An Antenna Selection Scheme for QRM-MLD Receivers 
Based on Error Rate Minimization

Ilmiawan SHUBHI† and Hidekazu MURATA†

† Graduate School of Informatics, Kyoto University  
Yoshida-honmachi, Sakyo-ku, Kyoto 606-8501, Japan  
E-mail: †contact-h28j@hanase.kuee.kyoto-u.ac.jp

Abstract Multiple-input multiple-output (MIMO) systems have become one of the key elements in wireless communication technologies. To capture its most advantages, antenna selection can be implemented to select only a certain number of antennas from a larger number of available antennas. This antenna selection, however, should be tailored based on the detection algorithm used in the system. In this paper, an antenna selection scheme for a MIMO system which uses QRM-MLD receivers is proposed. Numerical results obtained through computer simulations show that the proposed scheme is able to provide a near optimum performance in terms of bit error rate (BER). In addition, the proposed scheme is feasible owing to its moderate computational complexity.

Key words MIMO, Antenna Selection, QRM-MLD

1. Introduction

Multiple-input multiple-output (MIMO) has become a key element in recent wireless communication technologies. Utilizing multiple antennas, MIMO provides a drastic improvement in spectral efficiency [1]. It should be noted, however, MIMO requires a higher hardware cost, power consumption, and signal processing complexity for implementation. A promising approach to capture the advantages of MIMO systems is to select a small number of best antennas from a larger set of available antennas. The performance of systems that uses such selection techniques has been shown to be significantly better than that of the systems using the same number of processing antennas without any selection [2].

We consider a MIMO system which employs a maximum likelihood detection algorithm based on QR decomposition and M-algorithm (QRM-MLD). Using QRM-MLD, a near MLD performance in terms of bit error rate (BER) can be achieved with lower computational complexity. The reduction on the computational complexity can be obtained as QRM-MLD calculates branch metric only for a certain number of candidates [3].

In previous literatures, some antenna selection schemes have been presented. In [4] – [6], antenna selection schemes to maximize the channel capacity are proposed. In [7], antenna selection is constructed to minimize the BER. Research in [7], however, only considers the basic detection algorithms such as zero forcing (ZF), maximum mean square error (MMSE), and MLD.

As an MLD-based detection algorithm, the performance of QRM-MLD is bounded by the minimum Euclidean distance between all possible transmitted symbols. Thus, the antenna subset having the maximum minimum Euclidean distance (MMED) should be selected for the detection process. The detection process in QRM-MLD, however, is conducted in a recursive manner and have a potential to suffer from error propagation. As the conventional MMED scheme [7] only considers the total Euclidean distance in its selection process, conventional MMED becomes not suitable for QRM-MLD detection, especially when the number of candidates in QRM-MLD is relatively small.

This paper proposes an antenna selection scheme which is designed to optimize the QRM-MLD performance in terms of BER. In the proposed scheme, the minimum Euclidean distance in each stage of selection is stored and considered for the antenna selection process. In addition, an M-algorithm is also employed to reduce the computational complexity. By maximizing the minimum Euclidean distance in each stage of selection, the proposed scheme is able to provide an excellent BER for QRM-MLD even when the number of candidates in QRM-MLD is relatively small.

The remainder of this paper are organized as follows. In Sect. 2, the system model is described. Afterward, the proposed scheme is presented in Sect. 3. Sect. 4 details the numerical results obtained through our computer simulation. Finally, we give our conclusions at Sect. 5.

2. System Model

2.1 MIMO with antenna selection

Figure 1 shows the system model considered in this paper. A MIMO system with $M$ transmit antennas transmits $M$ modulated symbols through a wireless channel. In
the receiver side, \( N \) receive antennas are available. Let \( y = [y_1, y_2, \ldots, y_N]^T \) where \( y_n \) is the received signal for \( n \)th receive antenna. The received signals can be written as

\[
y = Hx + n
\]

(1)

where \( H \) is an \( N \times M \) matrix of Rayleigh fading channel with zero mean and a unit variance, \( x \) is a vector of \( M \times 1 \) transmitted symbols, and \( n \) is a vector of \( N \times 1 \) additive white Gaussian noise (AWGN) with zero mean and \( N_0 \) variance. In this paper, channel state information (CSI) is known perfectly at the receivers. Based on CSI from each antenna, the receiver selects \( C \) best antennas out of \( N \) available antennas. The detection process are then conducted using the received signals from those \( C \) selected antennas.

2.2 QRM-MLD

Let \( U \) be the antenna subset which is selected for the detection process. The received signals in this antenna subset can be denoted as

\[
y_U = H_Ux + n_U
\]

(2)

where \( H_U \) is the \( C \times M \) sub-matrix of \( H \) and \( n_U \) is the \( C \times 1 \) sub-vector of \( n \) which corresponds to the antenna subset \( U \). In QRM-MLD, the first step of the detection process is to decompose \( H_U \) into a unitary matrix, \( Q_U \), and an upper triangular matrix, \( R_U \). Therefore, Eq. (2) can be written as

\[
y_U = Q_U R_U x + n_U
\]

(3)

Multiplying both sides of Eq. (3) with \( Q_U^H \), we can obtain

\[
y_U = R_U x + \tilde{n}_U
\]

(4)

where \( \tilde{y}_U = Q_U^H y_U \) and \( \tilde{n}_U = Q_U^H n_U \).

To obtain the transmitted symbols, the ML criterion is given by

\[
\hat{x} = \arg\min_{x \in \mathcal{X}^M} \| \tilde{y}_U - R_U x \|_F^2
\]

\[
= \arg\min_{x \in \mathcal{X}^M} \left( \sum_{j=1}^M | \tilde{y}_{i,j} - \sum_{i=1}^M r_{i,j} x_i |^2 \right)
\]

(5)

where \( \mathcal{X}^M \) is the set of all possible vectors of \( M \times 1 \) transmitted symbols, \( \tilde{y}_{i,j} \) is the \( j \)th element of vector \( \tilde{y}_U \), and \( r_{i,j} \) is the \( j \)th element of matrix \( R_U \).

Denotes \( \mathcal{X} \) as the set of all possible symbols from one transmit antenna. At its first detection stage, QRM-MLD calculates the branch metric for all elements of \( \mathcal{X} \). Afterward, \( K \) candidates with the smallest branch metric are selected as the surviving nodes while the other candidates are discarded. In the \( m \)th \((1 < m < M)\) stage, the branch metric of \( K | \mathcal{X} | \) nodes are calculated. Again, \( K \) candidates with the smallest branch metric are selected as the surviving nodes. Finally, in the \( M \)th stage, the node with the minimum accumulated branch metric is selected as the result of the QRM-MLD algorithm together with its ancestor nodes.

2.3 MMED antenna selection

In an MLD-based detection algorithm such as QRM-MLD, the probability of symbol errors is bounded by the minimum Euclidean distance between all possible transmitted symbols. Therefore, the antenna subset having the largest minimum Euclidean distance should be selected for the detection process. In this paper, the scheme using this criterion is called MMED. In MMED, the selected antenna subset, \( U \), can be obtained by

\[
\hat{U} = \arg\max_{U \in \mathcal{U}} \min_{x_p, x_q \in \mathcal{X}^M, p \neq q} \| H_U (x_p - x_q) \|_F^2
\]

\[
= \arg\max_{U \in \mathcal{U}} \min_{e \in \mathcal{E}^M, e \neq 0} \| H_U e \|_F^2
\]

(6)

where \( \mathcal{U} \) is the set of all possible antenna subsets, \( x_p \) and \( x_q \) are two possible vectors of transmitted symbols, and \( \mathcal{E}^M \) is the set of all possible error vectors.

3. Proposed Scheme

Equation (6) shows that the selection process in MMED is conducted by directly multiplying matrix \( H \) with error vector \( e \). The Frobenius norm of the multiplication result is then calculated. On the other words, MMED only considers the total Euclidean distance in its selection process. Therefore, the error events in the early stage of QRM-MLD cannot be reduced by the conventional MMED. In addition, the direct multiplication in MMED requires a large number of Euclidean distance calculations and makes it unfeasible.

Our proposed scheme starts its selection process by determining all possible unique error vectors for one transmitted symbol. In Fig. 2, the set of all unique error vectors, \( \mathcal{E} \), for quadrature phase shift keying (QPSK) are shown. Each of the unique error vector are then denoted as \( E \), where \( E \in \mathcal{E} \). After obtaining \( \mathcal{E} \), the Euclidean distances are then calculated recursively. For each antenna subset, \( M \) stages of antenna selection are conducted. To reduce the computational complexity, the calculation of Euclidean distances in each
stage of selection is conducted only for a certain number of error vectors using M-algorithm. Hereafter, we call our proposed scheme MMED-M.

Figure 3 shows a tree diagram of MMED-M antenna selection for the case of $M = 3$ using QPSK modulation. In the figure, $d_{m,q}$ represents the $q$th largest Euclidean distance at $m$th stage. Denotes $r_{i,j}^U$ as the element of $R$ at the $i$th row and $j$th column. At the first stage of selection, Euclidean distances are calculated by multiplying $r_{i,j}^U$ with all unique error vectors, $\mathcal{E}$. The nodes having large Euclidean distances are then discarded. In Fig. 3, $d_{1,3} > d_{1,2} > d_{1,1}$. In this example, therefore, the nodes having the Euclidean distance of $d_{1,3}$ are discarded.

We can also observe in Fig. 3 that the Euclidean distances obtained from the multiplication between $r_{i,j}^U$ with error vector $[2]$, $[-2]$, $[2i]$, and $[-2i]$, are equal. In MMED-M, the nodes havingnow the Euclidean distance are considered as one node. Therefore, in Fig. 3, three nodes which have the Euclidean distance of $d_{1,2}$ are discarded. Denotes $G$ as the number of surviving nodes in each stage of selection. The number of required Euclidean distance calculations for each antenna subset can be written as

$$N_{ED} = |\mathcal{E}| + (M - 1)G|\mathcal{E}|.$$ (7)

Table 1 shows an example of the values of the minimum Euclidean distance at each stage of MMED-M selection for the case of three transmit antennas. The values of Euclidean distances for two antenna subsets are shown. In the conventional MMED, Euclidean distances are obtained from a direct multiplication between $H_U$ and $e$. This process is equal with considering only the Euclidean distances at the third stage of MMED-M. As $U_2$ has a larger Euclidean distance in this stage compared to $U_1$, the conventional MMED selects $U_2$ for conducting the detection process.

This selection, however, is not suitable when QRM-MLD is used for detection. As QRM-MLD conducts the detection process in a recursive manner, its performance is determined by the detection stage having the smallest Euclidean distance. If we select antenna subset $U_1$ for example, the error event of QRM-MLD will most likely occur at the second stage of detection. Similarly, if we select $U_2$, the error event of QRM-MLD will most likely occur at the first stage of detection.

Considering this characteristic, MMED-M stores and considers the minimum value of Euclidean distance in each stage of selection. This process is required to reduce the error propagation in QRM-MLD, and thus, gives a better BER performance. In Table 1, MMED-M considers 1.4 as the minimum Euclidean distance of $U_1$ and 1.3 as the minimum Euclidean distance of $U_2$. As the value of minimum Euclidean distance for $U_1$ is larger than that of $U_2$, MMED-M will select $U_1$ to be used in the detection process.

4. Numerical Results

4.1 Computational Complexity

Figure 4 shows the number of complex multiplications required by MMED and MMED-M in their antenna selection process. In this comparison, QPSK modulation is employed and the number of collaborating antennas, $C$, is equal to $M$. For MMED-M, $G$ is set to 2. As can be seen in the figure, MMED-M has a significantly lower computational complexity compared to MMED. For the case of $M = 4$ and $N = 8$ for example, the number of complex multiplications in MMED-M is 97% lower than that of the conventional MMED.

4.2 BER performance

Figures 5 and 6 show the BER performance of MMED and MMED-M when QRM-MLD is used as the detection algorithm. In these figures, $M = 4$ and $C = 4$. For MMED-M,
MMED only considers the total Euclidean distance from all possible error vectors. Therefore, the error events at the early stage of QRM-MLD cannot be reduced. In MMED-M, the Euclidean distances at each stage of selection is considered in the selection process and reduce the error events in the early stage of QRM-MLD detection. Using the proposed scheme, it can be seen from Fig. 5 that the performance degradation for the case of \( K = 2 \) is relatively small compared to the case of \( K = 4 \). Furthermore, as can be observed from Fig. 6, this performance degradation becomes negligible when a larger number of available antennas is used.

5. Conclusion

In this paper, an antenna selection scheme suitable for QRM-MLD is proposed. The antenna selection is designed to minimize the error rate. In the proposed scheme, the minimum Euclidean distance in each stage of selection is stored and considered in the antenna selection process. By maximizing the Euclidean distance in each stage of selection, the proposed scheme is able to provide an excellent BER performance even when the number of candidates in QRM-MLD is relatively small. In addition, through the M-algorithm, the computational complexity of MMED-M is significantly lower than that of the conventional MMED and makes it feasible for implementations.

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