Improved Symbol-Based Belief Propagation Detection for Large-Scale MIMO

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Abstract—In this paper, BP detection based on belief propagation in real domain for large-scale MIMO systems is proposed. Numerical results have shown that, with quadrature phase shift keying (QPSK) modulation, this approach can show 1 dB performance improvement at the BER of $10^{-2}$, compared to conventional single-edge based BP (SE-BP) in complex domain. Based on the proposed BP detection, its symbol-based variation is also investigated for applications in large-scale MIMO systems with a high-order modulation. This symbol-based method successfully reduces computational complexity by avoiding large dimensional matrix inversion and decomposition. Since the proposed method can also shrink the constellation size, its complexity can be further reduced. Numerical simulation results and complexity comparison have demonstrated that the proposed symbol-based BP detection can show advantages in both performance and complexity compared to existing ones. Therefore, it is suitable for large-scale MIMO system applications, especially for those with high-order modulations.

Index Terms—Large-scale MIMO, belief propagation (BP), symbol-based, message passing, iterative detection.

I. INTRODUCTION

By transmitting multiple data streams concurrently and in the same frequency band, multiple-input multiple-output (MIMO) system successfully improves system capacity and data rate over the single-antenna system. The resultant higher spectral efficiency and better link reliability have made it increasingly popular for both academia and industry. Nowadays, MIMO in combination with spatial multiplexing has been adopted by the latest standards such as 3GPP LTE-Advanced [1] and IEEE 802.11n [2]. In order to fulfill the ever-increasing demands of future wireless communication, systems are required to be equipped with an order of higher magnitude of antenna arrays than conventional MIMO systems. That is how the popular concept of large-scale MIMO comes out.

Without any doubt, large-scale MIMO has ranked one of the key technologies of next generation wireless communication systems, such as 5G, with its significant improvement in spectral efficiency, link reliability, and coverage compared to conventional MIMO [3]. Unfortunately, its huge size hinders the use of optimal data detection methods, such as maximum likelihood (ML), since its computational complexity grows exponentially with the number of transmit antennas, which becomes prohibitive for large-scale MIMO. Even those near-optimal detections such as soft-output $K$-Best and sphere decoding (SD), which may be favorable for conventional MIMO, also suffers a lot from their excessive computational complexity in the scenario of large-scale MIMO systems with a high-order constellation. Although several improved low-complexity variations, such as lattice reduction (LS) aided detection [4] and distributed $K$-Best approach [5], have been proposed, the efficient detection which perfectly balances both performance and complexity remains challenging for large-scale MIMO. To this end, the sub-optimal detection approach, minimum mean-squared error (MMSE), is proposed recently by [6]. However, its successful application relies on Neumann approximation to deal with large-scale matrix inversion, and the approximate error is proportional to the antenna ratio $(M^2/N)$, where $M$ and $N$ are the numbers of transmitting and receiving antennas, respectively.

Therefore, the dominating computation complexity lays in ML method, $K$-Best method, SD method, or MMSE method has put the barrier which could not be override for large-scale MIMO detection. In order to bypass this bottleneck, several alternative algorithms, which are less computation-intensive, have been recently proposed, such as likelihood ascent search (LAS) algorithm, reactive tabu search (RTS) algorithm, and belief propagation (BP) algorithm [7–10]. Among those candidates, the BP algorithm provides better performance in general, and is less vulnerable to the local minimum problem. Second, BP algorithm is robust and does not requires a carefully selected initial solution vector. Last but the most important, BP algorithm is matrix-inverse free, which make it very attractive for large-scale MIMO detection. In [11], Markov rand field (MRF)-based model and factor graph (FG)-based model with Gaussian approximation of interference (GAI) are incorporated with BP algorithm. Unfortunately, this bit-based BP detection is only suitable for large-scale MIMO systems with low modulation order, such as binary phase shift keying (BPSK). In [12], a symbol-based BP detection with non-binary low-density parity check (LDPC) codes has been shown to outperform the classical bit-based algorithm. However, its iterative detection is defined over high-order constellation in complex domain, and therefore results in overwhelming complexity in message passing. Furthermore, its inter- and intra-iteration scheduling will introduce very long latency.

In this paper, the BP detection defined over real domain is proposed for the first time to reduce the constellation size. Furthermore, the proposed method is generalized to symbol-based BP detection for high-order constellation, such as quadrature...
amplitude modulation (QAM) and so on. Simulation and comparison have demonstrated its advantages of lower complexity and better performance over existing approaches.

The remainder of the paper is organized as follows. Section II describes the system models over both complex and real domains of large-scale MIMO systems. Section III presents the FG representation of MIMO channels and theoretical foundation of BP detection based on FGs with GAI. In addition, the proposed low-complexity symbol-based BP detection in reduced real constellation is also introduced in the same section. Numerical simulation results and complexity comparison are given in Section IV. Section V concludes the entire paper.

II. LARGE-SCALE MIMO SYSTEM

A. System Model in Complex Domain

We consider the uplink in a large-scale MIMO system, where the base station (BS) is equipped with \( N \) receiving antennas serving \( M (> N) \) single-antenna users at the same time. The complex transmitted vector \( x \) is denoted by \( \tilde{x} = [\tilde{x}_1, \tilde{x}_2, \ldots, \tilde{x}_M]^T \). Each entry of the vector is mapped to one point of a rectangular complex QAM, which is composed of \( Q = |\Theta| = 2^M \) distinct points. Therefore, we have \( \tilde{x} \in \mathbb{C}^M \).

According to the complex MIMO model, the \( N \)-dimensional received vector \( r = [\tilde{r}_1, \tilde{r}_2, \ldots, \tilde{r}_N]^T \) can be obtained by the following equation:

\[
\tilde{r} = \tilde{H}\tilde{x} + \tilde{n},
\]

where \( \tilde{H} = \{ h_{i,j} \}_{i=1,...,N; j=1,...,M} \) denotes the complex-valued channel matrix, which is assumed to be independent and identically distributed (i.i.d) Rayleigh fading composed of complex Gaussian distributed variable of \( \sim \mathcal{CN}(0,1) \). And \( \tilde{n} = [\tilde{n}_1, \tilde{n}_2, \ldots, \tilde{n}_N]^T \) represents the additive white Gaussian noise (AWGN) with \( \tilde{n}_i \sim \mathcal{CN}(0, \sigma^2) \).

B. Equivalent Model in Real Domain

Based on the aforementioned complex channel model, the equivalent real model can be derived using the real value decomposition (RVD) scheme [13]. The real model of Eq. (1) can be expressed as:

\[
r = Hx + n,
\]

where \( r = [r_1, r_2, \ldots, r_{2N}]^T, x = [x_1, x_2, \ldots, x_{2M}]^T, \) and the \( 2N \times 2M \) matrix \( H \) are all real-valued. They are derived according to the following mappings:

\[
\begin{align*}
\tilde{r} &\in \mathbb{C}^N \xrightarrow{r_{2k-1} \rightarrow \Re\{\tilde{r}_k\}, r_{2k} \rightarrow \Im\{\tilde{r}_k\}} r \in \mathbb{R}^{2N}, \\
\tilde{H} &\in \mathbb{C}^{N \times M} \xrightarrow{h_{2k-1,2m-1} \rightarrow \Re\{h_{k,m}\}, h_{2k,2m-1} \rightarrow \Im\{h_{k,m}\}} H \in \mathbb{R}^{2N \times 2M}, \\
\tilde{x} &\in \mathbb{C}^M \xrightarrow{x_{2k-1} \rightarrow \Re\{\tilde{x}_k\}, x_{2k} \rightarrow \Im\{\tilde{x}_k\}} x \in \mathbb{R}^{2M}, \\
\tilde{n} &\in \mathbb{C}^N \xrightarrow{n_{2k-1} \rightarrow \Re\{	ilde{n}_k\}, n_{2k} \rightarrow \Im\{	ilde{n}_k\}} n \in \mathbb{R}^{2N},
\end{align*}
\]

where \( \Re\{\cdot\} \) and \( \Im\{\cdot\} \) denote the real and imaginary parts of complex variable \( \cdot \), respectively. Note that for \( x_i \in \Omega \) we have

\[
\Omega = \{(-\sqrt{Q} + 1), \ldots, -1, +1, \ldots, (+\sqrt{Q} - 1)\},
\]

where \( \Omega \) is the set of in-phase or quadrature parts of points in the complex constellation \( \Theta \). From Eq. (4), we know that \( |\Theta| = \sqrt{Q} \), which implies the constellation size of transmitted symbols reduce from \( Q \) to \( \sqrt{Q} \). As a consequence, a complex \( N \times M \) MIMO system with a complex constellation \( \Theta \) can be equivalent to a real \( 2N \times 2M \) MIMO system with a real constellation \( \Omega \).

Given \( r \) and \( H \), the optimal maximum a posteriori probability (MAP) detector selects \( s_i \) that maximizes the a posteriori likelihood:

\[
p(x_i | r, H) = \sum_{x \setminus x_i} p(x | r, H).
\]

In other word, the MAP estimate of \( s_i \) can be given by

\[
\hat{x}_i = \arg \max_{x_i \in \Omega} p(x_i | y, H).
\]

III. BP DETECTION BASED ON FG

A. FG for MIMO Channels

For LDPC decoders, factor graph is employed to represent message passing between variable nodes and check nodes. The MIMO channel can also be represented by factor graph in a similar manner. Eq. (2) reveals that the dependency between symbol nodes and observation nodes is determined by the channel responses \( h_{i,j} \). Therefore, the fully connected FG of the MIMO channel can be illustrated in Figure 1 as follows.

![Factor graph of a MIMO system.](image)

The nodes \( \{x_1, x_2, \ldots, x_{2M}\} \), referred as “symbol nodes”, are responsible for a priori information updating of the transmitted information. And the nodes \( \{r_1, r_2, \ldots, r_{2N}\} \), referred as “observation nodes”, compute and store the a posteriori information observed at the receiver side.

In FG for MIMO channels, the dependency is determined by the channel response with statistically distribution. Therefore, the number of major connections would substantially not become so large with the increase of antennas [14]. As a result, the effective number of critical loops is not that large, which makes BP detection promising for large-scale MIMO systems.

B. Symbol-Based BP Detection in Real Domain

The essential of BP iterative detection lies in message updating and passing between symbol nodes and observation nodes, which can be summarized in two steps as follows:

- **Step 1**: Each symbol node updates its a priori information according to the a posteriori information obtained from observation nodes in each iteration but the first one. Then the updated information is passed to all the connected observation nodes.
\( \beta_{j,i}^{(l)}(s_k) = \log \frac{\sum_{x_i=s_k} p^{(l)}(r_j|x, h_j) p^{(l-1)}(x^{2M\setminus i}) / p^{(l-1)}(x_0^{2M\setminus i})}{\sum_{x_i=s_0} p^{(l)}(r_j|x, h_j) p^{(l-1)}(x^{2M\setminus i}) / p^{(l-1)}(x_0^{2M\setminus i})} = \log \frac{\sum_{x_i=s_k} p^{(l)}(r_j|x, h_j) \exp \sum_{T : x_i=s_k} \alpha_j^{(l-1)}(s_k)}{\sum_{x_i=s_0} p^{(l)}(r_j|x, h_j) \exp \sum_{T : x_i=s_0} \alpha_j^{(l-1)}(s_k)} . \)  

(12)

- Step 2: Each observation node computes its \textit{a posteriori} information based on its neighbouring symbol nodes, and then passes it back to those symbol nodes.

The message passed from the symbol node \( x_i \) to observation node \( r_j \), is denoted by \( F_{x_i \rightarrow r_j} \). And the message passed from the observation node \( r_j \) to symbol node \( x_i \), is denoted by \( \Omega_{r_j \rightarrow x_i} \).

1) A Prior Information at Symbol Nodes: For each node, soft information is used for message updating and passing. The \textit{a prior} log-likelihood ratio (LLR) vector of symbol nodes in real constellation \( \Omega \) is defined as follows:

\[ \alpha_{x_i \rightarrow r_j}^{(l)} = [\alpha_{x_i \rightarrow r_j}^{(l)}(s_1), \ldots, \alpha_{x_i \rightarrow r_j}^{(l)}(s_{\sqrt{2}-1})], \]  

(7)

which denotes the message passing from Symbol Node \( i \) to Observation Node \( j \) during the \( l \)-th iteration. Its entries are given by:

\[ \alpha_{i,j}^{(l)}(s_k) = \log \frac{p^{(l)}(x_i = s_k)}{p^{(l)}(x_i = s_0)}, k = 1, \ldots, \sqrt{2} - 1, \]  

(8)

where \( p^{(l)}(x_i = s_k) \) denotes the \textit{a prior} probability that the transmitted symbol \( x_i \) is equal to \( s_k \in \Omega \). Specially, for quadrature phase shift keying (QPSK) modulaion with \( \Omega = \{-1, +1\} \), (7) can be rewritten as \( \alpha_{x_i \rightarrow r_j}^{(l)} = \alpha_{x_i \rightarrow r_j}^{(l)+1} \), whose single entry is given by:

\[ \alpha_{i,j}^{(l)+1} = \log \frac{p^{(l)}(x_i = +1)}{p^{(l)}(x_i = -1)}. \]  

(9)

2) A Posteriori Information at Observation Nodes: Similar to symbol nodes, the message passed from observation node \( r_j \) to symbol node \( x_i \), during the \( l \)-th iteration, representing the \textit{a posteriori} information given \( y \) and \( H \), is defined as follows:

\[ \beta_{j,i}^{(l)} = [\beta_{j,i}^{(l)}(s_1), \ldots, \beta_{j,i}^{(l)}(s_{\sqrt{2}-1})]. \]  

(10)

Its entries can be calculated as follows:

\[ \beta_{j,i}^{(l)}(s_k) = \log \frac{\sum_{x_i=s_k} p^{(l)}(r_j|x, h_j, H)}{\sum_{x_i=s_0} p^{(l)}(r_j|x, h_j, H)} \]  

(11)

where \( x^{2M \setminus i} = (x_1, \ldots, x_{i-1}, x_{i+1}, \ldots, x_{2M}) \), and \( H = (h_1^T, \ldots, h_{2M}^T)^T \). We assume \( x_0^{2M \setminus i} = (x_1 = s_0, \ldots, x_{i-1} = s_0, x_{i+1} = s_0, \ldots, x_{2M} = s_0) \). Based on Eq. (9), we can rewrite Eq. (11) as shown in Eq. (12), where the transmitted symbols are assumed to be independent.

3) Message Updating of Observation Nodes: The observation nodes update \( \beta_{j,i} \) according to (12), where

\[ p^{(l)}(r_j|s, h_j) \]  

can be referred as likelihood probability. Hence, the formula for calculating likelihood probability and \textit{a priori} information is required. In FG-based BP detection approach with GAI, the received signal \( r_j \) can be written as follows:

\[ r_j = h_{j,i} x_i + \sum_{k=1, k \neq i}^{2N} h_{j,k} x_k + n_j = h_{j,i} x_i + z_{j,i}. \]  

(13)

Here, the interference term \( z_{j,i} \) is modeled with \textit{Gaussian} approximation of \( N(\mu_{z,j,i}, \sigma^2_{z,j,i}) \) with

\[ \mu_{z,j,i} = \sum_{k=1, k \neq i}^{2M} h_{j,k} E\{x_k\}, \sigma^2_{z,j,i} = \sum_{k=1, k \neq i}^{2M} h_{j,k}^2 \text{Var}\{x_k\} + \sigma^2. \]  

(14)

Now we can calculate the likelihood probability with the following equation:

\[ p^{(l)}(r_j|x, h_j) = \frac{1}{\sqrt{2\pi\sigma_{z,j,i}}} \exp \left( \frac{(r_j - \mu_{z,j,i} - h_{j,i} x_i)^2}{2\sigma^2_{z,j,i}} \right). \]  

(15)

Based on Eq. (12) and (15), we can further obtain Eq. (16). Using the approximation \( \log(e^x + e^y) \approx \max(x, y) \), Eq. (16) can be approximated as Eq. (17). This algorithm is named as full edge based BP (FE-BP) algorithm. The message updating and passing procedure of FE-BP algorithm is illustrated in Figure 2.

![Fig. 2. Message passing between variable nodes and observation nodes.](image-url)
\[
\beta_{j,i}(s_k) = \log \left( \frac{\sum_{x_i = s_k} \exp \left( -\frac{\left( r_j - \mu_{j,i}^{(l-1)} - h_{j,i} x_i \right)^2}{2(\sigma_{j,i}^{2})^{(l-1)}} \right)}{\sum_{x_i \neq s_k} \exp \left( -\frac{\left( r_j - \mu_{j,i}^{(l-1)} - h_{j,i} x_i \right)^2}{2(\sigma_{j,i}^{2})^{(l-1)}} \right)} \right),
\]

\[\beta_{j,i}^{(l)}(s_k) \approx \max_{x_i \neq s_k} \left( \sum_{t \neq j} \alpha_{t,i}^{(l-1)}(s_k) - \frac{\left( r_j - \mu_{j,i}^{(l-1)} - h_{j,i} x_i \right)^2}{2(\sigma_{j,i}^{2})^{(l-1)}} \right) - \max_{x_i \neq s_k} \left( \sum_{t \neq j} \alpha_{t,i}^{(l-1)}(s_k) - \frac{\left( r_j - \mu_{j,i}^{(l-1)} - h_{j,i} x_i \right)^2}{2(\sigma_{j,i}^{2})^{(l-1)}} \right).\]

Specially, for QPSK modulation, Eq. (10) can be rewritten as
\[
\beta_{j,i}^{(l)}(s_k) = \beta_{j,i}^{(l)}(+1), \quad \text{whose single entry is given by:}
\]
\[
\beta_{j,i}^{(l)}(+1) = \frac{2h_{j,i}(r_j - \mu_{j,i}^{(l-1)})}{(\sqrt{2})^{(l-1)}}.
\]

4) Message Updating of Symbol Nodes: At symbol node side, we can update \(\alpha_{i,j}^{(l)}\) by
\[
\alpha_{i,j}^{(l)}(s_k) = \sum_{t=1,t \neq j}^{2N} \beta_{t,i}^{(l-1)}(s_k),
\]
which is the standard BP massage updating method. Based on Eq. (8) and (20), together with
\[
\sqrt{Q-1} \sum_{k=0}^{Q-1} p^{(l)}(x_i = s_k) = 1,
\]
the a priori probability can be easily obtained as follows:
\[
p^{(l)}(x_i = s_k) = \frac{\exp(\alpha_{i,j}^{(l)}(s_k))}{1 + \sum_{m=1}^{Q-1} \exp(\alpha_{i,j}^{(l)}(s_m))},
\]
with \(k = 1, \ldots, \sqrt{Q} - 1\). Considering the a posteriori information updated in Eq. (14) and (16), we define the a priori probability vector as follows:
\[
P^{(l)}(x_i = s_k) = \left[ p^{(l)}_{i,j}(s_1), \ldots, p^{(l)}_{i,j}(s_{\sqrt{Q}-1}) \right],
\]
which should be included in a priori information \(E_{x_i \rightarrow r_j}\), together with \(\alpha_{i,j}^{(l)}\). Specially, for QPSK modulation, Eq. (23) can be simplified as \(p_{x_i \rightarrow r_j}^{(l)} = p_{i,j}^{(l)}(+1)\), whose single entry is given by
\[
p_{i,j}^{(l)}(+1) = \frac{\exp(\alpha_{i,j}^{(l)}(+1))}{1 + \exp(\alpha_{i,j}^{(l)}(+1))}.
\]

5) Decision Process for Output: Soft output after \(L\) iterations is given by
\[
\gamma(s_k) = \sum_{l=1}^{2N} \beta_{t,i}^{(L)}, k = 1, \ldots, \sqrt{Q} - 1.
\]

The details of output decision process are listed as follows:

---

**Algorithm 1 Decision Process for Output**

Require: \(s = [s_1, \ldots, s_{\sqrt{Q}-1}, s_0], \gamma = [\gamma_1, \ldots, \gamma_{\sqrt{Q}-1}, \gamma_0].\)

1: \(i = \text{index}, \gamma_{\text{max}} = \max\{\gamma\}\)
2: if \(\gamma_{\text{max}} > 0\) then
3: \(\hat{x} = s(\text{index})\)
4: else
5: \(\hat{x} = s(\text{end})\)
6: end if

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IV. SIMULATION RESULTS AND COMPARISON

A. Numerical Simulation Results

For Rayleigh fading channel, the numerical results of the proposed symbol-based BP detection in real domain are given. Here, different antenna configurations and modulation modes are considered to offer a fair evaluation of the proposed approach. There are a total of four plots here. Each plot is presented for a specific purpose, which will be detailed in the following. For all simulations, the number of BP detection iterations is set to 7. No channel coding scheme is considered.

1) Numerical Results with QPSK Modulation: Figure 3 shows the BER performances of proposed BP detection in real constellation, general SE-BP detection in complex constellation [12], and linear detection based on MMSE in MIMO system, together with BER performance in single input single output (SISO) channel with AWGN. According to Figure 3, we know that the proposed BP detection and general SE-BP detection, which suffer from the complexity of large dimensional inversion, all outperform MMSE detection significantly. Furthermore, the proposed BP detection shows better performance than the general SE-BP detection due to an effect of increased randomness of the connection strength by increasing nodes in FG. For instance, at the BER of \(10^{-2}\), the performance gap is around 1 dB.

In Figure 4, the simulation results of proposed BP detection in real constellation with difference antenna configurations are given. The three configuration sets are: \(M = N = 16, 32, \) and 64, respectively. It is observed that with the increase of antennas’ number, the BP detection performance also improves, approaching the SISO AWGN performance. This perfectly matches the theoretical behavior of large-scale MIMO systems. Thus, the proposed BP detection approach is promising for large-scale MIMO system, especially when
the antenna ratio $M^2/N$ relatively large (see the following for more details).

2) Numerical Results with 16-QAM Modulation: It has been mentioned in [6] that approximate matrix inversion relying on Neumann series would reduce the complexity of linear detection based on MMSE for large-scale MIMO systems. However, this approximation does not work when the antenna ratio $M^2/N$ is high. Here, we define the Transmitting antennas' number Squared to Receiving antennas' number Ratio $M^2/N$ as TSRR. Illustrated in Figure 5, this approximation approach shows similar performance as the exact one based on Cholesky decomposition, when TSRR is small ($M = 8, N = 128$). However, when TSRR increases ($M = 8, N = 64$), even more approximation terms are employed, the performance is not satisfying. Here, the variable $k$ denotes $k$-term Neumann approximation.

 Luckily, the proposed BP detection approach is still effective when TSRR is relatively large ($>1$). As illustrated in Figure 6, the proposed BP detection outperforms exact MMSE detection in both cases when TSRR equals 16 and 2, respectively. It is noted that the proposed BP detection is matrix inverse free, which is very preferable for large-scale MIMO applications.

In conclusion, for large-scale MIMO systems, no matter in low or high order modulation, no matter what antenna configuration is employed, the proposed symbol-based BP detection in real domain always outperforms MMSE detection. Furthermore, this method is matrix inversion free. Those advantages make it very suitable for large-scale MIMO systems.

B. Complexity Comparison

Here, the complexities of different BP detections are analyzed. The complexity of the proposed BP detection involves a posteriori information updating at observation nodes (Eq. (14) and (18)), denoted by POST.UP. And a priori information updating at symbol nodes (Eq. (24)), denoted by PRI.UP. On the average, the complexity comparison of different BP detections is listed in Table I. According to Table I, the complexity of
FE-BP grows exponentially with $M$, which is same as MAP detection. Intuitively, the proposed BP and the general SE-BP are of the same magnitude of complexity. In fact, the general SE-BP is defined in complex domain, whereas the proposed BP is defined in real domain. Hence, the proposed BP is more preferable for hardware implementation due to its lower complexity, especially for high-order ($Q$) constellation. For example, for antenna configuration of $M = 8$ and $N = 32$ with 256-QAM, the proposed BP can achieve about 75% complexity reduction compared to SE-BP.

<table>
<thead>
<tr>
<th>BP algorithms</th>
<th>POSTUP</th>
<th>PRLUP</th>
</tr>
</thead>
<tbody>
<tr>
<td>FE-BP</td>
<td>$O(Q^M+1 N(M-1))$</td>
<td>$O(Q(N-1)M)$</td>
</tr>
<tr>
<td>General SE-BP</td>
<td>$O(QN(M-1))$</td>
<td>$O(Q(N-1)M)$</td>
</tr>
<tr>
<td>Proposed BP</td>
<td>$O(2\sqrt{Q}(2(M-2))$</td>
<td>$O(2\sqrt{Q}(2N-2)M)$</td>
</tr>
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V. Conclusion

In this paper, the symbol-based BP detection in real domain is proposed. Simulation results with different modulation modes and antenna configurations have demonstrated the performance advantage of the proposed approach compared with the general BP detection as well as the MMSE approach. Also, the lower constellation size and matrix inverse free property makes the proposed method computation-efficiency, and therefore very suitable for large-scale MIMO systems. Further work will be directed towards BP detection for MIMO systems with more complicated antenna configurations and its cooperation with channel codes.

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