Suboptimal Maximum Likelihood Detection Using Gradient-based Algorithm for MIMO Channels

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Abstract— This paper proposes a suboptimal maximum likelihood detection (MLD) algorithm for multiple-input multiple-output (MIMO) communications. The proposed algorithm regards transmitted signals as continuous variables in the same way as a common method for the discrete optimization problem, and then searches candidates of the transmitted signals in the direction of a modified gradient vector of the metric. The vector enhances components in the gradient that are likely to cause the noise enhancement from which the zero-forcing (ZF) or minimum mean square error (MMSE) algorithms suffer. This method sets the initial guess to the solution by the ZF or MMSE algorithms, which can be recursively calculated. Also, the proposed algorithm requires the same complexity order as that of the ZF algorithm. Computer simulations demonstrate that it is superior in BER performance to conventional suboptimal algorithms of which complexity order is equal to that of ZF.

Fig. 1 MIMO system

I. INTRODUCTION

In the recent wireless mobile communications, the demand for high data-rate transmission has increased rapidly. The multiple-input multiple-output (MIMO) is one of the most promising techniques to increase the data-rate and system capacity, because it can effectively take advantage of the random fading [1].

The optimal signal detection for the MIMO system is the maximum likelihood detection (MLD), which can achieve the minimum bit error rate (BER) [2]-[3]. However, MLD requires a prohibitively large amount of computational complexity that exponentially increases with both the number of data streams and that of constellations. Therefore, suboptimal detection algorithms that can reduce the complexity are required. The zero-forcing (ZF) algorithm needs a very small amount of complexity but exhibits poor BER performance owing to the noise enhancement. The minimum mean square error (MMSE) algorithm can alleviate this degradation to a certain extent but cannot achieve sufficient BER performance.

To cope with this problem, the sphere-decoding applies the QR decomposition (QRD) to a channel matrix and then attempts to reduce the search space by searching candidates that lie within a certain radius [4]. Since the detection ordering affects performance of such QRD-based algorithms, ordering-QRD employs a detection ordering method on the MMSE criterion and applies it to the decision feedback signal detection using QRD [5]. As another QRD-based algorithm, the combination of the QRD-based detection and the M-algorithm has been proposed in [6]. A major problem for these algorithms is that a large number of candidates still need to be searched in order to maintain sufficient BER performance, especially for coded systems.
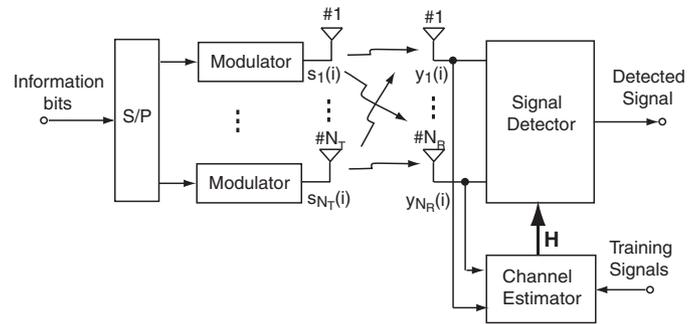
Another approach introduces the linear detection into MLD. ZF-MLD sets the search space to signal candidates that differ the initially detected signals by ZF in only one symbol [7]. Another application of the linear detection is to combine the MMSE detection and MLD according to the estimated signal to interference plus noise ratio (SINR) [8]. These methods, however, cannot exploit all of the available diversity because the linear detection uses a degree of freedom to suppress undesired signals. Therefore, the use of the linear detection should be limited for only determining the initial guess. Following this strategy, the sphere-projection algorithm sets the initial guess to the solution by ZF and extends the search space in a direction of the dominant noise enhancement [9]. Since it needs the eigenvalue decomposition to determine the direction, it requires a large amount of complexity.

This paper proposes a new suboptimal algorithm for the MIMO signal detection that limits the use of the linear detection without the eigenvalue decomposition. The proposed algorithm sets the initial guess to the solution of ZF or MMSE and then searches signal candidates in the direction of a modified gradient vector of the metric, which can reduce the search space. Also, the proposed algorithm outperforms the conventional ones of which complexity order is equal to that of ZF.

II. System Model

Fig. 1 shows a MIMO system with N_T transmit antennas and N_R receive antennas. The channel is assumed to be a time-invariant flat fading, and let h_{lk} denote the impulse response between the l-th ($1 \le l \le N_R$) receive antenna and the k-th ($1 \le k \le N_T$) transmit antenna. Also, let T and $s_k(i)$ be the symbol duration and the transmitted signal from k-th transmit antenna at discrete time iT. Thus, the signal received by the l-th receive antenna at time iT, $y_l(i)$, can be expressed as

$$y_l(i) = \sum_{k=1}^{N_T} h_{lk} s_k(i) + n_l(i), \tag{1}$$

where $n_l(i)$ is an additive white Gaussian noise at the l-th receive antenna. $n_l(i)$ is statistically independent with respect to indices i and l, which is given by

$$\langle n_{l_1}^*(i_1) n_{l_2}(i_2) \rangle = \sigma_n^2 \delta_{l_1 l_2} \delta_{i_1 i_2}. \tag{2}$$

σ_n^2 is the average power of the noise, and $\langle \ \rangle$ and * denote the ensemble average and complex conjugation, respectively.

For simplicity, (1) is rewritten in a vector form as

$$\mathbf{y}(i) = \mathbf{H}\mathbf{s}(i) + \mathbf{n}(i), \tag{3}$$

where the N_R-by-1 received signal vector $\mathbf{y}(i)$, the N_R-by-N_T impulse response matrix $\mathbf{H}$, the N_T-by-1 transmitted signal vector $\mathbf{s}(i)$, and the N_R-by-1 noise vector $\mathbf{n}(i)$ are defined as

$$\mathbf{y}^{\mathrm{H}}(i) = \begin{bmatrix} y_1^*(i) \ y_2^*(i) \ \cdots \ y_{N_R}^*(i) \end{bmatrix}, \tag{4}$$

$$\mathbf{H}^{\mathrm{H}} = \begin{bmatrix} \mathbf{h}_1 \ \mathbf{h}_2 \ \cdots \ \mathbf{h}_{N_R} \end{bmatrix}, \tag{5}$$

$$\mathbf{h}_l^{\mathrm{H}} = \begin{bmatrix} h_{l1} \ h_{l2} \ \cdots \ h_{lN_T} \end{bmatrix}, \tag{6}$$

$$\mathbf{s}^{\mathrm{H}}(i) = \begin{bmatrix} s_1^*(i) \ s_2^*(i) \ \cdots \ s_{N_T}^*(i) \end{bmatrix}, \tag{7}$$

$$\mathbf{n}^{\mathrm{H}}(i) = \begin{bmatrix} n_1^*(i) \ n_2^*(i) \ \cdots \ n_{N_R}^*(i) \end{bmatrix}. \tag{8}$$

$\mathbf{h}_l$ is an N_T-by-1 vector and the superscript $^{\mathrm{H}}$ denotes Hermitian transposition.

The channel estimator in **Fig**. 1 performs channel estimation by using both training signals and $y_l(i)$, and provides estimates of the channel impulse responses for the signal detector. The detector performs signal detection of $\mathbf{s}(i)$, which will be detailed below. From now on, the ideal channel estimation is assumed.

III. Signal Detection

A. Maximum Likelihood Detection (MLD)

Let us consider MLD of $\mathbf{s}(i)$. The likelihood function $P[\mathbf{y}(i)|\mathbf{H}, \mathbf{s}(i)]$ is derived from (2) and (3) as

$$P\big[\mathbf{y}(i)|\mathbf{H}, \mathbf{s}(i)\big] = \frac{1}{(\pi\sigma_n^2)^{N_R}} \exp\Big[- \frac{\parallel \mathbf{y}(i) - \mathbf{H}\mathbf{s}(i) \parallel^2}{\sigma_n^2} \Big]. \tag{9}$$

Since the maximization of $P[\mathbf{y}(i)|\mathbf{H}, \mathbf{s}(i)]$ is equivalent to the minimization of $\parallel \mathbf{y}(i) - \mathbf{H}\mathbf{s}(i) \parallel^2$, MLD searches the candidate of $\mathbf{s}(i)$ that minimizes a cost function $L[\mathbf{s}(i)]$ given by

$$L[\mathbf{s}(i)] = \parallel \mathbf{y}(i) - \mathbf{H}\mathbf{s}(i) \parallel^2. \tag{10}$$

MLD is the optimal detection and can achieve the best BER performance. However, its computational complexity grows exponentially with the number of transmit antennas N_T, and that of constellations M. This is because the complexity is proportional to the number of signal candidates, which also increases exponentially with N_T and M.

B. Proposed Algorithm

1) Discrete Optimization Problem: MLD can be classified as a discrete optimization problem that requires a large amount of complexity, that is NP-hard. One general method for the solution of this problem is to relax the discrete constraint on the required parameters so that they can be regarded as continuous variables and then to quantize the solution of the resultant continuous optimization problem [10]-[11]. The proposed algorithm is based on this idea and will be explained below.

First, $\mathbf{s}(i)$ in the cost function of (10) is replaced by an N_T-by-1 complex vector $\mathbf{x}$ that has continuous variable as its elements, which results in

$$L(\mathbf{x}) = \parallel \mathbf{y}(i) - \mathbf{H}\mathbf{x} \parallel^2. \tag{11}$$

Partially differentiating (11) with respect to $\mathbf{x}^*$ obtains a gradient vector as

$$\begin{aligned} \frac{\partial L(\mathbf{x})}{\partial \mathbf{x}^*} &= -\mathbf{H}^{\mathrm{H}} \mathbf{y}(i) + \mathbf{H}^{\mathrm{H}} \mathbf{H}\mathbf{x} \\ &= -\mathbf{H}^{\mathrm{H}} \big[\mathbf{y}(i) - \mathbf{H}\mathbf{x} \big]. \end{aligned} \tag{12}$$

Let $\hat{\mathbf{x}}$ denote $\mathbf{x}$ that minimizes $L(\mathbf{x})$. As the minimum norm solution, $\hat{\mathbf{x}}$ is given by

$$\hat{\mathbf{x}} = \mathbf{H}^+ \mathbf{y}(i), \tag{13}$$

where $\mathbf{H}^+$ denotes the pseudoinverse of $\mathbf{H}$.

When $N_R \ge N_T$ and rank($\mathbf{H}$) $= N_T$, $\mathbf{H}^+$ is expressed as [12]

$$\mathbf{H}^+ = \big(\mathbf{H}^{\mathrm{H}} \mathbf{H} \big)^{-1} \mathbf{H}^{\mathrm{H}}, \tag{14}$$

and $\hat{\mathbf{x}}$ is then written as

$$\hat{\mathbf{x}} = \big(\mathbf{H}^{\mathrm{H}} \mathbf{H} \big)^{-1} \mathbf{H}^{\mathrm{H}} \mathbf{y}(i). \tag{15}$$

Quantizing $\hat{\mathbf{x}}$ of (15) results in the solution by ZF.

When $\mathbf{H}^{\mathrm{H}} \mathbf{H}$ is a singular matrix, $\mathbf{H}^+$ can be numerically obtained as

$$\mathbf{H}^+ = \lim_{\delta' \to +0} \big(\mathbf{H}^{\mathrm{H}} \mathbf{H} + \delta' \mathbf{I}_{N_T} \big)^{-1} \mathbf{H}^{\mathrm{H}}, \tag{16}$$

where $\mathbf{I}_{N_T}$ is the N_T-by-N_T identity matrix. Fixing δ' at σ_n^2 and substituting the resultant into (13) yields

$$\hat{\mathbf{x}} = \mathbf{P}\mathbf{H}^{\mathrm{H}} \mathbf{y}(i), \tag{17}$$

$$\mathbf{P} = \big(\mathbf{H}^{\mathrm{H}} \mathbf{H} + \sigma_n^2 \mathbf{I}_{N_T} \big)^{-1} \tag{18}$$

where $\mathbf{P}$ is an N_T-by-N_T Hermite matrix.

Also quantizing $\hat{\mathbf{x}}$ of (17) leads to the solution by the MMSE algorithm. The MMSE algorithm can partially alleviate the noise enhancement from which the ZF algorithm suffers but

cannot achieve sufficient BER performance. The reason is that MMSE, which is considered as the linear detection as well as ZF, uses the degree of freedom to suppress undesired signal and thus cannot exploit all of the available diversity.

2) Noise Enhancement: To improve the performance of the MMSE algorithm, $\hat{\mathbf{x}}$ of (17) is analyzed. First, substituting (3) into (17) yields

$$\hat{\mathbf{x}} = \mathbf{s}(i) - \sigma_n^2 \mathbf{Ps}(i) + \mathbf{PH}^{\mathrm{H}}\mathbf{n}(i). \tag{19}$$

Thus the autocorrelation matrix of $\hat{\mathbf{x}} - \mathbf{s}(i)$ is given by

$$\langle [\hat{\mathbf{x}} - \mathbf{s}(i)][\hat{\mathbf{x}} - \mathbf{s}(i)]^{\mathrm{H}} \rangle = \sigma_n^4 \mathbf{P}^2 + \sigma_n^2 \mathbf{PH}^{\mathrm{H}}\mathbf{HP}, \tag{20}$$

where $\langle \mathbf{s}(i)\mathbf{s}^{\mathrm{H}}(i) \rangle = \mathbf{I}_{N_T}, \langle \mathbf{n}(i)\mathbf{n}^{\mathrm{H}}(i) \rangle = \sigma_n^2 \mathbf{I}_{N_R}$, and the property that $\mathbf{s}(i)$ and $\mathbf{n}(i)$ are statistically independent of each other were used.

The first and second terms of (20), of which average power are in proportional to σ_n^4 and σ_n^2, come from the second and third terms of (19), respectively. With $\sigma_n^2 \ll 1$, the second term of (19) can be neglected. Thus, we focus on the third term of (19) below.

To analyze the dominant term, the singular value decomposition (SVD) is applied to $\mathbf{H}$, which results in

$$\mathbf{H} = \mathbf{U\Sigma V}^{\mathrm{H}}. \tag{21}$$

$\mathbf{U}$ and $\mathbf{V}$ are N_R-by-N_R and N_T-by-N_T unitary matrices, which can be expressed as

$$\mathbf{U} = \begin{bmatrix} \mathbf{u}_1 \ \mathbf{u}_2 \cdots \mathbf{u}_{N_R} \end{bmatrix}, \tag{22}$$
$$\mathbf{V} = \begin{bmatrix} \mathbf{v}_1 \ \mathbf{v}_2 \cdots \mathbf{v}_{N_T} \end{bmatrix}, \tag{23}$$

where $\mathbf{u}_l$ and $\mathbf{v}_k$ are N_R-by-1 and N_T-by-1 vectors, respectively.

$\mathbf{\Sigma}$ in (21) is an N_R-by-N_T matrix. With rank$(\mathbf{H}) = W(\le \min(N_T, N_R))$, $\mathbf{\Sigma}$ is given by

$$\mathbf{\Sigma} = \begin{bmatrix} \mathbf{D} & \mathbf{O}_{W,N_T-W} \\ \mathbf{O}_{N_R-W,W} & \mathbf{O}_{N_R-W,N_T-W} \end{bmatrix}, \tag{24}$$

$$\mathbf{D} = \mathrm{diag}\begin{bmatrix} \lambda_1^{1/2} \ \lambda_2^{1/2} \ \cdots \ \lambda_W^{1/2} \end{bmatrix}, \tag{25}$$

where $\mathbf{O}_{l,k}$ is an l-by-k null matrix. $\mathbf{D}$ is a W-by-W diagonal matrix and its elements, $\lambda_w^{1/2}(1 \le w \le W)$ are the singular values of $\mathbf{H}$ and $0 < \lambda_1^{1/2} \le \lambda_2^{1/2} \ \cdots \ \le \lambda_W^{1/2}$.

Substituting (21) into $\mathbf{P}$ and $\mathbf{PH}^{\mathrm{H}}\mathbf{n}(i)$ yields

$$\mathbf{P} = \mathbf{V}\big(\mathbf{\Sigma}^{\mathrm{H}}\mathbf{\Sigma} + \sigma_n^2 \mathbf{I}_{N_T}\big)^{-1}\mathbf{V}^{\mathrm{H}}, \tag{26}$$

$$\mathbf{PH}^{\mathrm{H}}\mathbf{n}(i) = \mathbf{V}\big(\mathbf{\Sigma}^{\mathrm{H}}\mathbf{\Sigma} + \sigma_n^2 \mathbf{I}_{N_T}\big)^{-1}\mathbf{\Sigma}^{\mathrm{H}}\mathbf{U}^{\mathrm{H}}\mathbf{n}(i)$$
$$= \sum_{w=1}^{W} \mathbf{v}_w \lambda_w^{1/2}\big(\lambda_w + \sigma_n^2\big)^{-1}\big[\mathbf{u}_w^{\mathrm{H}}\mathbf{n}(i)\big], \tag{27}$$

where (22)-(25) were used.

When σ_n^2 is negligible, $\lambda_w^{1/2}\big(\lambda_w + \sigma_n^2\big)^{-1} \simeq \lambda_w^{-1/2}$. In addition, as $\lambda_w^{1/2}$ becomes very small, the noise is enhanced in the direction of $\mathbf{v}_w$. In this case, decision errors are likely to occur in the direction of $\mathbf{v}_w$ and search for signal candidates in this direction with $\hat{\mathbf{x}}$ as a start point is promising, which is pointed out by [9].

3) Gradient-based Method: The proposed algorithm that follows the above strategy is given by

$$\tilde{\mathbf{x}}(r) = \hat{\mathbf{x}} + \mu_r \mathbf{g}(i), \tag{28}$$

$$\mathbf{g}(i) = -\mathbf{P}^q \frac{\partial L(\mathbf{x})}{\partial \mathbf{x}^*}\bigg|_{\mathbf{x}=\hat{\mathbf{s}}(i,0)}, \tag{29}$$

$$\hat{\mathbf{s}}(i,0) = \mathrm{Dec}\big[\hat{\mathbf{x}}\big], \tag{30}$$

$$\hat{\mathbf{s}}(i,r) = \mathrm{Dec}\big[\tilde{\mathbf{x}}(r)\big], \tag{31}$$

where $r(\ge 1)$ is a signal candidate index and q is a nonnegative integer. Also, Dec[ ] denotes the quantization, $\hat{\mathbf{s}}(i,0)$ represents a hard decision of $\hat{\mathbf{x}}$, and μ_r is a complex number.

$\mathbf{g}(i)$ of (29) enhances $\mathbf{v}_w$'s in the gradient vector that correspond to very small singular values. This is evident from

$$\mathbf{g}(i) = \sum_{w=1}^{W} \mathbf{v}_w \lambda_w^{1/2}\big(\lambda_w + \sigma_n^2\big)^{-q}\Big\{\mathbf{u}_w^{\mathrm{H}}\big[\mathbf{y}(i) - \mathbf{H}\hat{\mathbf{s}}(i,0)\big]\Big\}, \tag{32}$$

which is obtained in the same way as (27).

μ_r is determined as follows. Let $\hat{\mathbf{x}}_k$ and $a(r)$ denote the k-th element of $\hat{\mathbf{x}}$ and a symbol that differs the k-th element of $\hat{\mathbf{s}}(i,0)$, respectively. μ_r is given by

$$\mu_r = \big[a(r) - \hat{\mathbf{x}}_k\big]/\mathbf{g}(i)_k \tag{33}$$

where $\mathbf{g}(i)_k$ is the k-th element of $\mathbf{g}(i)$. With μ_r of (33), the k-th element of $\tilde{\mathbf{x}}(r)$ becomes equal to $a(r)$. This means that the k-th element of a hard decision of $\tilde{\mathbf{x}}(r)$ is changed into $a(r)$. Since the number of $a(r)$ for each k is $M-1$, the number of μ_r is equivalent to the number of generated signal candidates $(M-1)N_T$. Let a set C be $\big\{\hat{\mathbf{s}}(i,r')|0 \le r' \le (M-1)N_T\big\}$. The finally detected signal $\hat{\mathbf{s}}(i)$ is selected as the candidate of C that minimizes the cost function, which is given by

$$\hat{\mathbf{s}}(i) = \arg\min_{\hat{\mathbf{s}}(i,r')} \| \mathbf{y}(i) - \mathbf{H}\hat{\mathbf{s}}(i,r') \|^2 . \tag{34}$$

4) Recursive Form of Initial Guess: To reduce the complexity furthermore, the proposed algorithm calculates $\hat{\mathbf{x}}$ in the following recursive form. First, $\mathbf{H}^{\mathrm{H}}\mathbf{H}$ is rewritten by using (5) as

$$\mathbf{H}^{\mathrm{H}}\mathbf{H} = \sum_{l=1}^{N_R} \mathbf{h}_l \mathbf{h}_l^{\mathrm{H}}. \tag{35}$$

Similarly, $\mathbf{H}^{\mathrm{H}}\mathbf{y}(i)$ is given by

$$\mathbf{H}^{\mathrm{H}}\mathbf{y}(i) = \sum_{l=1}^{N_R} \mathbf{h}_l y_l(i). \tag{36}$$

Therefore

$$\big(\mathbf{H}^{\mathrm{H}}\mathbf{H} + \alpha\mathbf{I}\big)^{-1}\mathbf{H}^{\mathrm{H}}\mathbf{y}(i) = \Big(\sum_{l=1}^{N_R} \mathbf{h}_l\mathbf{h}_l^{\mathrm{H}} + \alpha\mathbf{I}_{N_T}\Big)^{-1}\sum_{l=1}^{N_R}\mathbf{h}_l y_l(i). \tag{37}$$

$$\alpha = \begin{cases} 0 & \text{for ZF} \\ \sigma_n^2 & \text{for MMSE} \end{cases} \tag{38}$$

Applying the matrix inversion lemma [12] to (37) yields an RLS-like recursive form as

$$\mathbf{k}(l) = \frac{\mathbf{P}(l-1)\mathbf{h}_l}{1 + \mathbf{h}_l^{\mathrm{H}}\mathbf{P}(l-1)\mathbf{h}_l}, \qquad (39)$$

$$e(l) = y_l^*(i) - \mathbf{z}^{\mathrm{H}}(l-1)\mathbf{h}_l, \qquad (40)$$

$$\mathbf{z}(l) = \mathbf{z}(l-1) + \mathbf{k}(l)e^*(l), \qquad (41)$$

$$\mathbf{P}(l) = \mathbf{P}(l-1) - \mathbf{k}(l)\mathbf{h}_l^{\mathrm{H}}\mathbf{P}(l-1), \qquad (42)$$

where $\mathbf{k}(l)$ and $\mathbf{P}(l)$ are an N_T-by-1 vector and an N_T-by-N_T matrix, respectively. The N_T-by-1 vector $\mathbf{z}(l)$ is defined as

$$\mathbf{z}(l) = \left(\sum_{l'=1}^{l} \mathbf{h}_{l'}\mathbf{h}_{l'}^{\mathrm{H}} + \alpha\mathbf{I}_{N_T} \right)^{-1} \sum_{l'=1}^{l} \mathbf{h}_{l'}\mathbf{y}_{l'}(i), \qquad (43)$$

where $\mathbf{z}(N_R) = \hat{\mathbf{x}}$.

The initial conditions for the recursion are

$$\mathbf{P}(0) = \delta^{-1}\mathbf{I}_{N_T}, \qquad (44)$$

$$\delta = \begin{cases} \varepsilon & \text{for ZF} \\ \sigma_n^2 & \text{for MMSE} \end{cases}, \qquad (45)$$

$$\mathbf{x}(0) = \mathbf{0}_{N_T}, \qquad (46)$$

where $\mathbf{0}_{N_T}$ is an N_T-by-1 null vector and ε is a small positive constant.

IV. COMPUTATIONAL COMPLEXITY

Let us evaluate the computational complexity of the proposed algorithm. For comparison, the complexities of ZF, ZF-MLD [7], Ordering QRD [5], and MLD algorithms are calculated. Note that the complexity of the proposed algorithm without the recursive form of the initial guess (39)-(42) was evaluated for a strict comparison.

Fig. **2**(**a**) and (**b**) show the number of complex multiplications and additions which the proposed and conventional algorithms requires with $N_T = N_R$ and QPSK modulation. It can be seen that MLD requires the largest amount of complexity while ZF needs the smallest complexity. The ZF-MLD and ordering QRD algorithms require much smaller computational complexity than that of ML, but their complexities are still larger than that of ZF algorithm. In both figures, the computational complexity of the proposed algorithm is less than that of the ordering QRD algorithm and almost the same as that of the ZF-MLD. Note that the complexity of the proposed algorithm can be reduced furthermore when the recursive form (39)-(42) is used.

V. COMPUTER SIMULATION

A. Simulation Condition

Computer simulations were conducted to clarify the performance of the proposed low-complexity algorithm on the time-invariant and uncorrelated Rayleigh flat fading channel. The simulation parameters are listed in **Table I**.
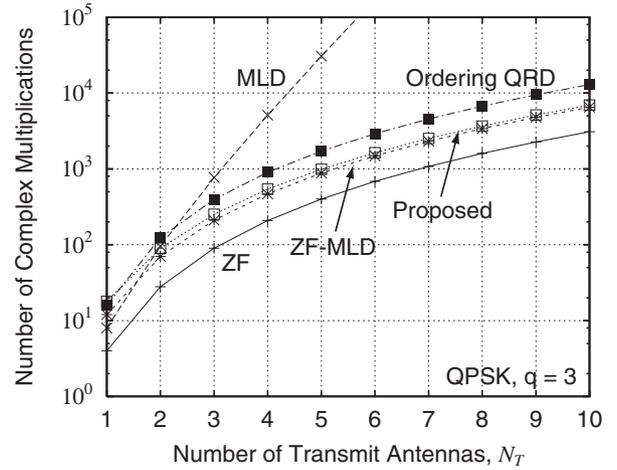
(a) Complex multiplication
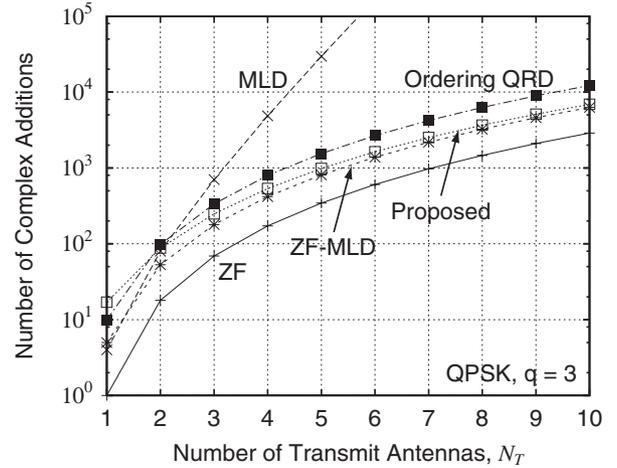
(b) Complex addition

Fig. 2 Computational complexity

TABLE I SIMULATION PARAMETERS

Modulation	QPSK, 16QAM
Number of transmit antennas, N_T	4
Number of receive antennas, N_R	4
Channel	Rayleigh flat fading channel

B. Simulation Results

Fig. **3** shows the BER performance of the proposed algorithm with q as a parameter. As q increases, the BER performance improves. This is because the components in the gradient vector that cause the noise enhancement are more enhanced and the search in the direction of the modified gradient vector is more likely to find the correct signal. Since the improvement is saturated with $q = 3$, q is set equal to 3 below.

Fig. **4** shows the BER performance of the proposed and conventional algorithms with QPSK modulation. The performance of MLD can be considered as the lower bound. The proposed algorithm is superior in the BER performance to the
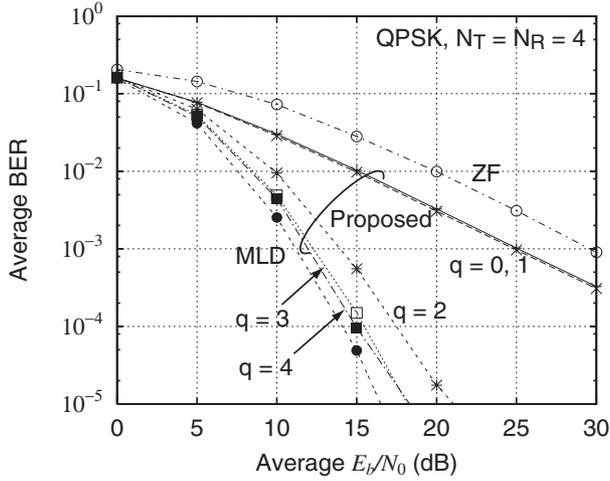
Fig. 3　BER performance with q as a parameter
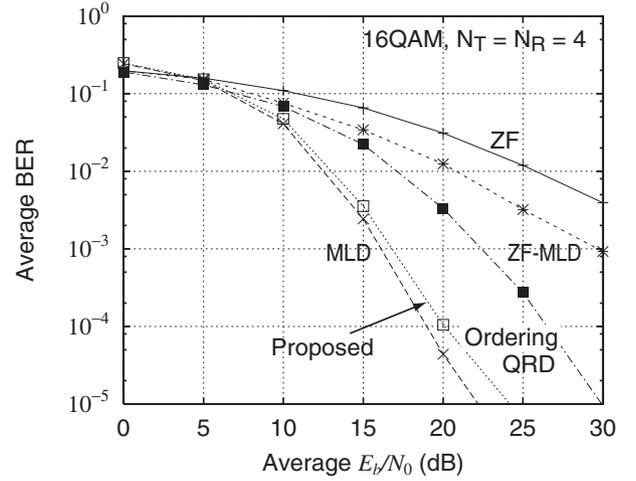
Fig. 5　BER performance with 16QAM
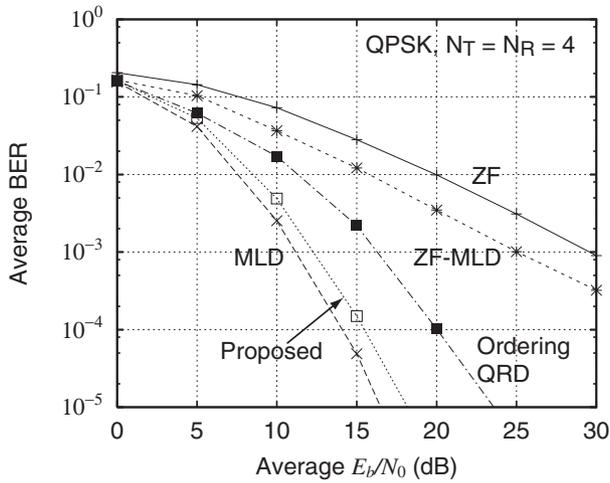
Fig. 4　BER performance with QPSK

conventional ones of which the complexity order is the same as that of ZF. The difference between MLD and the proposed algorithm at BER $= 10^{-3}$ is about 1 dB in E_b/N_0.

The BER performance of the proposed and conventional algorithms with 16QAM modulation scheme are also shown in **Fig**. **5**. The proposed algorithm also outperforms the conventional ones.

VI. CONCLUSION

This paper proposed a suboptimal MIMO MLD algorithm, which is based on a common method for the discrete optimization problem. After regarding transmitted signals as continuous variables, the proposed algorithm sets the initial guess to the solution by the ZF or MMSE algorithms and searches signal candidates in the direction of a modified gradient vector of the metric. The computational complexity of the proposed algorithm is less than that of the ordering QRD [5] and almost the same as that of ZF-MLD [7]. Computer simulation

demonstrated that the proposed algorithm is superior to the conventional low-complexity ones in BER performance.

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