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Modifed SIC Algorithm based on Lattice Reduction Aided for MIMO OFDM Detection

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Abstract: The lattice reduction aided(LRA) algorithm has attracted widely attention of researchers in MIMO systems because of its low complexity to achieve full diversity. However, most lattice reduction auxiliary algorithms do not directly improve system performance. In this paper, a modified lattice reduction successive interference cancellation (SIC) algorithm is proposed for MIMO OFDM system mild changing the complexity of LRA algorithm. At present, the MMSE SQRD algorithm has the problem of regarding too much useful signals as the residual interference which cannot be cancelled by successive interference cancellation. Since the diagonal elements of useful signals are non-zero, the components of the symbols to be detected still present in the interference term, treating all the signals as interference will be resulted in performance loss. To solve this problem, the modified matrix is proposed.by moving this symbol component into the signal term, the proposed algorithm can provide the better performance than MMSE SQRD algorithm. The analysis shows that the LRA-MMSE-SIC algorithm of proposed in this paper significantly improves the system performance with mild increasing the complexity. The simulation results show that the performance of the proposed algorithm is improved by 1dB and 8dB compared with the comparison algorithm when the bit error rate is 10^{-3}.

Keywords: MIMO OFDM; SIC; Log-likelihood ratio(LLR);SQRD

1. Introduction

Nowadays, MIMO OFDM communication system has been widely applied because of it supports higher data rate and higher reliability than single antenna communication system [1-3] at present. As we all know, the detection algorithms mainly include linear detection methods and nonlinear detection methods[4].Linear detection algorithms such as zero-forcing (ZF) detection algorithm and minimum mean square error (MMSE) detection algorithm.The ZF algorithm perfectly removes interference components from the received signal. Because severe noise enhancement occurs by using the ZF filter, minimum mean square error (MMSE) filter can be an alternative solution to mitigate this problem. But these linear detection algorithms have their own shortcomings. The ZF detection algorithm only considers the impact of multipath channel, and does not consider the noise. Although ISI is not generated during signal transmission, noise will be amplified in frequency selective channels, especially when the channel has deep fading poles, resulting in serious performance degradation. The MMSE detection can be regarded as a compromise between channel noise and inter-symbol residual interference. When the channel has deep fading poles in frequency domain, the amplification of noise can be limited, and the performance is better than zero-forcing detection. Although the MMSE limits the amplification of noise, it also introduces some interference, which limits the improvement of system performance, and these two algorithms improve the system performance slowly[5-7].

In order to solve these problems, researchers have proposed nonlinear detection algorithms. In [8] , the SIC detection algorithm , which is a layer-by-layer signal detection algorithm, and the detected signal is regarded as the interference of the undetected layer signal to eliminate the influence of the signal in the detection layer on the undetected layer signal. It is worth noting that the accuracy of the first detected signal has a great influence on the next detection. In order to improve the performance of the algorithm, a

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detection algorithm based on QR decomposition was also a serial detection algorithm in [9]. The detection algorithm based on QR decomposition using QR decomposition method and other mathematical methods reduce the operation of multiple matrix pseudo-inverse, then decrease the complexity of the detection algorithm. It is noteworthy that the QR decomposition plays an important role in the detection process. The performance of the detection algorithm based on QR decomposition depends on the main diagonal value of the matrix obtained by QR decomposition of the channel matrix. A sorted QR decomposition detection algorithm is proposed. The algorithm sorts the columns of the channel matrix and uses QR decomposition for the matrix after the sorting, with the aim of making the values on the main diagonal of the matrix R satisfy the detection order of the transmitted signal. This has the advantage of effectively reducing the error propagation and improving the accuracy of the detection algorithm. Several typical detection algorithms based on QR sorting in [10-13] are proposed, including QR sorting algorithm based on MMSE criterion and QR decomposition algorithm based on Schmidt orthogonalization. The above sorted QR algorithms are designed to make the order of the elements on the main diagonal of the matrix satisfy the optimal detection order at the receiving end. In [13], simulation results show that soft-output MMSE SQRD detection also suffers from the error propagation. To reduce the error propagation effects, a straightforward method is to employ soft SIC MMSE SQRD detection.

Recently, lattice reduction algorithm has been widely used for MIMO OFDM system. Because they can achieve the same diversity as ML detectors with low complexity [14,15].In all lattice reduction algorithm, LLL algorithm is considered to be the most practical one. The lattice reduction algorithm is a powerful preprocessing technique that can be used for linear receivers and successive interference cancellation (SIC) [16,17] methods. The LR-aided MIMO receiver first finds the set of small, nearly orthogonal matrices for the given channel matrix and decodes the symbols using this matrix rather than the original channel matrix. Different LR algorithms (such as LLL [18] or Seysen [19]) can be used to generate near orthogonal matrices of a given lattice. Compared with the hard discrimination method, the soft discrimination method has higher system performance.

In this paper, we first provide a soft-output MMSE SQRD detection based on lattice reduction assisted(LRA) with soft SIC for MMSE OFDM system, then we proposed a modified soft-output MMSE SQRD detection to further alleviate error propagation. Although LR-assisted successive interference can be used as a linear detector to achieve lower computational complexity, this receiving method achieves excellent performance. Although the signal can be achieved by using the LR-assisted SIC algorithm, there is a situation that the algorithm treats part of the useful signal as interference during the detection process, and therefore, the BER performance is not satisfactory. In order to improve the system performance, this paper uses the preprocessing matrix to remove some of the useful signals when reconstructing the interference at the receiver, which effectively solves the above problem and thus further improves the system BER. The organizational structure of this paper is as follows. The second part describes the MIMO OFDM system model. The third part describes a soft-output MMSE SQRD detection based on LRA with soft SIC and the modified soft-output SIC detection based on LRA in detail. The fourth part describes the complexity analysis of the proposed algorithm. The fifth part shows the system simulation results. The sixth part concludes this paper.

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2. System Model

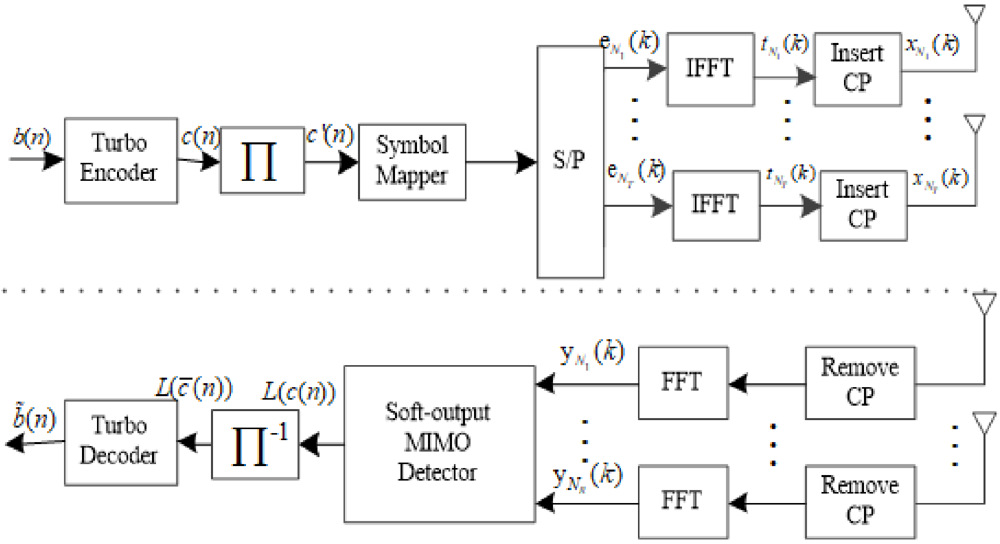

Figure 1. The MIMO OFDM system model

We consider a turbo coded MIMO OFDM system with N_T transmit antennas and $N_R$receive antennas. At the transmitter, the information bits are turbo-encoded to obtain an information sequence of length N. The encoder outputs $c(n)$, and then$\grave{c}(n)$is obtained after random interleaver processing. Finally,$\grave{c}(n)$is modulated to obtain a complex data sequence. QPSK and 16QAM are used in this paper. Taked QPSK as an example :The modulated signal is converted into data $e_{N_t}(k)$after serial-parallel conversion. Finally, the transmitted data stream of each antenna is processed by IFFT and insertion of cyclic prefix to obtain the transmitted signal $x_{N_t}(k)$.For the sake of convenience, the system takes the kth carrier as an example, the kth carrier transmitted signal vector $\mathbf{X}_c \in \mathbb{C}^{N_T \times 1}$ can be defined as $\mathbf{X} = (x_{N_1}, x_{N_2}, \cdots, x_{N_T})^T$.When the QPSK modulation signal is expressed as a complex number in the low-pass equivalent system, the signal can be written as a two-dimensional real vector. The transmitted signal vector can be rewritten as a real vector $\mathbf{X} \in \Re^{2N_T \times 1}$,the vector $\mathbf{X}$ can be redefined as$\mathbf{X} = (x_{N_1}, x_{N_2}, \cdots, x_{N_{2T}})^T$,where x_{N_t}can be represented by$x_{2i} = \Re[x_{2i}]$and$x_{2i-1} = \Re[x_i]$,$i = 1, 2, \cdots, N_T$.When the transmitted signal can be represented by a real number vector, the received signal can also be represented by a real number vector as follows :$\mathbf{Y} = \Re^{2N_R \times 1}$,the received signal can be expressed as ,

$$\mathbf{Y} = \mathbf{H}\mathbf{X} + \mathbf{N} \tag{1}$$

In the above formula, $\mathbf{N} = \Re^{2N_R \times 1}$represents the additive Gaussian white noise vector, which can be expressed as$\mathbf{N} = (n_1, n_2, \cdots, n_{N_{2R}})^T$, where n_{2i-1} and n_{2i} denote respectively the complex and real parts of the Gaussian noise data on the ith antenna. In addition, the channel matrix $\mathbf{H} = \Re^{2N_R \times 2N_T}$can be expressed as :

$$\mathbf{H} = \begin{bmatrix} \mathbf{h}_{1,1} & \mathbf{h}_{1,2} & \cdots & \mathbf{h}_{1,N_T} \\ \mathbf{h}_{2,1} & \mathbf{h}_{2,2} & \cdots & \mathbf{h}_{2,N_T} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{h}_{N_1,1} & \mathbf{h}_{N_2,2} & \cdots & \mathbf{h}_{N_R,N_T} \end{bmatrix} \tag{2}$$

where $\mathbf{h_{j,i}} = \Re^{2 \times 2}$ can be expressed as :

$$\mathbf{h_{j,i}} = \begin{pmatrix} \Re[h(j,i)] & -\Im[h(j,i)] \\ \Im[h(j,i)] & \Re[h(j,i)] \end{pmatrix} \tag{3}$$

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Where $\mathbf{h_{j,i}}$ represents the channel impulse response between the jth receiving antenna and the ith transmitting antenna.

The received signal $r_{Nr}(k)$ obtains the input value of the soft-input soft-output MIMO detector through serial-to-parallel conversion, CP removal and FFT transformation.Let $c_i^j(k)$ denote the jth corresponding coding bit of the ith transmission symbol of e_i, then the optimized MAP detection output posterior probability LLR function is :

$$\begin{aligned} L\left(c_i^j(k) \mid y(k)\right) &= \ln \frac{P\left(c_i^j(k)=0 \mid y(k)\right)}{P\left(c_i^j(k)=1 \mid y(k)\right)} = \ln \frac{\sum_{\forall x(k) \cdot c_i^j(k)=0} P(e(k) \mid y(k))}{\sum_{\forall x(k) c_i^j(k)=1} P(e(k) \mid y(k))} \\ &= \ln \frac{\sum_{\forall x(k) c_i^j(k)=0} P(|y(k)|e(k))P(e(k))}{\sum_{\forall x(k) c_i^j(k)=1} P(|y(k)|e(k))P(e(k))} \end{aligned} \tag{4}$$

Obviously, according to the above formula, the estimated value $\hat{e}_i(k)$ of the transmission symbol $e_i(k)$ can be further obtained, and the posterior probability LLR function is :

$$\begin{aligned} L_{i,j}{}^{pos}(k) &= \ln \frac{P\left(c_i^j(k)=0 \mid \hat{e}_i(k)\right)}{P\left(c_i^j(k)=1 \mid \hat{e}_i(k)\right)} \\ &= \ln \frac{\sum_{e \in \mathbb{Z}_0} P(e_i(k)=e \mid \hat{e}_i(k))}{\sum_{e \in \mathbb{Z}_1} P(e_i(k)=e \mid \hat{e}_i(k))} \\ &= \ln \frac{\sum_{e \in \mathbb{Z}_0{}^j} P(\hat{e}_i(k) \mid e_i(k)=e) P(e_i(k)=e)}{\sum_{e \in \mathbb{Z}_1{}^j} P(\hat{e}_i(k) \mid e_i(k)=e) P(e_i(k)=e)} \end{aligned} \tag{5}$$

where$\mathbb{Z}_t^j \triangleq \{e : e \in \mathbb{Z}, c^j = t\}$,$P(e_i(k)=e)isP(e_i(k)=e) = \prod_{l=1}^{Mc} P\left(c_i^l(k)=c^l\right)$,$c^l$is the lth binary bit corresponding to the transmission symbol and denote the constellation mapping symbol set. It can be further obtained that

$$\begin{aligned} L_{i,j}{}^{pos}(k) &= \ln \frac{\sum_{e \in Z_0^j} P(\hat{e}_i(k) \mid e_i(k)=e) \prod_{l \neq j} P\left(c_i^l(k)=c^l\right)}{\sum_{e \in Z_1^j} P(\hat{e}_i(k) \mid e_i(k)=e) \prod_{l \neq j} P(c_i^l(k)=c^l)} + \ln \frac{P\left(c_i^l(k)=0\right)}{P(c_i^l(k)=1)} \\ &= L_{i,j}{}^{\text{ext}}(k) + L_{i,j}{}^{apr}(k) \end{aligned} \tag{6}$$

According to the first part of (6), the input signal of turbo decoder can be obtained. The resulting LLRs are then deinerleaved and delivered to the turbo decoder. Finally, channel decoding can be performed by mean of a decoder [20].

3. Based on Lattice Reduction Aided MIMO OFDM Detection Method

3.1. MMSE SQRD detection based on LRA with soft SIC

The poor performance of linear detection algorithm is mainly due to the destruction of high orthogonality in channel matrix. If MIMO detection is performed on almost orthogonal matrices, performance improvement can be achieved. Therefore, the LLL algorithm deserves more attention. This paper extends the channel matrix to :

$$\bar{\mathbf{H}} = \begin{bmatrix} \mathbf{H} \\ \sigma_n \mathbf{I}_{2N_T} \end{bmatrix} \tag{7}$$

Where $\bar{\mathbf{H}} \in \mathbb{R}^{2(N_T+N_R) \times 2N_T}$ is the channel expansion matrix,$\mathbf{I}_{2N_T} \in \mathbb{R}^{2N_T \times 2N_T}$ unit matrix, σ_n represents the noise variance, the size of the channel matrix $\mathbf{H}$ is $2N_T \times 2N_T$, and the size of the channel expansion matrix $\bar{\mathbf{H}}$ is $2(N_T+N_R) \times 2N_T$.

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If the received signal is extended by channel expansion, the extended received signal $\bar{\mathbf{Y}}$ is:

$$\bar{\mathbf{Y}} = \begin{pmatrix} \mathbf{Y} \\ \mathbf{0}_{2N_T} \end{pmatrix} = \mathbf{H}\mathbf{X} + \begin{pmatrix} \mathbf{N} \\ -\sigma_n \mathbf{X} \end{pmatrix} \tag{8}$$

Where $\mathbf{0}_{2N_T}$ and $\bar{\mathbf{Y}} \in \Re^{2(N_T+N_R)\times 1}$ represent the $2N_T$ dimensional zero vector and the extended received signal vector, respectively.

In this paper, LRA is applied to extend the channel to improve the system performance.

$$\bar{\mathbf{H}} = \begin{bmatrix} \mathbf{H} \\ \sigma_n \mathbf{I}_{2N_T} \end{bmatrix} = \bar{\mathbf{Q}}\bar{\mathbf{R}} \begin{bmatrix} \bar{\mathbf{Q}}_1 \\ \bar{\mathbf{Q}}_2 \end{bmatrix} \bar{\mathbf{R}} \tag{9}$$

Rewritten in the form of 9 versus 8:

$$\mathbf{Y} = \mathbf{H}_{equ}\mathbf{T}^{-1}\mathbf{X} + \mathbf{N} \tag{10}$$

Where

$$\mathbf{H}_{equ} = \bar{\mathbf{Q}}\bar{\mathbf{R}} = \begin{bmatrix} \bar{\mathbf{Q}}_1 \\ \bar{\mathbf{Q}}_2 \end{bmatrix} \bar{\mathbf{R}} \tag{11}$$

$$\bar{\mathbf{N}} = \begin{pmatrix} \mathbf{N} \\ -\sigma_n \mathbf{X} \end{pmatrix} \tag{12}$$

In Eq. (10) and Eq. (11), $\bar{\mathbf{Q}} \in \Re^{2(N_T+N_R)\times 2(N_T+N_R)}$, $\mathbf{T} \in \Re^{2N_T\times 2N_T}$ and $\bar{\mathbf{R}} \in \Re^{2(N_T+N_R)\times 2N_T}$ represent unitary matrix $\mathbf{Q}^T\mathbf{Q} = \mathbf{I}_{2N_R+2N_T}$, a unimodular matrix and a right upper triangular matrix, respectively. Moreover, $\bar{\mathbf{Q}}_1 \in \Re^{2(N_T+N_R)\times 2N_T}$, $\bar{\mathbf{Q}}_2 \in \Re^{2(N_T+N_R)\times 2N_R}$.

Like the SIC algorithm, the received signal of the LRA-SIC algorithm is processed by the unitary matrix $\bar{\mathbf{Q}}$:

$$\mathbf{C}^{(2N_T)} = (\bar{\mathbf{Q}})^T\bar{\mathbf{Y}} = \bar{\mathbf{R}}\mathbf{T}^{-1}\mathbf{X} + (\bar{\mathbf{Q}})^T\bar{\mathbf{N}} = \bar{\mathbf{R}}\mathbf{T}^{-1}\mathbf{X} - \sigma\mathbf{Q}_2^T\mathbf{T}^{-1}\mathbf{X} + \mathbf{Q}_1^T\bar{\mathbf{N}} \tag{13}$$

Where $\mathbf{C}^{(2N_T)} \in \Re^{2N_T\times 1}$ and $\bar{\mathbf{N}} \in \Re^{2(N_T+N_R)\times 1}$ represent the output signal after preprocessing and expanded the noise vector respectively. For convenience, let $\mathbf{Z} = \mathbf{T}^{-1}\mathbf{X}$.

Extract the kth carrier, ith element of the preprocessed output signal $\mathbf{C}^{(2N_T)}$, and rewrite equation (13) as:

$$\mathrm{c}_i = \bar{r}_{i,i}(k)z_i(k) + \sum_{j=i+1}^{2N_R} \bar{r}_{i,j}(k)z_j(k) + \bar{n}_i(k) \tag{14}$$

where $\bar{r}_{i,j}(k)$ represents the element in row i, column j of matrix $\bar{\mathbf{R}}(k)$. If the mean values $\mu_j(k)$, $j = i+1, i+2, \cdots, 2N_R$ for symbols $i+1$ through $2N_R$ are known, the estimate for symbol i after interference cancellation can be expressed as :

$$\hat{Z}_i = \bar{r}_{i,i}{}^{-1}(k)\left(c_i(k) - \sum_{j=i+1}^{2N_R} \bar{r}_{i,j}(k)\mu_j(k)\right) \tag{15}$$

For the above estimates, the conditional mean $\mu_{\hat{Z}_i}$ and the conditional variance $\nu_{\hat{Z}_i}$ sent with the symbol Z_i are :

$$\mu_{\hat{z}_i}(k) = E\{\hat{z}_i(k) \mid z_i(k)\} = z_i(k) \tag{16}$$

$$\begin{aligned} \nu_{\hat{z}_i} &= E\left\{\left(\hat{z}_i - \mu_{\hat{z}_i}(k)\right)^2 \mid z_i(k)\right\} \\ &= \bar{r}_{i,i}{}^{-2}(k)\left(\sigma^2 + \sum_{j=i+1}^{2N_T} \nu_j(k)\right) \end{aligned} \tag{17}$$

Where $\nu_j(k)$ is the reconstruction variance of symbol j. The conditional probability distribution of estimate $\hat{z}_i(k)$ can be approximated as Gaussian distribution. Thus, the conditional

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probability density obtained from the conditional mean and conditional variance of the estimates is ,

$$p(\hat{z}_i \mid z_i = x) = \frac{1}{\sqrt{\pi \nu_{\hat{z}_i}}} \exp\left(\frac{-(\hat{z}_i - z)^2}{\nu_{\hat{z}_i}} \right) \tag{18}$$

Finally, the likelihood ratio of the estimated signal can be obtained by the above calculation. To obtain the original emission symbol vector, the following compensation procedure can be applied:

$$\hat{\mathbf{x}}_i = slicing(T\hat{\mathbf{z}}) \tag{19}$$

Where $slicing(x)$ is the operation of mapping x to the nearest constellation point. $\hat{\mathbf{x}}$ represents the estimated signal of the transmitted signal, which is used as the input signal of the turbo decoder to complete the detection process.

3.2. Modified soft-output SIC detection based on LRA

In this part, a modified Lattice Reduction Aided successive interference cancellation algorithm is proposed.In Equation (13), the second part $-\sigma \mathbf{Q}_2^T \mathbf{T}^{-1}\mathbf{X}$ on the right side is regarded as the residual interference that cannot be eliminated by successive interference cancellation. For the sake of convenience, let $\mathbf{Z} = \mathbf{T}^{-1}\mathbf{X}$, then $-\sigma \mathbf{Q}_2^T \mathbf{T}^{-1}\mathbf{X}$ can be rewritten as $-\sigma \mathbf{Q}_2^T \mathbf{Z}$. Since the diagonal element of $-\sigma \mathbf{Q}_2^T \mathbf{Z}$ is non-zero and contains the component of the signal $\mathbf{Z}$ to be detected, treating all $-\sigma \mathbf{Q}_2^T \mathbf{Z}$ as interference will lead to performance loss. Based on the above description, and extracting the kth carrier, Equation (13) is rewritten as :

$$\begin{aligned} \mathbf{C}(k) &= \left(\bar{\mathbf{R}}(k) - \sigma \mathbf{\Lambda}_{\mathbf{Q}^T{}_2}(k) \right) \mathbf{Z}(k) - \sigma \left(\mathbf{Q}_2^T(k) - \mathbf{\Lambda}_{\mathbf{Q}^T{}_2}(k) \right) \mathbf{Z}(k) + \mathbf{Q}_1^T(k) \bar{\mathbf{N}}(k) \\ &= \left(\bar{\mathbf{R}}(k) - \sigma \mathbf{\Lambda}_{\mathbf{Q}^T{}_2}(k) \right) \mathbf{Z}(k) + \bar{\mathbf{N}}'(k) \end{aligned} \tag{20}$$

Where $\mathbf{\Lambda}_{\mathbf{Q}^T{}_2}(k)$ represents a diagonal matrix composed of $\mathbf{Q}^T{}_2(k)$ diagonal elements, and $\bar{\mathbf{N}}'(k) = -\sigma \left(\mathbf{Q}_2^T(k) - \mathbf{\Lambda}_{\mathbf{Q}^T}(k) \right) \mathbf{Z}(k) + \mathbf{Q}_1^T(k) \bar{\mathbf{N}}(k)$ represents residual interference and noise that cannot be eliminated. Since $-\sigma \mathbf{Q}_2^T(k)$ is not regarded as interference, Equation (14) is further rewritten as :

$$c_i = (\bar{r}_{i,i}(k) - \sigma q_{2,ii}(k)) z_i(k) + \sum_{j=i+1}^{2N_R} \bar{r}_{i,j}(k) z_j(k) + \bar{n}_i'(k) \tag{21}$$

Where $q_{2,ii}(k)$ denotes the ith diagonal element in $\mathbf{Q}_2^T(k)$ and $\bar{n}_i'(k)$ denotes the jth element in $\bar{\mathbf{N}}'(k)$. On the right side of (21), The first item constitutes the desired signal component; the second item represents the interference caused by already detected symbols; and the third item represents the noise plus the remaining interference from undetected sybols,which does not include the signal component. It means that the algorithm proposed in this paper is more accurate than the above algorithm in calculating the posterior probability and LLR. Conditional mean (16) and conditional variance (17) may be written as:

$$\mu_{\hat{z}_i}(k) = (\bar{r}_{i,i}(k) - \sigma q_{2,ii}(k)) z \tag{22}$$

$$\nu_{\hat{z}_i} = \bar{r}_{i,i}^{-2}(k) \left(\left(1 - q_{2,ii}^2(k) \right) \sigma^2 + \sum_{j=i+1}^{2N_T} \nu_j(k) \right) \tag{23}$$

To simplify the conditional probability density calculation, a new symbol estimation signal is defined, and the k carrier waves of the first symbol can be further rewritten as follows:

$$\hat{z}_i = \bar{r}_{i,i}^{-1}(k) \left(1 - q_{2,ii}^2(k) \right)^{-1} \left(c_i(k) - \sum_{j=i+1}^{2N_R} \bar{r}_{i,j}(k) \mu_j(k) \right) \tag{24}$$

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The conditional mean and variance of the newly defined symbol estimates are as follows :

$$\mu_{\hat{z}_i}(k) = z \tag{25}$$

$$\nu_{\tilde{z}_i} = \bar{r}_{i,i}^{-2}(k)\left(1 - q_{2,ii}^2(k)\right)^{-2}\left(\left(1 - q_{2,i}^2(k)\right)\sigma^2 + \sum_{j=i+1}^{2N_T} |\bar{r}_{i,i}(k)|^2 \ni_j (k)\right) \tag{26}$$

The likelihood ratio of the estimated signal can be obtained by (4) - (6) and (18). Finally, Equation (19) is used to compensate the estimated signal to obtain the original transmitted signal vector.

4. Complexity

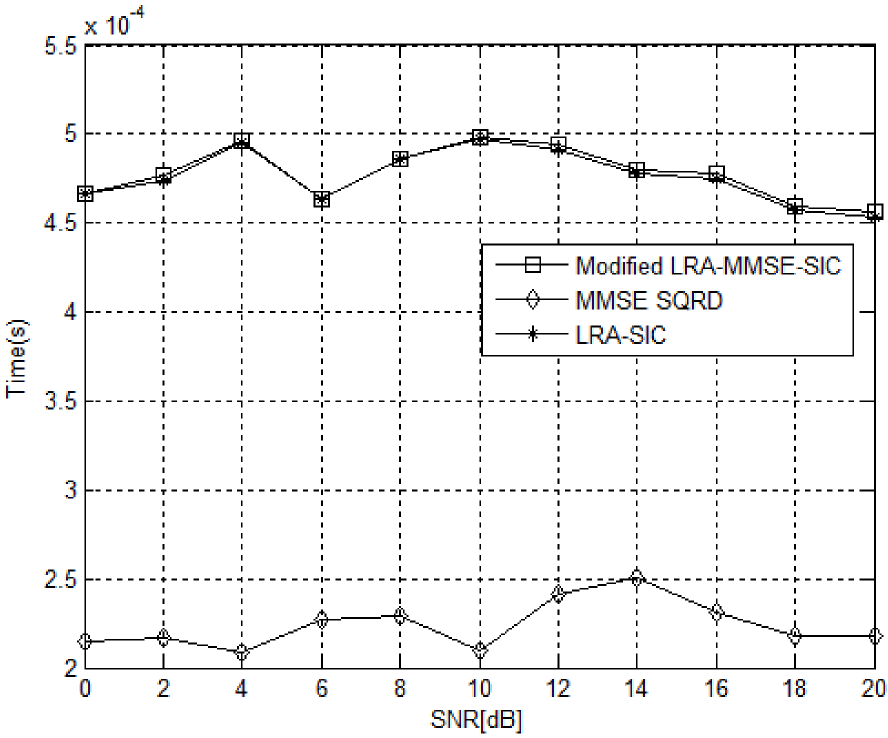

Figure 2. Running time comparison

The maximum likelihood detection algorithm has the best detection performance among the known algorithms, but in reality they are often not adopted because of its high complexity[21,22].Its complexity is $\mathcal{O}(C^t)$, which increases exponentially with the modulation order and the number of transmit antennas, where C is the number of constellation points and t is the number of transmit antennas[23].The MMSE-SQRD detection algorithm firstly adopts the sorted QR decomposition of the extended channel matrix $\mathbf{H}$, and then performs layer-by-layer signal detection.Its complexity is $\mathcal{O}(n^3)$, which is mainly determined by the size of the main diagonal of $\mathbf{R}$ of the upper triangular matrix[24].The SIC algorithm based on lattice reduction technology, its complexity is largely determined by the number of column exchanges of the lattice matrix. Suppose $N_t = N_r = n$, then the number of base matrix column exchanges is $\mathcal{O}(n^2 lgB)$, where B is the longest base vector norm, so the total complexity of the lattice reduction is $\mathcal{O}(n^4 lgB)$, and in actual detection we usually convert the complex matrix to the equivalent real matrix, but this will double the channel matrix H and the complexity becomes $\mathcal{O}(2n^4 lgB)$. On the other hand, the complexity of SIC detection algorithm after QR decomposition is equal to that of linear detection algorithm, and the extra computational workload can be ignored. The

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modified LRA-MMSE SIC algorithm updates the interfering part of the algorithm based on the LAR-SIC, but the complexity is the same as the LAR-SIC algorithm.

We can observe from the graph that approximately unchanged of the time taken by LRA-SIC algorithm is reduced in the proposed algorithm, but compared to the MMSE SQRD algorithm, the running time has increased slightly. In Figure 2, we have plotted the time taken to estimate one transmitted vector for an 4 4 MIMO OFDM system with QPSK and observed approximately 82% reduction in time consumption. This time graph is simulated in MATLAB 2011 b on an Intel Core i5 3.50 GHz with 8 GB RAM PC running Windows 7.

5. Simulation Results

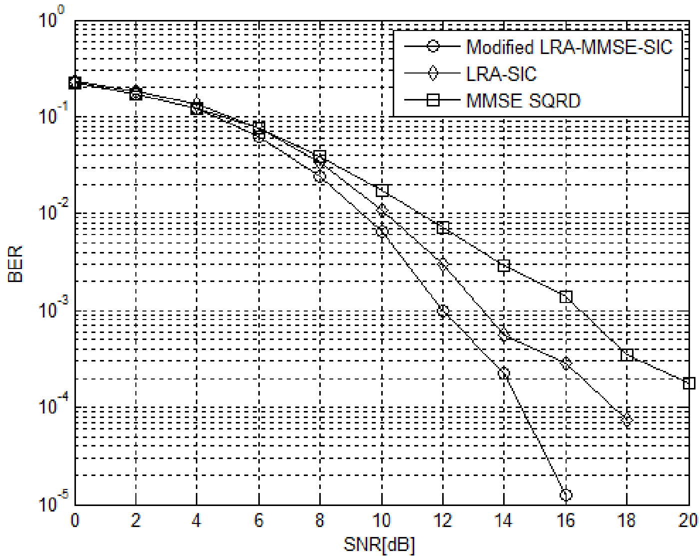

Figure 3. BER performance of the proposed detection compared with other algorithm.QPSK and $N_T = N_R = 2$ and conventional LLL with $\delta = 0.75$ are used

In this part, this paper compares several algorithms and the proposed algorithm through Monte Carlo simulation. The simulation assumes that the channel model is multipath Rayleigh channel under ideal channel estimation. A receiving user is configured in the system, the system bandwidth is 10 MHz, the normal CP frame structure is adopted, a transmission Time Interval (TTI) contains 14 OFDM symbols per frame, the bandwidth is configured to be 512 sub-carriers, of which 300 sub-carriers are used to transmit data symbols, and the other carriers are set to be imaginary sub-carriers, the frequency interval between carriers is 15 kHz, the modulation mode is QPSK and 16 QAM, the receiving and transmitting antennas are configured to be or, the turbo coding uses generated polynomial $(7, 5)$ and the encoding rate is $1/2$, and the log-map decoding mode is adopted.

Figure 3 is the BER performance curve of the proposed algorithm and MMSE SQRD algorithm under the condition of QPSK modulation and LLL with $\delta = 0.75$,transceiver antenna 2×2 . It is obvious from the figure that the system performance of the proposed algorithm is obviously superior to the comparison algorithm. This is because the algorithm in this paper does not regard all signals of $-\sigma \mathbf{Q}_2^T \mathbf{Z}$ as interference, and uses mathematical transformation to eliminate the interference on the $-\sigma \mathbf{Q}_2^T \mathbf{Z}$ diagonal, so as to accurately estimate the original signal of the signal.When the bit error rate is 10-3, the performance of the proposed LRA MMSE SQRD algorithm is about 4.2dB higher than that of the MMSE SQRD algorithm, and the performance of the proposed modified LRA MMSE SQRD algorithm is about 5.2dB higher than that of the MMSE SQRD algorithm.

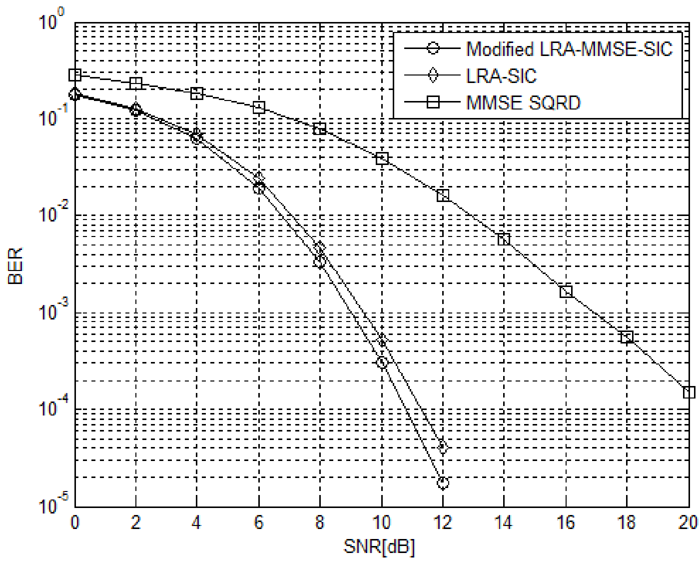

Figure 4. BER performance of the proposed detection compared with other algorithm.QPSK and $N_T = N_R = 4$ and conventional LLL with $\delta = 0.75$ are used

Figure 4 is the BER performance curve of the proposed algorithm and MMSE SQRD algorithm under the condition of QPSK modulation and LLL with $\delta = 0.75$,transceiver antenna 4×4. It is obvious from the diagram that the system performance of the proposed algorithm is obviously superior to the comparison algorithm, but the performance distinction between the two algorithms proposed in this paper is slightly reduced.When the bit error rate is 10^-3, the performance of LRA-MMSE-SIC algorithm is about 4.3dB higher than that of MMSE SQRD algorithm, and the performance of modified LRA-MMSE-SIC algorithm is about 5.3dB.

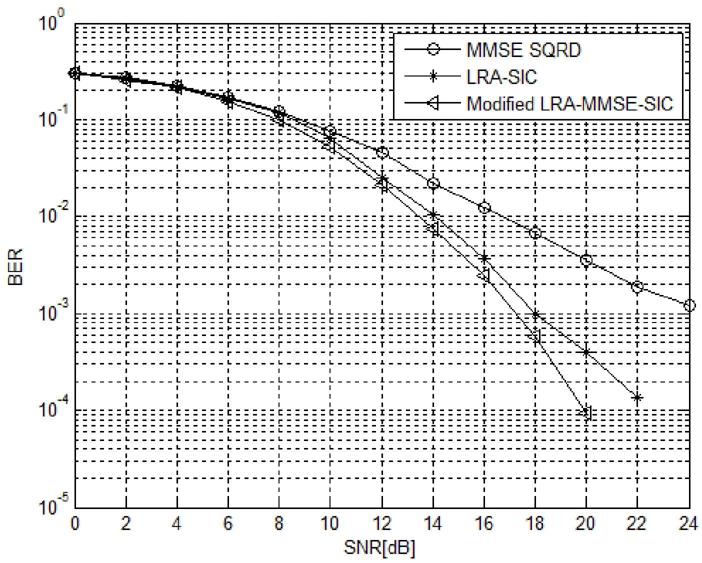

Figure 5. BER performance of the proposed detection compared with other algorithm.16QAM and $N_T = N_R = 4$ and conventional LLL with $\delta = 0.75$ are used

Figure 5 shows the BER performance curve of the proposed algorithm and MMSE SQRD algorithm under the condition of 16QAM modulation and LLL with $\delta = 0.75$,transceiver antenna 4×4. It is obvious from the figure that the system performance improvement of the proposed algorithm is more obvious.When the bit error rate is 10^-3,

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the performance of LRA-MMSE-SIC algorithm is about 6dB higher than that of MMSE SQRD algorithm, and the performance of modified LRA-MMSE-SIC algorithm is about 6.2dB.

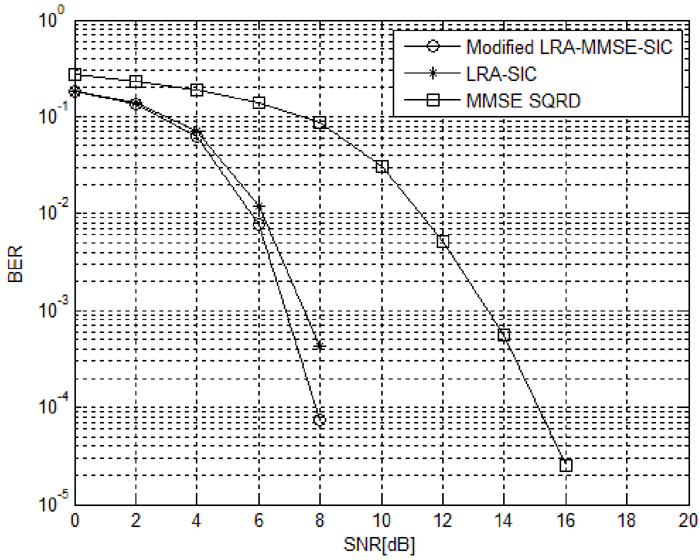

Figure 6. BER performance of the proposed detection compared with other algorithm.16QAM and $N_T = N_R = 4$ and conventional LLL with $\delta = 0.99$ are used

Figure 6 is the BER performance curve of the proposed algorithm and MMSE SQRD algorithm under the condition of QPSK modulation and LLL with $\delta = 0.99$,transceiver antenna 4×4 .When the bit error rate is $^{-4}$, the performance of the proposed LRA MMSE SQRD algorithm is about 3dB higher than that of the MMSE SQRD algorithm, and the performance of the proposed modified LRA MMSE SQRD algorithm is about 4.1dB higher than that of the MMSE SQRD algorithm.

6. Conclusion

In this paper, the LRA MMSE SQRD algorithm is proposed. This method uses LRA algorithm to enhance the orthogonality between constellation points, and uses MMSE expansion to reduce the influence of noise. The method combined with LLR clipping also reduces the list size required to achieve maximum achievable performance. In order not to increase the complexity of the algorithm, the concept of modified matrix is adopted. The modified matrix can eliminate the residual useful signal which is often used as interference in the current LRA SIC algorithm, which can effectively improve the accuracy of the algorithm.From the simulation results, it can be observed that the performance of the proposed algorithm is significantly improved, while the complexity is basically not increased.At the same time, this paper also confirms that the proposed method has a more significant performance improvement than the current MMSE SQRD algorithm.

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