Reduced Complexity Message Passing Detection Algorithm in Large-Scale MIMO Systems

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***Abstract*—Large-scale multiple-input multiple-output (MIMO) has been identified as a key technology for the upcoming fifth generation (5G) wireless communication systems. The message passing detection (MPD) algorithm achieves much better performance compared to the minimum mean square error (MMSE) detection in large-scale MIMO systems. However, the computation complexity of the MPD algorithm grows quickly when the order of employed modulation scheme increases, making it inefficient for practical software or hardware implementation. In this paper, an improved MPD algorithm based on probability approximation is proposed to significantly reduce the computation complexity by intelligently choosing a limited number of symbol probabilities used in the iteration process. Simulation results demonstrate that the improved MPD algorithm achieves considerable computation complexity reduction compared with the original MPD algorithm. Besides, the improved MPD algorithm substantially reduce the number of stored symbol probabilities.**

***Index Terms*—large-scale MIMO systems, message passing, iterative detection algorithm**

I. Introduction

Large-scale multiple-input multiple-output (MIMO) systems [1], which can achieve high spectral efficiency, power efficiency and link reliability [2], will be one of the crucial technologies in the fifth generation (5G) communication systems [3]. Higher spectral efficiency and better link reliability have made large-scale MIMO systems increasingly attractive for both academia and industry. We consider the detection problem in multi-input multi-out (MIMO) systems. Various detection algorithms have been proposed like zero forcing (ZF), minimum mean square error (MMSE) [4], [5] and serial interference cancellation (SIC). With the increasing demand of future wireless communication, systems are required to be equipped with a higher order magnitude of antenna arrays than the conventional MIMO systems. The number of antennas in MIMO systems therefore will be scaled up to achieve higher data rates [6]. As the number of receive antennas used in the base station increases, many signal detection algorithms favored by conventional MIMO wireless systems, such as K-Best [7] and sphere decoding (SD) [8], will suffer from high computational complexity. Several low complexity detection algorithms [9]–[15] which achieve near-optimal performance in large-scale MIMO systems, have been proposed recently.

One recent iterative message passing detection (MPD) algorithm has been proposed in [16]. This MPD algorithm employs channel hardening theory [17] in a massive MIMO system and approximates the sum of interference using a Gaussian distribution. This algorithm is matrix-inverse free, which makes it very attractive for large-scale MIMO detection. In addition, this algorithm has a comparable complexity as an MMSE detector [18] and better performance than an MMSE detector in a massive MIMO system. However, the complexity of the MPD algorithm grows with the number of users and the order of modulation, presenting an implementation challenge for a high-order massive MIMO system.

In this paper, we focus on a scheme which greatly reduces the computational complexity of the iterative part of the MPD algorithm. The improved MPD algorithm is called the probability approximation message passing detection (PA-MPD) algorithm. Simulation results show that the proposed algorithm achieves a much lower computation complexity compared with the MPD algorithm. The main contributions of this work are as follows:

- An improved message passing algorithm which chooses a part of the symbol probabilities to calculate the messages in each iteration is proposed.
- Extensive simulations for different uplink users and base station antennas are performed in this work. When configured properly, the numerical results demonstrate that the proposed PA-MPD algorithm has significantly lower computation complexity with negligible loss of BER performance compared to the original MPD algorithm.

The rest of the paper is organized as follows. We review the system model and the original MPD algorithm in Section II. The proposed PA-MPD algorithm is presented in Section III. The comparisons between original MPD algorithm and PA-MPD algorithm in respect of performance and complexity is presented in Section IV. At last, the conclusion is drawn in Section V.

II. Preliminaries

A. System Model

We consider a MIMO system with K transmit antennas and N receive antennas. The input-output relationship is given by

$$\tilde{\mathbf{y}} = \tilde{\mathbf{H}}\tilde{\mathbf{x}} + \tilde{\mathbf{n}}. \tag{1}$$

Let $\tilde{\mathbf{x}} = [\tilde{x}_1, \tilde{x}_2, \cdots, \tilde{x}_K]^T \in \mathbb{C}^{K\times 1}$ denote the transmitted symbol vector, where each element $\tilde{x}_i$ is a QAM modulated symbol. $\tilde{\mathbf{y}} = [\tilde{y}_1, \tilde{y}_2, \cdots, \tilde{y}_N]^T \in \mathbb{C}^{N\times 1}$ is the received signal vector in the base station (BS). $\tilde{\mathbf{H}} \in \mathbb{C}^{N\times K}$ denotes the channel gain matrix. The channel gain $\tilde{H}_{ij}$ is assumed to follow independent Gaussian distribution with zero mean and variance $\sigma_j^2 = 1$. $\tilde{\mathbf{n}} \in \mathbb{C}^{N\times 1}$ denotes the Additive White Gaussian Noise (AWGN) with $\tilde{n}_i \sim \mathcal{CN}(0, \sigma_n^2)$.

This system model Eq. (1) can be written in the real-valued model

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{n}, \tag{2}$$

where

$$\mathbf{H} \triangleq \begin{bmatrix} \Re(\tilde{\mathbf{H}}) & -\Im(\tilde{\mathbf{H}}) \\ \Im(\tilde{\mathbf{H}}) & \Re(\tilde{\mathbf{H}}) \end{bmatrix}, \mathbf{y} \triangleq \begin{bmatrix} \Re(\tilde{\mathbf{y}}) \\ \Im(\tilde{\mathbf{y}}) \end{bmatrix}, \mathbf{x} \triangleq \begin{bmatrix} \Re(\tilde{\mathbf{x}}) \\ \Im(\tilde{\mathbf{x}}) \end{bmatrix},$$
$$\mathbf{n} \triangleq \begin{bmatrix} \Re(\tilde{\mathbf{n}}) \\ \Im(\tilde{\mathbf{n}}) \end{bmatrix}.$$

$\Re(.)$ and $\Im(.)$ denote the real and imaginary parts, respectively. Note that $\mathbf{H} \in \mathbb{R}^{2N\times 2K}$, $\mathbf{y} \in \mathbb{R}^{2N}$, $\mathbf{n} \in \mathbb{R}^{2N}$, and $\mathbf{x} \in \mathbb{R}^{2K}$. For a QAM alphabet $\mathbb{A}$, the elements of $\mathbf{x}$ in Eq. (2) belong to the underlying PAM alphabet $\mathbb{B}$. Note that we have $\mathbb{B} = \{(-\sqrt{M}+1), ..., -1, +1, ..., (+\sqrt{M}-1)\}$.

The object of the maximum-likelihood (ML) detection problem is to find the transmitted vector $\hat{\mathbf{x}}$ which minimizes the Euclidean cost:

$$\begin{aligned} \hat{\mathbf{x}} = & \arg\min(\mathbf{y} - \mathbf{H}\mathbf{x})^T(\mathbf{y} - \mathbf{H}\mathbf{x}) \\ & \mathbf{x} \in \mathbb{B}^{2K} \end{aligned} \tag{3}$$

The precision computation of Eq. (3) requires exponential complexity in K. As K grows, the computation complexity increases dramatically. This computation complexity is unacceptable in larger-scale MIMO systems.

B. Original Message Passing Detection Algorithm

The original MPD algorithm in [16] are as follows. Note that the details of the following formulas can be found in [16]. We give a brief introduction to the key parts of the original MPD algorithm in order to establish the foundation for our proposed PA-MPD algorithm later.

In the original MPD algorithm, the authors made the following steps: Consider the real-valued system model in Eq. (2). They multiply $\mathbf{H}^T$on both sides of Eq. (2):

$$\mathbf{H}^T\mathbf{y} = \mathbf{H}^T\mathbf{H}\mathbf{x} + \mathbf{H}^T\mathbf{n}, \tag{4}$$

From Eq. (4), they write the following:

$$\mathbf{z} = \mathbf{J}\mathbf{x} + \mathbf{v}, \tag{5}$$

where

$$\mathbf{z} \triangleq \frac{\mathbf{H}^T\mathbf{y}}{N}, \mathbf{J} \triangleq \frac{\mathbf{H}^T\mathbf{H}}{N}, \mathbf{v} \triangleq \frac{\mathbf{H}^T\mathbf{n}}{N}. \tag{6}$$

The ith element of $\mathbf{z}$ can be written as

$$z_i = J_{ii}x_i + \sum_{j=1, j\neq i}^{2K} J_{ij}x_j + v_i, \tag{7}$$

where

$$g_i \triangleq \sum_{j=1, j\neq i}^{2K} J_{ij}x_j + v_i, \tag{8}$$

$\mathbf{J}$ and $\mathbf{z}$ are calculated from the channel estimation part. Note that the variable g_i defined in Eq. (8) denotes the interference-plus-noise term, which involves the off-diagonal elements of $\mathbf{H}^T\mathbf{H}/N$. The MPD algorithm [16] assumes g_i to have a Gaussian distribution with mean μ_i and variance σ_i^2. By central limit theorem, this approximation is accurate for large K, N (the details refer to [16]).

μ_i is computed as

$$\begin{aligned} \mu_i = \mathbb{E}(g_i) &= \sum_{j=1, j\neq i}^{2K} J_{ij}\mathbb{E}(x_j) \\ &= \sum_{j=1, j\neq i}^{2K} J_{ij} \sum_{\forall s \in \mathbb{B}} s p_j(s). \end{aligned} \tag{9}$$

The variances are computed as

$$\begin{aligned} \sigma_i^2 = \mathrm{Var}(g_i) &= \sum_{j=1, j\neq i}^{2K} J_{ij}^2 \mathrm{Var}(x_j) + \sigma_v^2 \\ &= \sum_{j=1, j\neq i}^{2K} J_{ij}^2 (\sum_{\forall s \in \mathbb{B}} s^2 p_j(s) - \mathbb{E}(x_j)^2) + \sigma_v^2. \end{aligned} \tag{10}$$

Note that $\sigma_v^2 = \sigma_n^2/(2N)$. Because of the above Gaussian approximation, the a $posteriori$ probability (APP) of symbol $x_i \in \mathbb{B}$ is computed as

$$p_i(s) \propto \exp(\frac{-(z_i - J_{ii}s - \mu_i)^2}{2\sigma_i^2}). \tag{11}$$

In the original MPD algorithm, the bit probabilities are obtained as

$$\Pr(b_i^p = 1) = \sum_{\forall s \in \mathbb{B}: p\text{th bit in } s \text{ is } 1} p_i(s). \tag{12}$$

where b_i^p is the pth bit in the ith user's symbol. $b_i^p = 1$ if $\Pr(b_i^p = 1) \geqslant 0.5$ and 0 otherwise.

C. Channel Estimation for MPD

The scheme to obtain the estimation of $\mathbf{H}^T\mathbf{H}$ for original MPD algorithm is as follows. Suppose the channel is slowly fading, where the channel matrix $\mathbf{H}$ remains constant over one frame duration The length of one frame is L channel uses. Each frame consists of a pilot part and a data part. The pilot part consists of K channel uses, and the data part consists of $L-K$ channel uses. Let $\mathbf{X}_p = P\mathbf{I}_{2K}$ denote the pilot matrix. In the ith channel use, user i transmits a pilot tone with amplitude P and the other users remain silent.

The received pilot matrix at the BS is then given by

$$\begin{aligned} \mathbf{Y}_p &= \mathbf{H}\mathbf{X}_p + \mathbf{W}_p \\ &= P\mathbf{H} + \mathbf{W}_p, \end{aligned} \tag{13}$$

where $P = \sqrt{KE}$, E is the average symbol energy. $\mathbf{W}_p$ is the noise matrix. The estimation of the matrix $\mathbf{J}$ is

$$\hat{\mathbf{J}} = \frac{\mathbf{Y}_p^T\mathbf{Y}_p}{NP^2} - \frac{\sigma_v^2}{P^2}\mathbf{I}_{2K}. \tag{14}$$

An estimate of the vector z is obtained as

$$\hat{\mathbf{z}} = \frac{\mathbf{Y}_p^T y}{NP}. \tag{15}$$

The estimates $\hat{\mathbf{J}}$ and $\hat{\mathbf{z}}$ are used as inputs to the MPD algorithm in place of $\mathbf{J}$ and $\mathbf{z}$. Note that the details of above formulas can be found in [16]

III. Proposed PA-MPD Iterative Algorithm

On the basis of the original MPD algorithm and channel hardening theory in [16], we proposed PA-MPD algorithm. The proposed PA-MPD algorithm is as follows. Firstly, we obtain the estimations of $\mathbf{J}$ and $\mathbf{z}$. They are computed form Eqs. (14) and (15). Then, based on the real-valued system model in Eq. (2), we consider M-QAM modulation in this Section.

For M-QAM (i.e., $s \in \mathbb{B} = \{(-\sqrt{M}+1), ..., -1, +1, ..., (+\sqrt{M}-1)\}$). $\mathbb{E}(x_j)$ and $\mathrm{Var}(x_j)$ in Eqs. (9) and (10) can be written as

$$\begin{aligned}\mathbb{E}(x_j) &= s_0 p_j(s_0) + s_1 p_j(s_1) + ... \\ &\quad + s_{\sqrt{M}-1} p_j(s_{\sqrt{M}-1}),\end{aligned} \tag{16}$$

$$\begin{aligned}\mathrm{Var}(x_j) &= \mathbb{E}(x_j^2) - \mathbb{E}(x_j)^2 \\ &= s_0^2 p_j(s_0) + s_1^2 p_j(s_1) + ... \\ &\quad + s_{\sqrt{M}-1}^2 p_j(s_{\sqrt{M}-1}) - \mathbb{E}(x_j)^2.\end{aligned} \tag{17}$$

From the original MPD algorithm, we need to use all $\sqrt{M}$ symbol probabilities (i.e., $p_j(s), \forall s \in \mathbb{B}$) to calculate each $\mathbb{E}(x_j)$ and $\mathrm{Var}(x_j)$ in Eqs. (16) and (17) during each iteration. This scheme will bring a lot of multiplications and additions. In addition, the number of multiplications and additions grows with the number of users and the order of modulation, presenting an implementation challenge for a high-order massive MIMO system. By observing the value of the symbol probabilities of $x_i (\forall i \in 2K)$ after each iteration, we find out that some symbol probabilities of x_i are very small (almost close to 0) after the first iteration and most of these small symbol probabilities will become smaller in the remaining iteration.

Approximation scheme for message passing: In our proposed scheme, we reduce the number of symbol probabilities used in Eqs. (16) and (17). In other words, we use a part of all $\sqrt{M}$ symbol probabilities and obtain the estimations of $\mathbb{E}(x_j)$ and $\mathrm{Var}(x_j)$. The rule of selecting symbol probabilities is based on the magnitude of the probability value. Starting from the second iteration, we select the largest n symbol probabilities to calculate $\mathbb{E}(x_j)$ and $\mathrm{Var}(x_j)$. Because of the negligible effect of the $\sqrt{M}-n$ small symbol probabilities, the estimations of $\mathbb{E}(x_j)$ and $\mathrm{Var}(x_j)$ obtained from our scheme are very close to the real values. Therefore, if the value of n is appropriate, the performance loss of the proposed algorithm is negligible.

The proposed PA-MPD algorithm for M-QAM is described in **Algorithm** 1. Suppose we use n maximum symbol probabilities out of all $\sqrt{M}$ symbol probabilities in calculating $\mathbb{E}(x_j)$ and $\mathrm{Var}(x_j)$. The algorithm is initialized with $p_i^0(s) = 1/\sqrt{M}$.

At the end of the tth iteration of the detection algorithm described above, we obtain the probabilities of the ith user's symbol information, $p_i^t(s)$ $(s \in \mathbb{B})$.

Algorithm 1: The proposed PA-MPD algorithm

input : $\mathbf{z}, \mathbf{J}, \sigma_v^2$

Initialize : $p_i^0(s) \leftarrow 1/\sqrt{M}$, $i = 1, ..., 2K$
for $t = 1$ **do**
  for $i = 1$ **to** $2K$ **do**
    $\mu_i = \sum_{j=1, j\neq i}^{2K} J_{ij} \sum_{\forall s \in \mathbb{B}} s p_j^{t-1}(s)$
    $\sigma_i^2 = \sum_{j=1, j\neq i}^{2K} J_{ij}^2 (\sum_{\forall s \in \mathbb{B}} s^2 p_j^{t-1}(s) - \mathbb{E}(x_j)^2)$
    $+\sigma_v^2$
    $p_i^t(s) \propto \exp(\frac{-(z_i - J_{ii}s - \mu_i)^2}{2\sigma_i^2})$
for $t = 2$ **to** $number\_of\_iterations$ **do**
  for $i = 1$ **to** $2K$ **do**
    for $j = 1$ **to** $2K$ **do**
      A_j is a collection of n maximum symbol probabilities
      of x_j from $(t-1)$th iteration
    $\mu_i = \sum_{j=1, j\neq i}^{2K} J_{ij} \sum_{p_j^{t-1}(s) \in A_j} s p_j^{t-1}(s)$
    $\sigma_i^2 = \sum_{j=1, j\neq i}^{2K} J_{ij}^2 (\sum_{p_j^{t-1}(s) \in A_j} s^2 p_j^{t-1}(s)$
    $-\mathbb{E}(x_j)^2) + \sigma_v^2$
    $p_i^t(s) \propto \exp(\frac{-(z_i - J_{ii}s - \mu_i)^2}{2\sigma_i^2})$

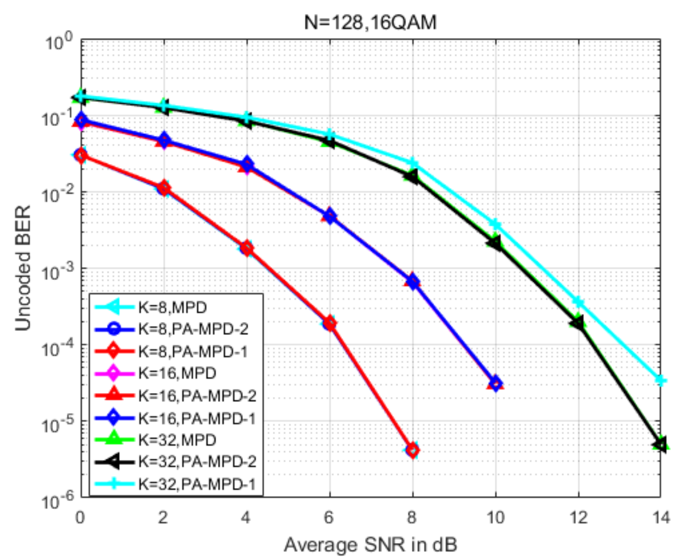

Fig. 1. Uncoded BER performance of the PA-MPD algorithm and the MPD algorithm for different values of K (=8,16,32) for a fixed N = 128 under 16-QAM.

IV. Performance and Computational Complexity Comparisons

A. BER Performance Comparisons

In this subsection, we present the uncoded BER performance of the PA-MPD algorithm obtained through simulations with various system parameters. Here, different antenna configurations and modulation modes are considered to provide a fair evaluation of the proposed scheme. There are a total of 3 plots here. Each plot is presented for a specific purpose, which will be detailed in the following. The PA-MPD-a corresponds to the scheme with $n = a$. No channel coding scheme is considered.

1)*Numerical Results with* 16-*QAM Modulation*:

Fig. 1 shows the uncoded BER performance of the proposed PA-MPD algorithm and the original MPD algorithm for a fixed number of receiver antennas at the BS ($N = 128$) with varied number of users ($K = 8, 16, 32$) under 16-QAM. PA-MPD-1 and PA-MPD-2 correspond to the scheme with $n = 1$ and 2, respectively. When $K = 8$ or 16, PA-MPD-1 has almost the same BER performance as the MPD algorithm. When $K = 32$, PA-MPD-1 has a loss of 0.7dB at the BER of 10^{-4}. The performance of PA-MPD-1 become slightly worse than the original MPD algorithm with the increase of K, but the performance of PA-MPD-1 could be good enough for certain MIMO systems. In each case of these antenna configurations, PA-MPD-2 has the nearly same BER performance as the original MPD algorithm. In general, both PA-MPD-1 and PA-MPD-2 have much lower computation complexity than the original MPD algorithm.

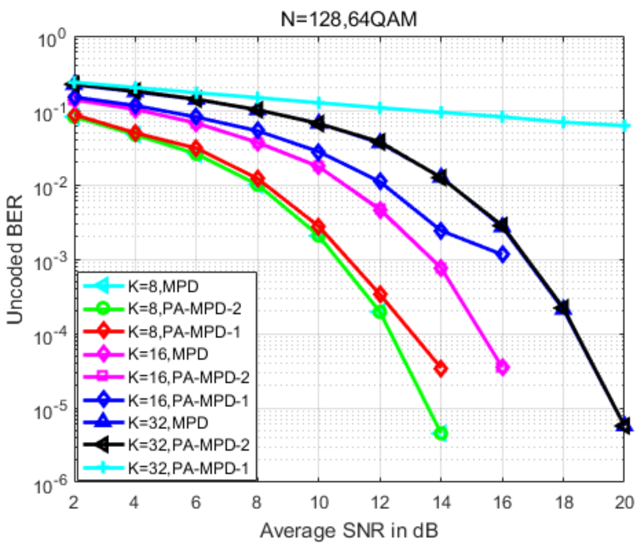

Fig. 2. Uncoded BER performance of the PA-MPD algorithm and the MPD algorithm for different values of K for a fixed N = 128 under 64-QAM (13 iterations).

2)*Numerical Results with* 64-*QAM Modulation*:

Fig. 2 shows the uncoded BER performance of the PA-MPD algorithm and the original MPD algorithm with different K values for a fixed N under 64-QAM. It is observed that the performance of PA-MPD-1 was much worse than that of PA-MPD-2 under the selection configurations. This is because the number of symbol probabilities used in PA-MPD-1 is too small. In contrast, PA-MPD-2 performs almost the same as the original MPD algorithm. Since PA-MPD-2 already has almost the same performance as the original MPD algorithm, $n = 2$ is enough for the PA-MPD algorithm under 64-QAM for the sake of computation complexity reduction. For example, for antenna configuration of $K = 16$ and $N = 128$ with 64-QAM, it is calculated that the proposed PA-MPD algorithm (PA-MPD-2) can achieve about 65% computation complexity reduction compared to the original MPD algorithm (the details of the computation complexity are shown in the next section). Moreover, the number of stored symbol probabilities is reduced from $\mathcal{O}(M)$ to $\mathcal{O}(n^2)$. In this case, the number stored symbol probabilities for PA-MPD-2 is about $\frac{1}{16}$ of that of the original MPD algorithm.

3)*Numerical Results with* 256-*QAM Modulation*:

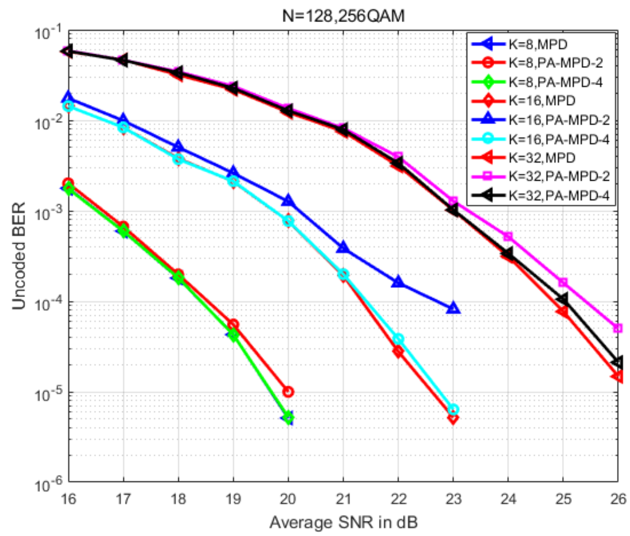

Fig. 3. Uncoded BER performance of the PA-MPD algorithm and the MPD algorithm for different values of K for a fixed N = 128 under 256-QAM (13 iterations).

Fig. 3 shows the uncoded BER performance of the PA-MPD algorithm and the original MPD algorithm with different K values for a fixed N under 256-QAM. It is observed that when $K = 8$, PA-MPD-2 has a loss of 0.1dB at the BER of 10^{-4} compared with the original MPD algorithm. When $K = 32$, the BER loss increases to 0.6dB. When $K = 16$, the loss increases to 1.4dB. This is also because the number of symbol probabilities used in PA-MPD-2 is small. When we increase the value of n to 4, the performance becomes better. Based on the above simulation results, it is concluded that the proposed algorithm is suitable for large-scale MIMO system applications, especially for those with high-order modulations.

B. Computation Complexity Analysis

Here, the complexities of the PA-MPD algorithm and the original MPD algorithm are analyzed. The computation complexity is analyzed in terms of the number of real-valued multiplications and additions.

Table I shows the computation complexity comparison between the proposed PA-MPD algorithm and the original MPD algorithm under M-QAM. Suppose we use n maximum symbol probabilities out of all $\sqrt{M}$ symbol probabilities during the calculation of $\mathbb{E}(x_j)$ and $\mathrm{Var}(x_j)$. The number of multiplications and additions in PA-MPD-n consists of two parts. The number of the first part of multiplications is $(2\sqrt{M}+1)(2K-1)2K$, which comes from the first iteration.

TABLE I
NUMBER OF REAL-VALUED MULTIPLICATIONS AND ADDITIONS FOR THE ORIGINAL MPD ALGORITHM AND THE PA-MPD ALGORITHM UNDER M-QAM IN t ITERATIONS

multiplications	original MPD	$(2\sqrt{M}+1)(2K-1)2Kt$
	PA-MPD-n	$(2n+1)(2K-1)2K(t-1)+(2\sqrt{M}+1)(2K-1)2K$
additions	original MPD	$((2\sqrt{M}+1)(2K-1)-2)2Kt$
	PA-MPD-n	$((2n+1)(2K-1)-2)2K(t-1)+((2\sqrt{M}+1)(2K-1)-2)2K$

The number of the second part is $(2n+1)(2K-1)2K(t-1)$, which comes from the remaining $t-1$ iterations. Here, t is the number of iterations employed. Similarly, the numbers of the first and second parts of additions are $((2\sqrt{M}+1)(2K-1)-2)2K$ and $((2n+1)(2K-1)-2)2K(t-1)$, respectively.

Our proposed algorithm can reduce $2(\sqrt{M}-n)(2K-1)2K(t-1)$ multiplications and $2(\sqrt{M}-n)(2K-1)2K(t-1)$ additions in t iterations. As the number of t increases, our scheme will reduce more multiplications and additions. The number of multiplications (iteration process) in the MPD algorithm is $\frac{(2\sqrt{M}+1)t}{(2n+1)(t-1)+(2\sqrt{M}+1)}$ times of the PA-MPD algorithm. The number of additions (iteration process) in the MPD algorithm is $\frac{((2\sqrt{M}+1)(2K-1)-2)t}{((2n+1)(2K-1)-2)(t-1)+(2\sqrt{M}+1)(2K-1)-2}$ times of the PA-MPD algorithm. The detailed numerical comparisons between the MPD algorithm and the PA-MPD algorithm under 256-QAM are shown in Table II.

TABLE II
COMPARISON BETWEEN THE COMPLEXITIES(IN NUMBER OF REAL-VALUED MULTIPLICATIONS AND ADDITIONS) OF THE PROPOSED PA-MPD ALGORITHM AND THE ORIGINAL MPD ALGORITHM UNDER 256-QAM FOR N=128. NUMBER OF ITERATIONS FOR PA-MPD ALGORITHM AND ORIGINAL MPD ALGORITHM IS 13

	multiplications in iteration process	additions in iteration process
MPD(K=8)	102960	102544
PA-MPD-4(K=8)	33840	33424
PA-MPD-2(K=8)	22320	21904
MPD(K=16)	425568	424736
PA-MPD-4(K=16)	139872	139040
PA-MPD-2(K=16)	92256	91424
MPD(K=32)	1729728	1728064
PA-MPD-4(K=32)	568512	566848
PA-MPD-2(K=32)	374976	373312

For antenna configuration of $K=16$ and $N=128$ with 256-QAM, the proposed PA-MPD algorithm (PA-MPD-4) can achieve about 68% complexity reduction compared to the original MPD algorithm. The proposed PA-MPD algorithm is more suitable for hardware implementation due to its lower computation complexity, especially for high-order constellation.

V. CONCLUSION

In this paper, we have considered a probability approximation scheme used in the MPD algorithm for detection in large MIMO systems. The proposed algorithm (PA-MPD) is based on a novel channel hardening strategy in [16]. Compared to the MPD algorithm in [16], the proposed scheme can achieve significant computation complexity reduction in the iteration process. Simulation results show that the PA-MPD algorithm provides almost the same BER performance with much lower complexity compared to original algorithm.

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