Low-complexity detection of quadrature spatial modulation

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Quadrature spatial modulation (QSM) is a recently proposed multiple-input multiple-output transmission scheme which improves the spectral efficiency of classical spatial modulation (SM) by increasing the number of information bits transmitted by antenna indices. In QSM, a complex data symbol is decomposed into its real and imaginary components; then, these two components are independently transmitted using the SM principle. A low-complexity, near-maximum likelihood (ML) error performance achieving detection scheme is proposed for QSM to reduce the overall computational complexity of the ML detector. First, the proposed detector determines the set of most probable active transmit antennas and the corresponding possible transmission patterns. Then, ML-based detection is used to determine the transmitted complex data vector by performing a search over these transmission patterns and M-ary constellation symbols. It has been shown via computer simulations that the proposed detection algorithm exhibits near-ML bit error rate performance with considerably lower decoding complexity.

Introduction: Spatial modulation (SM) is a novel multiple-input multiple-output (MIMO) transmission scheme in which incoming data bits determine the index of the activated transmit antenna besides the M-ary constellation symbol, which is transmitted over this activated antenna [1]. SM has attracted a great deal of attention in the past few years due to its attractive advantages over classical MIMO systems and it has been regarded as a potential candidate for 5G wireless networks [2].

Generalised spatial modulation (GSM) systems were developed to improve the spectral efficiency of SM by increasing the number of active transmit antennas [3, 4]. To avoid inter-channel interference (ICI), the activated antennas transmit the same data symbol in the GSM scheme [3], while in the multiple active SM scheme [4], different antennas transmit different data symbols to boost the spectral efficiency.

Quadrature spatial modulation (QSM) is a novel scheme which provides a higher spectral efficiency than classical SM by increasing the number of information bits transmitted by active antenna indices [5]. In QSM, a complex data symbol is decomposed into its real and imaginary parts. Then, the real and imaginary parts of this data symbol are independently transmitted from one of the available transmit antennas using the SM principle. In other words, QSM provides $\log_2(N_t)$ bits per channel use (bpcu) improvement in spectral efficiency compared with SM, whose spectral efficiency is $\log_2(N_t M)$ bpcu, by independent application of the SM principle for the real and imaginary components of the complex data symbol, where N_t is the number of transmit antennas, which is an integer power of two. Furthermore, since two orthogonal carriers (cosine and sine) are used in QSM, ICI is avoided and a single radio frequency chain is sufficient at the transmitter.

In [5], maximum likelihood (ML) detection is used for QSM to achieve optimal bit error rate (BER) performance. In this Letter, we propose a low-complexity detection scheme for QSM to reduce the overall detection complexity. The proposed algorithm, first, determines N most probable candidates for active transmit antenna indices and by considering these N candidates, it determines the corresponding set of possible transmission patterns. Finally, by considering these possible transmission patterns and M-ary constellation symbols, ML-based detection is used to jointly detect the real and imaginary parts of the transmitted complex data symbol and the corresponding transmission pattern.

System model of QSM with ML detection: Consider a MIMO system with N_t transmit and N_r receive antennas. A total of $\log_2(N_t^2 M)$ information bits enter the QSM transmitter. A complex data symbol is selected from an M-QAM constellation $\mathcal{S}$ according to the first $\log_2(M)$ bits. This symbol is decomposed into its real and imaginary components as s_R and s_I, where $s = s_R + js_I$. Then, s_R and js_I are independently transmitted from the l_Rth and l_Ith transmit antennas using the SM principle, respectively, where $l_R, l_I \in \{1, 2, \ldots, N_t\}$ are determined according to the remaining $2\log_2 N_t$ bits. Therefore, the transmission vector $\boldsymbol{x} \in \mathbb{C}^{N_t\times 1}$ of the QSM scheme can be given as

$$\boldsymbol{x} = \left[0 \cdots 0\ s_R\ 0 \cdots 0\ js_I\ 0 \cdots 0\right]^{\mathrm{T}} \tag{1}$$

where the l_Rth and l_Ith elements of $\boldsymbol{x}$ are s_R and js_I, respectively. $\boldsymbol{x}$ is transmitted over a MIMO Rayleigh fading channel, which is characterised by $\boldsymbol{H} \in \mathbb{C}^{N_r\times N_t}$, whose elements are independent and identically distributed with $\mathcal{CN}(0, 1)$, where $\mathcal{CN}(0, \sigma^2)$ represents circularly symmetric complex Gaussian distribution with variance σ^2. The received signal vector $\boldsymbol{y} \in \mathbb{C}^{N_r\times 1}$ is obtained as

$$\boldsymbol{y} = \boldsymbol{Hx} + \boldsymbol{n} \tag{2}$$

where $\boldsymbol{n} \in \mathbb{C}^{N_r\times 1}$ is the noise vector whose elements distributed with $\mathcal{CN}(0, \sigma^2)$. $\boldsymbol{y}$ can be rewritten as

$$\boldsymbol{y} = \boldsymbol{h}_{l_R} s_R + j\boldsymbol{h}_{l_I} s_I + \boldsymbol{n} \tag{3}$$

where $\boldsymbol{h}_{l_R}$ and $\boldsymbol{h}_{l_I}$ are the l_Rth and l_Ith columns of the channel matrix $\boldsymbol{H}$, respectively. At the receiver, ML detector is used with the assumption of perfect channel state information to obtain optimal BER performance. ML detector jointly detects the real and imaginary parts of the data symbol and the corresponding activated antenna indices by calculating $N_t^2 M$ decision metrics as

$$\left[\hat{l}_R, \hat{l}_I, \hat{s}_R, \hat{s}_I\right] = \underset{l_R, l_I, s_R, s_I}{\arg\min} \left\|\boldsymbol{y} - \left(\boldsymbol{h}_{l_R} s_R + j\boldsymbol{h}_{l_I} s_I\right)\right\|^2 \tag{4}$$

where $\hat{l}_R$ and $\hat{l}_I$ denote the detected active antenna indices correspond to $\hat{s}_R$ and $\hat{s}_I$, respectively, which form the detected complex symbol as $\hat{s} = \hat{s}_R + j\hat{s}_I$.

Proposed detection algorithm: The complexity of the ML detector grows considerably with higher order MIMO systems and constellations. For this reason, we introduce a new low-complexity detection algorithm to reduce the overall detection complexity of the QSM scheme with ML detector while ensuring near-ML performance.

Consider the QSM signal model given in (2). The proposed suboptimal detection algorithm is based on compressed sensing (CS) which can operate even for under-determined systems ($N_t > N_r$) if $\boldsymbol{x}$ has a sparse structure. When the ratio of number of non-zero elements to total number of the elements in $\boldsymbol{x}$ is at most ~20%, which can be ensured by selecting $N_t \geq 8$ for QSM, $\boldsymbol{x}$ satisfies sparsity property. Detection of a such system can be regarded as the sparse reconstruction problem. Since most of the CS algorithms are applied to real signal models, the received signal vector $\boldsymbol{y}$ should be decomposed into its real and imaginary parts as

$$\begin{bmatrix} R(\boldsymbol{y}) \\ I(\boldsymbol{y}) \end{bmatrix} = \begin{bmatrix} R(\boldsymbol{H}) & -I(\boldsymbol{H}) \\ I(\boldsymbol{H}) & R(\boldsymbol{H}) \end{bmatrix} \begin{bmatrix} R(\boldsymbol{x}) \\ I(\boldsymbol{x}) \end{bmatrix} + \begin{bmatrix} R(\boldsymbol{n}) \\ I(\boldsymbol{n}) \end{bmatrix} \tag{5}$$

$$\tilde{\boldsymbol{y}} = \tilde{\boldsymbol{H}}\tilde{\boldsymbol{x}} + \tilde{\boldsymbol{n}} \tag{6}$$

where $R(\cdot)$ and $I(\cdot)$ stand for the real and imaginary operators, respectively. Equation (6) can be transformed into an l_1-norm optimisation problem as

$$\min_{\tilde{\boldsymbol{x}}} \|\tilde{\boldsymbol{x}}\|_1 \quad \text{s.t.} \quad \|\tilde{\boldsymbol{y}} - \tilde{\boldsymbol{H}}\tilde{\boldsymbol{x}}\|_2 \leq \epsilon \tag{7}$$

where $\varepsilon > 0$, and $\|\cdot\|_1$ and $\|\cdot\|_2$ denote l_1 and l_2-norm of a vector, respectively. By using Lagrangian formulation, (7) can be converted to a quadratic programming (QP) type optimisation problem which can be formulated as

$$\min_{\boldsymbol{z}} \frac{1}{2}\boldsymbol{z}^{\mathrm{T}}\boldsymbol{Bz} + \boldsymbol{c}^{\mathrm{T}}\boldsymbol{z} \quad \text{s.t} \quad \boldsymbol{z} \geq 0 \tag{8}$$

where $\boldsymbol{z} = [\tilde{\boldsymbol{x}}_+; \tilde{\boldsymbol{x}}_-]$, $\boldsymbol{c} = \lambda\boldsymbol{1} + \left[-\tilde{\boldsymbol{H}}^{\mathrm{T}}\tilde{\boldsymbol{y}}; \tilde{\boldsymbol{H}}^{\mathrm{T}}\tilde{\boldsymbol{y}}\right]$ and

$$\boldsymbol{B} = \begin{bmatrix} \tilde{\boldsymbol{H}}^{\mathrm{T}}\tilde{\boldsymbol{H}} & -\tilde{\boldsymbol{H}}^{\mathrm{T}}\tilde{\boldsymbol{H}} \\ -\tilde{\boldsymbol{H}}^{\mathrm{T}}\tilde{\boldsymbol{H}} & \tilde{\boldsymbol{H}}^{\mathrm{T}}\tilde{\boldsymbol{H}} \end{bmatrix}. \tag{9}$$

In (8), $\tilde{\boldsymbol{x}}_+$ and $\tilde{\boldsymbol{x}}_-$ are non-negative vectors that collect the positive and negative coefficients of $\tilde{\boldsymbol{x}}$, respectively, $\boldsymbol{1}$ denotes an all-ones column vector and $\lambda = \sigma\sqrt{2\ln N_t}$ is the regularisation parameter. (8) can be easily solved by using MATLAB function *quadprog*. Let $\boldsymbol{g} \in \mathbb{C}^{N_t\times 1}$ is the reconstructed version of the transmission vector $\boldsymbol{x}$ using the CS algorithm, we consider

$$\left[k_1\, k_2 \cdots k_N \cdots k_{N_t}\right]^{\mathrm{T}} = \operatorname{argsort}(|\boldsymbol{g}|) \tag{10}$$

where sort$(\cdot)$ reorders the elements of the input vector in descending order, and k_1 and k_{N_t} are the indices of the maximum and the minimum valued elements of $|\boldsymbol{g}|$. Then, N most probable active indices are determined as $\{k_1, \ldots, k_N\}$, where $2 \leq N < N_t$. Considering these N most probable active indices, a subchannel matrix $\hat{\boldsymbol{H}} \in \mathbb{C}^{N_r\times N}$ is constructed as

$$\hat{\boldsymbol{H}} = \left[\boldsymbol{h}_{k_1}\, \boldsymbol{h}_{k_2} \cdots \boldsymbol{h}_{k_N}\right] \tag{11}$$

where $\boldsymbol{h}_{k_j} \in \mathbb{C}^{N_r \times 1}$ is the k_jth column of $\boldsymbol{H}$ for $j \in \{1, 2, \ldots, N\}$. We have the following N different possible transmission patterns, if s_R and js_I are transmitted from the same antenna:

$$\hat{\boldsymbol{x}}_1 = \begin{bmatrix} s_R + js_I \\ 0 \\ \cdot \\ \cdot \\ \cdot \\ 0 \end{bmatrix}, \quad \hat{\boldsymbol{x}}_2 = \begin{bmatrix} 0 \\ s_R + js_I \\ 0 \\ \cdot \\ \cdot \\ 0 \end{bmatrix}, \ldots, \quad \hat{\boldsymbol{x}}_N = \begin{bmatrix} 0 \\ 0 \\ \cdot \\ \cdot \\ 0 \\ s_R + js_I \end{bmatrix}. \tag{12}$$

On the other hand, we have the following $N(N-1)$ different possible transmission patterns, if s_R and js_I are transmitted from two different antennas:

$$\hat{\boldsymbol{x}}_{N+1} = \begin{bmatrix} s_R \\ js_I \\ 0 \\ \cdot \\ \cdot \\ \cdot \\ 0 \end{bmatrix}, \ldots, \begin{bmatrix} 0 \\ \cdot \\ \cdot \\ \cdot \\ 0 \\ js_I \\ s_R \end{bmatrix}, \begin{bmatrix} js_I \\ s_R \\ 0 \\ \cdot \\ \cdot \\ \cdot \\ 0 \end{bmatrix}, \ldots, \quad \hat{\boldsymbol{x}}_{N^2} = \begin{bmatrix} 0 \\ \cdot \\ \cdot \\ \cdot \\ 0 \\ s_R \\ js_I \end{bmatrix}. \tag{13}$$

In (12) and (13), $\hat{\boldsymbol{x}}_i \in \mathbb{C}^{N \times 1}$ denotes ith possible transmission pattern where $i \in \{1, 2, \ldots, N^2\}$. Consequently, for each N value, $N + N(N-1) = N^2$ different transmission patterns are possible and the ML detector jointly detects the most probable transmission pattern by considering these N^2 possible transmission patterns and M-QAM constellation symbols as

$$\left(\hat{i}, \hat{s}_R, \hat{s}_I\right) = \underset{i, s_R, s_I}{\arg\min} \left\| \boldsymbol{y} - \hat{\boldsymbol{H}} \hat{\boldsymbol{x}}_i \right\|^2. \tag{14}$$

After the detection of the transmission pattern, one can easily determine the indices of active antennas and the corresponding complex data symbol, which are required for bit demapping operation.

Complexity comparison: By considering the total number of real multiplications, we calculate the computational complexity of the ML detector and the proposed low-complexity detector. The complexity of the ML detector given in (4) is evaluated as $\mathcal{O}(8N_t^2 M N_r)$. The proposed low-complexity detection algorithm is composed of QP and ML detection stages. The complexity of the QP stage is $\sim \mathcal{O}(8N_t^3)$ [6] while the complexity of the ML stage is calculated as $\mathcal{O}(8N^2 M N_r)$. Therefore, the overall complexity of the proposed algorithm can be given as $\sim \mathcal{O}(8N_t^3 + 8N^2 M N_r)$. We conclude from this result that the proposed detection algorithm considerably reduces the complexity of the ML detector for higher order constellations and MIMO configurations.

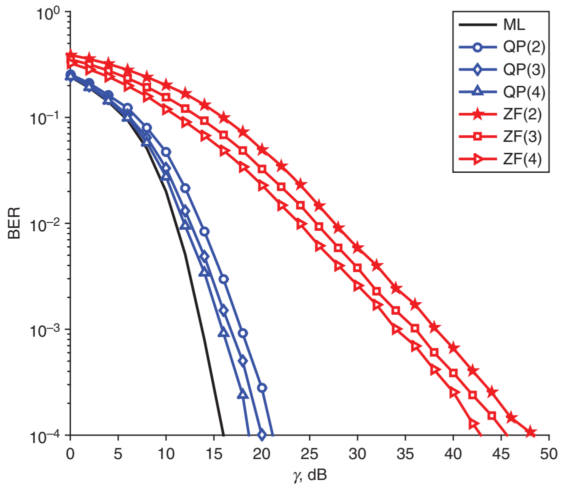

Fig. 1 *BER performance of ML, QP and ZF detectors for m = 10 bpcu, 8 × 8 MIMO system, 16-QAM*

Simulation results: In this section, BER performance of QSM is evaluated for different spectral efficiency values by using ML, the proposed QP and zero forcing (ZF) detectors.

In Figs. 1 and 2, we consider the BER performance of ML, ZF and the proposed QP detector for 10 and 12 bpcu spectral efficiency values, respectively, where ZF (N) and QP (N), $N \in \{2, 3, 4\}$ denote the employment of ZF and QP based detection for a given value of N, respectively. Please note that the ML stage of the proposed algorithm (10)–(14) can also be implemented for ZF detection, i.e. by considering $\boldsymbol{g} = \boldsymbol{H}^{+}\boldsymbol{y}$, where $(\cdot)^{+}$ denotes the pseudo-inverse of a matrix .

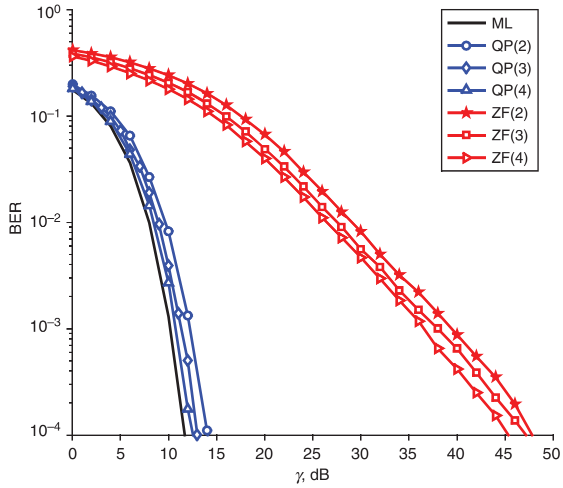

Fig. 2 *BER performance of ML, QP and ZF detectors for m = 12 bpcu, 16 × 16 MIMO system, 16-QAM*

In Figs. 1 and 2, we consider 8×8 and 16×16 MIMO systems, respectively, and evaluate the BER performance of different detectors with respect to received signal-to-noise ratio at each receive antenna (γ) for 16-QAM. As seen from Figs. 1 and 2, the proposed detector exhibits near-ML BER performance with increasing N values. As an example, compared with ML detector, the proposed detector with $N = 4$ provides approximately 68.75% and 87.5% reduction in decoding complexity for 10 and 12 bpcu cases, respectively.

Conclusion: The complexity of the ML detector can be a concern for higher order MIMO systems and constellations, which are gaining more and more attention for future wireless networks. In this Letter, we have proposed a near-optimal detection scheme for QSM with low-complexity. We have shown via Monte Carlo simulations and complexity comparisons that the proposed detector, which is based on QP problem, exhibits near-ML error performance with considerably lower decoding complexity.

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One or more of the Figures in this Letter are available in colour online.

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