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Low-Complexity GAI-BP Detection for MIMO Systems with Threshold-updating Strategy

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***Abstract*—Gaussian approximation of interference (GAI)-based BP (GAI-BP) serves as the state-of-the-art (SOA) BP detection algorithms for large-scale MIMO systems. Nevertheless, the GAI-BP suffers from high computational expense due to the exponentiation operations for computing the *a prior* probability. To address this issue, in this work, we propose a threshold-updating strategy-based GAI-BP (TU-GAI-BP) detection algorithm. The TU-GAI-BP first employs the threshold to select the target *a prior* probability which tends to be converged after several iterations, then freezes the probability in the following iterations. Simulation results prove that compared with the SOA GAI-BP, the proposed TU-GAI-BP achieves about 71% computational reduction and still remains comparable error performance in 32×16, 16-QAM MIMO scenario. Additionally, we design the hardware architecture for the proposed TU-GAI-BP detector.**

***Index Terms*—signal detection, Multiple-input multiple-output (MIMO), belief propagation (BP), Gaussian approximation of interference (GAI)**

I. Introduction

Due to its enhanced spectrum utilization and high energy efficiency, multiple-input multiple-output (MIMO) ranks as one of the most important role in wireless communication systems [1]. However, with the scale of the MIMO antennas tending to be larger and larger, the signal detection, aiming at recovering the transmitted symbols, becomes a main bottleneck for MIMO systems. Reviewing the MIMO signal detection approaches, the optimal solution is the *maximum a posterior* (MAP) or *maximum likelihood* (ML) detection. However, the MAP/ML detection lose their feasibility thanks to the exponentially increased computational complexity. To this end, several alternative solutions were proposed to achieve a trade-off between the error performance and the computational complexity. Specifically, one degraded variant of the MAP/ML is the near-optimal sphere decoding (SD) detection [2]. The SD detection limits the search space by circumventing the candidates with relatively low reliability, thus saving the computational complexity. Towards high efficiency of hardware implementation, the linear detection algorithms, such as zero forcing (ZF), linear minimum mean square error (LMMSE) [3], [4], and linear iteration detection algorithms, such as weighted *Neumann* series approximation (wNSA) [5], enjoy extensive attention for large-scale MIMO systems. However, the error performance of the aforementioned linear (iterative) detection algorithms remain unsatisfactory for MIMO systems equipped with massive antennas.

Recently, Belief propagation (BP) detection algorithms [6]–[8] attract extensive attentions for large-scale MIMO systems, owing to its good error performance and feasible hardware designing. The original BP detection was proposed in [6] for the vertical Bell labs layered space-time (VBLAST) architecture system. To diminish the computational complexity of the original BP detection, the authors in [7] proposed Guassian approximation of interference (GAI)-based BP detection (GAI-BP). However, this GAI-BP detection suffers from heavy error floor in high-order modulation MIMO systems. Consequently, in [8], the authors developed the real-domain GAI-BP (RD-GAI-BP) and employed the damping factor to relieve the error floor performance of the GAI-BP. This RD-GAI-BP serves as the state-of-the-art (SOA) BP detection in terms of error performance for extensive MIMO systems, but it requires to compute the *a prior* probability (in exponentiations) of the transmitted symbols in each iteration, leading to a high complexity expense.

In this work, we develop a novel GAI-BP detection by employing a threshold-updating (TU) strategy. The proposed TU-GAI-BP detection relies on the GAI-BP detection with layered-updating scheme. Specifically, we first measure the *a prior* probability of each transmitted symbol by comparing the deviation of the its maximum and second maximum results to a threshold in two consecutive iterations. Then, if the deviations is larger than the threshold, we will fixed the related *a prior* probability and will not update it in the following iterations. In this way, the TU-GAI-BP benefits from circumventing the computation of the “already stable” *a prior* probability, therefore saving the computational complexity and still remaining a good error performance. Simulation results indicate that the proposed TU-GAI-BP saves about 71% computational complexity while achieving a comparable error rate performance in MIMO systems with 16 transmit antennas, 32 receive antennas, and 16-QAM modulation. In addition, we design a hardware architecture for the proposed TU-GAI-BP detector, which exhibits its feasibility of the hardware implementation.

The remainder of this work are organized as follows. Section II presents a comprehensive overview of the massive MIMO channel model and introduces the GAI-BP algorithm.

TU-GAI-BP detection with the layered and threshold strategy is proposed detailly in section III. In section IV, an extensive evaluation is conducted over the error rate performance and computational complexity of the proposed algorithm. Section V presents the hardware architecture of the TU-GAI-BP detector. Finally, section VI concludes the entire paper.

II. Preliminaries

A. System Model

Considering a MIMO system involving N_t transmit antennas and N_r recieve antennas, then the recieve signal $y \in \mathbb{R}^{2N_r}$ (in real domain) is expressed as:

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

where $H \in \mathbb{R}^{2N_r \times 2N_t}$ is the channel matrix with each coefficient following Gaussian distribution with zero mean and unitary variance, and $x \in \mathbb{R}^{2N_t}$ is the transmitted symbol vector with each x_i chosen from the constellation $\sqrt{\mathcal{A}}$. The noise vector $\mathbf{n}$ satisfies $n_i \sim \mathcal{N}(0, \sigma^2)$.

B. GAI-BP Detection

Due to its good error performance, high hardware feasibility, and strong algorithmic robustness, GAI-BP becomes an attractive solution for large-scale MIMO detection.

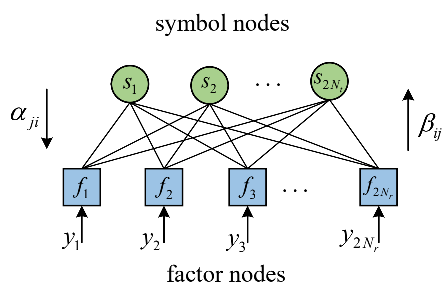

Fig. 1. The factor graph for a mimo system.

The GAI-BP detection relies on the factor graph (FG) model for a MIMO system, shown as Fig. 1. The factor graph (FG) comprises two node types: factor nodes (FN) and symbol nodes (SN). For the i-th FN, its corresponding received signal y_i is expressed as

$$y_i = h_{i,j}x_j + \sum_{k=1,k\neq i}^{2N_t} h_{i,k}x_k + n_i = h_{i,j}x_j + z_{i,j} + n_i, \tag{2}$$

where $z_{i,j}$ denotes the multiple-user interference (MUI). This MUI is approximated by the *Gaussian* distribution $\mathcal{N}(\mu_{z_{i,j}}, \sigma^2_{z_{i,j}})$ in the GAI-BP detection. In particular, the mean together with the variance are computed as

$$\begin{cases} \mu_{z_{i,j}} = \sum_{k=1,k\neq i}^{2N_t} h_{i,k} E\{x_k\} & (3) \\ \sigma^2_{z_{i,j}} = \sum_{k=1,k\neq i}^{2N_t} h^2_{i,k} \operatorname{Var}\{x_k\} + \sigma_i^2 & (4) \end{cases}$$

To update the E_{x_k} in each iteration, the *a prior* probability for each lattice point is computed as

$$p_{j,i}(x_j = u_k) \approx \exp\left(\alpha_{j,i}(k) - \max_m (\alpha_{j,i}(m))\right) \tag{5}$$

With the *Gaussian* approximation of interference derived above, the soft messages sent from the i-th FN to j-th SN is illustrated as

$$\beta_{i,j}(k) = \frac{(\phi_{i,j} - h_{i,j}u_1)^2}{2\sigma_{z_{i,j}}} - \frac{(\phi_{i,j} - h_{i,j}u_k)^2}{2\sigma_{z_{i,j}}}, \tag{6}$$

where u_k denotes the k-th lattice point in the real-domain constellation, and $\phi_{i,j} = y_j - \mu_{z_{j,i}}$. The soft message sent from j-th SN to i-th FN (denoted as $\alpha_{j,i}$) is updated as

$$\alpha_{j,i}(k) = \sum_{t=1,t\neq i}^{2N_r} \beta_{t,i}(k) \tag{7}$$

In this paper, the symbol log-likelihood ratio (LLR) is employed as the soft messages. For instance, $\alpha_{j,i}$ is defined as

$$\alpha_{j,i}(k) = \ln \frac{p(x_i = u_k)}{p(x_i = u_1)} \tag{8}$$

After achieving the maximum number of iterations (denoted as Q_L), the GAI-BP computes the output soft message for the j-th symbol as

$$\gamma_j(k) = \sum_{t=1}^{2N_r} \beta_{t,j}(k). \tag{9}$$

III. Proposed TU-GAI-BP Detection

Despite its advances in error performance, the GAI-BP suffers from relatively high computational complexity, since it requires too many iterations to converge. To relieve this concern, we proposed an improved GAI-BP detection with threshold updating (TU), which is called TU-GAI-BP in this paper. Specifically, we first utilize the layered strategy to make the GAI-BP converge fast. Then, we employ threshold updating to deactivate message updating procedures of the target SN, thus reducing the computational complexity.

A. Layered GAI-BP Detection

Layered updating is a classical strategy to bring down the complexity of the BP algorithm based on a graphical model. For instance, the layered BP decoding algorithm has been successfully applied in the 5G NR standard [9]. Likewise, the layered strategy can be employed in the GAI-BP. Fig. 2 depicts the step-by-step process of layered updating in the GAI-BP detection. It is observed that the i-th FN first updates the corresponding β messages regarding Eq. (5). Then, all of the SNs immediately compute the associated α messages as Eq. (7), with the incoming β messages. This layered updating operation is serially performed for each FN until the stopping condition is achieved. In this way, the useful soft information is exchanged between the FNs and SNs more sufficiently, hence accelerating the convergence speed of the GAI-BP.

However, the layered strategy in GAI-BP still suffers from relatively high computational costs. As Eq. (5) shows, layered

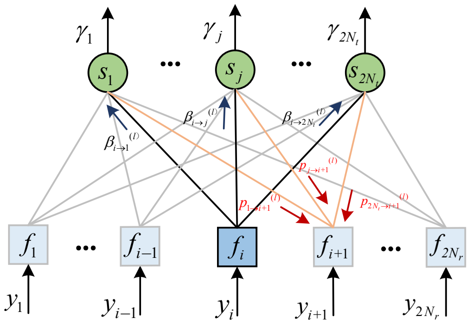

Fig. 2. The layered update progress for factor nodes and symbol nodes.

updating requires associated SNs nodes to update their output messages, leading to a substantial amount of exponential computations and consequently suffering from high computational complexity.

B. Threshold-updating Strategy

Although the layered strategy alleviates the complexity of the GAI-BP by improving its convergence speed, the GAI-BP still suffers from high computational complexity due to the exponentiation operation in Eq. (5), particularly in the high-order high-dimensional MIMO systems. In order to further reduce the complexity of this part, we propose a threshold-updating strategy in this subsection.

The basic idea of the threshold-updating strategy is that after several rounds of iterations, the *a prior* information with respect to some SNs tends to remain stable, therefore we can fix the related SNs and circumvent the message updating of these SNs to save the computational complexity. The target SNs can be found by setting a threshold, which is used to measure the distance between the maximum and the second maximum output *a prior* probability in two consecutive iterations. More specifically, denote $p_j^{(l)}(\mu_{M_1})$ and $p_j^{(l)}(\mu_{M_2})$ as the maximum and second maxim *a prior* probability of the j-th transmitted symbol in the l-th iteration, respectively. Then, the target SNs are found by performing a threshold judgment as

$$\begin{cases} p_j^{(l)}(\mu_{M_1}) - p_j^{(l)}(\mu_{M_2}) > \eta, \\ p_j^{(l-1)}(\mu_{M_1}) - p_j^{(l-1)}(\mu_{M_2}) > \eta, \end{cases} \tag{10}$$

where η is the threshold used to decide whether the results of the related SNs are converged. With the aforementioned derivations, if the *a prior* probability of the j-th transmitted symbol satisfies (10), it will be set as $p_j^{(l)}(\mu_{M_1}) = 1$, and $p_j^{(l)}(\mu_k) = 0$, where $k \in \left[1, \sqrt{|\mathcal{A}|}\right]$, $k \neq M_1$. In the following iterations, the *a prior* probability of the target SNs will not be updated until the detection is terminated. With this threshold-updating strategy, the computational complexity with respect to the updating of *a prior* probability is reduced, and the error performance loss is acceptable.

IV. Numerical Results

A. Error Rate Performance

Fig. 3 demonstartes the BER performance of the proposed TU-GAI-BP algorithm in 32×16 MIMO scenario over the Rayleigh channel with 16-QAM modulation. Considering the varying convergence speed of each detector, in order to achieve comparable performance, the number of iterations is set as $Q_L = 20$ for the GAI-BP, $Q_L = 10$ for the Layered GAI-BP, and $Q_L = 6$ for the TU-GAI-BP. It is observed that when compared to the SOA GAI-BP, the TU-GAI-BP detector just suffers a marginal performance degradation of 0.2 dB at BER of 10^{-3}. Besides, the proposed TU-GAI-BP achieves comparable performance with the Layered GAI-BP, which denotes that the threshold strategy has negligible impact on error performance while significantly bringing down the computational complexity.

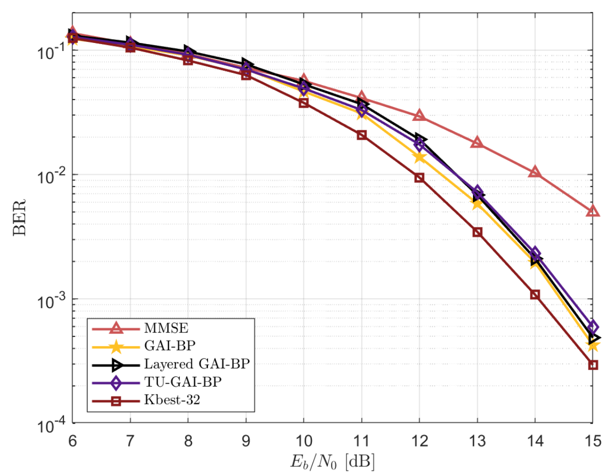

Fig. 3. Bit error rate (BER) performance of the proposed TU-GAI-BP detector in 32×16, 16-QAM uplink MIMO scenario.

B. Computational Complexity

For convenience, the computational complexity is measured by means of the multiplications per channel use. We suppose each addition holds half the complexity of multiplication and the exponentiation has twice the complexity of multiplication. The complexity is denoted with big $\mathcal{O}$ representation. The GAI-BP involves $\mathcal{O}\left(4Q_L N_r N_t \sqrt{|\mathcal{A}|}\right) + \mathcal{O}\left(4KN_t^2\right)$ multiplication, $\mathcal{O}\left(4Q_L N_r N_t \sqrt{|\mathcal{A}|}\right) + \mathcal{O}\left(4KN_t^2\right)$ addition, and $\mathcal{O}\left(4Q_L N_r N_t \sqrt{|\mathcal{A}|}\right)$ exponential operations, where Q_L is the maximum number of iterations, and K is the order of the wNSA employed to acquire initial information. The Layered GAI-BP converges faster than GAI-BP, thereby reducing the number of iterations and overall complexity while maintaining comparable performance. In addition, the proposed threshold strategy reduces the complexity with respect to the computation of *a prior* probability, further achieving computational reduction corresponding to the message updating as Eq. (5) and Eq. (7).

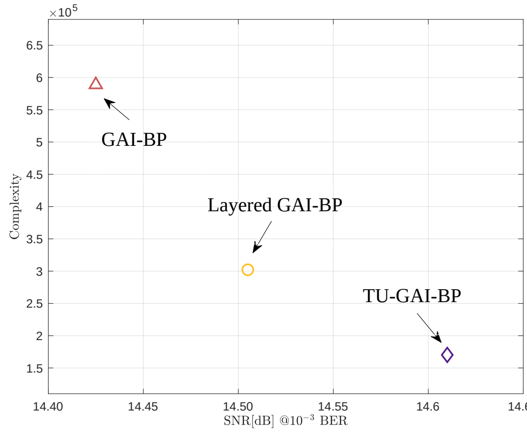

Fig. 4. The complexity comparison between GAI-BP, Layered GAI-BP and TU-GAI-BP.

Fig. 4 illustrates the complexity comparison of the aforementioned detectors in the 32×16 MIMO system with 16-QAM modulation. The related parameters are set the same as that in Fig. 3, and the other related K is 10. Comparison results exhibit that in comparison to the SOA GAI-BP, the proposed TU-GAI-BP saves about 71% computational complexity but suffers from 0.2 dB SNR loss at the target BER of 10^{-3}.

V. Hardware Architecture

The hardware architecture of the TU-GAI-BP detector is depicted in Fig. 5, where the received signal $\mathbf{y_i}$ serves as the input data for the detector. During each iteration, the FN updating module processes the posterior information β_{ij}, subsequently sent to the SN updating module for the computation of α_{ji} messages. The third module consists of probability calculation and threshold judgement, accelerating the convergence of information α_{ji}. These messages are utilized later in the next symbol node. Upon reaching the maximum number of iterations Q_L, the detector output the calculated soft message γ in the second module.

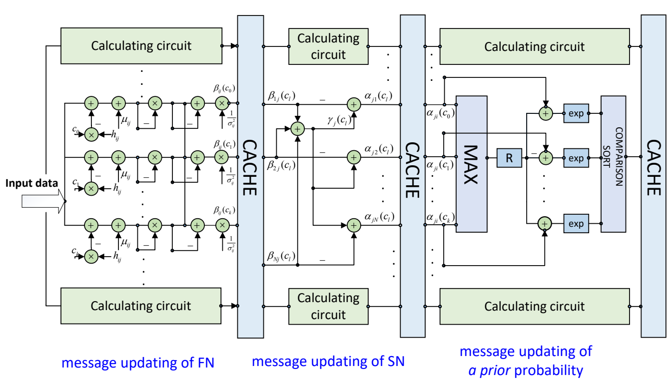

Fig. 5. The hardware aichtecture of the TU-GAI-BP detector.

VI. Conclusions

We develop a novel detection algorithm which is called TU-GAI-BP in this work. By employing a threshold to select the "already stable" *a prior* probability for the transmitted symbols after several iterations, the TU-GAI-BP detector can circumvent the message updating associated with the target transmitted symbols in the following iterations, thus saving its computational complexity. We also provide the numerical results together with the hardware architecture design of the proposed TU-GAI-BP detection. In comparison to the SOA GAI-BP detector, the proposed TU-GAI-BP exhibits its advances in computational complexity without sacrificing error performance. Future work will be directed toward optimizing threshold selection and exploring the integration of layered processing with other BP detection techniques.

VII. Acknowledgement

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