided iterative K-best decoder in order to validate our fixed point design.

6. REFERENCES

[1] "IEEE Standard for Information Technology- Local and Metropolitan Area Networks- Specific Requirements- Part 11: Wireless LAN Medium Access Control (MAC) and Physical Layer (PHY) Specifications Amendment 5: Enhancements for Higher Throughput." IEEE Standard 802.11n-2009 (Amendment to IEEE Standard 802.11-2007 as amended by IEEE Standard 802.11k-2008, IEEE Standard 802.11r-2008, IEEE Standard 802.11y-2008, and IEEE Standard 802.11w-2009), pp. 1-565, Oct. 2009.

[2] J. Jalden and B. Otterston. “On the Complexity of Sphere Decoding in Digital Communications.” IEEE Transaction on Signal Processing, vol. 53, no. 4, pp. 1474-1484, Apr. 2005.

[3] I. Lai, G. Ascheid, H. Meyr and T.-D. Chiueh. "Low-Complexity Channel-Adaptive MIMO Detection with Just-Acceptable Error Rate." IEEE 69th Vehicular Technology Conference: VTC-2009 Spring, Apr. 2009, pp. 1-5.

[4] B. M. Hochwald and S. Ten Brink. "Achieving Near-Capacity on a Multiple-Antenna Channel." IEEE Transactions on Communications, vol. 51, no. 3, pp. 389-399, Mar. 2003.

[5] C. Windpassinger and R. Fischer. “Low-Complexity Near-Maximum Likelihood Detection and Precoding for MIMO Systems Using Lattice Reduction.” Proceeding IEEE Information Theory Workshop, Mar. 2003, pp. 345-348.

[6] Q. Zhou and X. Ma. “An Improved LR-aided K-Best Algorithm for MIMO Detection.” Proceeding IEEE International Conference on Wireless Communication and Signal Processing (WCSP), Oct. 2012, pp. 1-5.

[7] M. Rahman, E. Rohani and G. Choi. "An Iterative Soft Decision Based Adaptive K-Best Decoder Without SNR Estimation." Asilomer Conference on Signals, Systems and Computers, Nov. 2014, pp. 1016-1020.

[8] M. Rahman, E. Rohani, J. Xu and G. Choi. "An Improved Soft Decision Based MIMO Detection Using Lattice Reduction." International Journal of Computer and Communication Engineering, vol. 3, no. 4, pp. 264-268, Apr. 2014.

[9] E. Rohani, J. Xu and G. Choi. "Low Power On-the-fly Reconfigurable Iterative MIMO Detection and LDPC Decoding Design." Journal on Applied Mechanics and Materials, vol. 496-500, pp. 1825-1829, Jan. 2014.

[10] M. Rahman, E. Rohani and G. Choi. "An Iterative LR-Aided MMSE Extended Soft MIMO Decoding Algorithm." International Conference on Computing, Networking and Communications, California, Feb. 2015.

[11] E. Agrell, T. Eirksson, A. Vardy and K. Zeger. “Closest Point Search in Lattices.” IEEE Transaction on Information Theory, vol. 48, no. 8, pp. 2201-2214, Aug. 2002.

[12] F. Sheikh, E. Wexler, M. Rahman, W. Wang, B. Alexandrov, D. Yoon, A. Chun and A. Hossein. "Channel-Adaptive Complex K-Best MIMO Detection Using Lattice Reduction." IEEE Workshop on Signal Processing Systems (SiPS), pp. 1-6, Oct. 2014.

[13] J. Jalden and P. Elia. “DMT Optimality of LR-Aided Linear Decoders for a General Class of Channels, Lattice Designs, and System Models.” IEEE Transaction on Information Theory, vol. 56, no. 10, pp. 4765-4780, Oct. 2010.

[14] M. Taherzadeh and A. Khandani. "On the Limitations of the Naive Lattice Decoding." IEEE Transaction on Information Theory, vol. 56, no. 10, pp. 4820-4826, Oct. 2010.

[15] M. Shabany and P. Glenn Gulak. “The Application of Lattice-Reduction to the K-Best Algorithm for Near-Optimal MIMO Detection.” IEEE International Symposium on Circuits and Systems (ISCAS), May 2008, pp. 316-319.

[16] M. Mahdavi and M. Shabany. "Novel MIMO Detection Algorithm for High-Order Constellations in the Complex Domain." IEEE Transaction on VLSI Systems, vol. 21, no. 5, pp. 834-847, May 2013.

[17] C. P. Schnorr and M. Euchner. “Lattice basis reduction: Improved practical algorithms and solving subset sum problems.” Mathematical Programming, vol. 66, pp. 181–191, Aug. 1994.

[18] K. Gunnam, G. Choi, W. Weihuang and M. Yeary. "Multi-Rate Layered Decoder Architecture for Block LDPC Codes of the IEEE 802.11n Wireless Standard." IEEE International Symposium on Circuits and Systems (ISCAS), May 2007, pp. 1645-1648.

[19] R. Horn and C. Johnson. "Matrix Analysis." Cambridge University Press, 1990.

[20] A. Maltsev, V. Pestretsov, R. Maslennikov and A. Khoryaev. "Triangular Systolic Array with Reduced Latency for QR-Decomposition of Complex Matrices." IEEE International Symposium on Circuits and Systems (ISCAS), May 2006, pp. 4-10.

[21] D. Chen and M. Sima. "Fixed-point CORDIC-based QR Decomposition by Givens Rotations on FPGA." International Conference on Reconfigurable Computing and FPGAs (ReConFig), Nov. 2011, pp. 327-332.

[22] A. K. Lenstra, H. W. Lenstra and L. Lovasz. "Factoring Polynomials with Rational Coefficients." Mathematische Annalen, vol. 261, no. 4, pp. 515-534, Dec. 1982.

[23] B. Gestner, W. Zhang, X. Ma and D. Anderson. "Lattice Reduction for MIMO Detection: from Theoretical Analysis to Hardware Realization." IEEE Transaction on Circuits and Systems, vol. 58, no. 4, pp. 813-826, Apr. 2011.

INSTRUCTIONS TO CONTRIBUTORS

The *International Journal of Signal Processing (SPIJ)* lays emphasis on all aspects of the theory and practice of signal processing (analogue and digital) in new and emerging technologies. It features original research work, review articles, and accounts of practical developments. It is intended for a rapid dissemination of knowledge and experience to engineers and scientists working in the research, development, practical application or design and analysis of signal processing, algorithms and architecture performance analysis (including measurement, modeling, and simulation) of signal processing systems.

As SPIJ is directed as much at the practicing engineer as at the academic researcher, we encourage practicing electronic, electrical, mechanical, systems, sensor, instrumentation, chemical engineers, researchers in advanced control systems and signal processing, applied mathematicians, computer scientists among others, to express their views and ideas on the current trends, challenges, implementation problems and state of the art technologies.

To build its International reputation, we are disseminating the publication information through Google Books, Google Scholar, Directory of Open Access Journals (DOAJ), Open J Gate, ScientificCommons, Docstoc and many more. Our International Editors are working on establishing ISI listing and a good impact factor for SPIJ.

The initial efforts helped to shape the editorial policy and to sharpen the focus of the journal. Started with Volume 9, 2015, SPIJ appears with more focused issues related to signal processing studies. Besides normal publications, SPIJ intend to organized special issues on more focused topics. Each special issue will have a designated editor (editors) – either member of the editorial board or another recognized specialist in the respective field.

We are open to contributions, proposals for any topic as well as for editors and reviewers. We understand that it is through the effort of volunteers that CSC Journals continues to grow and flourish.

SPIJ LIST OF TOPICS

The realm of Signal Processing: An International Journal (SPIJ) extends, but not limited, to the following:

- Biomedical Signal Processing
- Communication Signal Processing
- Detection and Estimation
- Earth Resources Signal Processing
- Industrial Applications
- Optical Signal Processing
- Radar Signal Processing
- Signal Filtering
- Signal Processing Technology
- Software Developments
- Spectral Analysis
- Stochastic Processes
- Acoustic and Vibration Signal Processing
- Data Processing
- Digital Signal Processing
- Geophysical and Astrophysical Signal Processing
- Multi-dimensional Signal Processing
- Pattern Recognition
- Remote Sensing
- Signal Processing Systems
- Signal Theory
- Sonar Signal Processing
- Speech Processing

CALL FOR PAPERS

Volume: 9 - **Issue: 4**

i. Paper Submission: September 30, 2015 **ii. Author Notification:** October 31, 2015

iii. Issue Publication: November 2015

CONTACT INFORMATION

Computer Science Journals Sdn BhD
B-5-8 Plaza Mont Kiara, Mont Kiara
50480, Kuala Lumpur, MALAYSIA

Phone: 006 03 6204 5627
Fax: 006 03 6204 5628

Email: cscpress@cscjournals.org

CSC PUBLISHERS © 2015
COMPUTER SCIENCE JOURNALS SDN BHD
B-5-8 PLAZA MONT KIARA
MONT KIARA
50480, KUALA LUMPUR
MALAYSIA

PHONE: 006 03 6204 5627
FAX: 006 03 6204 5628
EMAIL: cscpress@cscjournals.org