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Low-Complexity Iterative Detection Algorithm for Massive Data Communication in IIoT

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ABSTRACT As the fundamental problem of Industrial Internet of Things, massive data communication based on non-orthogonal multiple access is attractive. An iterative multiuser receiver provides a substantial performance improvement, but suffers from a distortion that the overestimation of output reliability values for bad channels. Furthermore, the main challenge lies in the high computational complexity. This paper develops an improved iterative multiuser receiver with independent channel information. In order to analyze its performance, JS-divergence is introduced to measure the correlation of exchanged information between the detector and the decoder. Low-complexity iterative detection algorithm based on JS-divergence values is proposed in this paper. The simulation results demonstrate that the proposed iterative multiuser receiver reduces the overestimation of reliability values and improves the system performance when Eb/N0 is less than 3 dB. The low-complexity iterative detection algorithm can terminate in advance when JS-divergence values of all users reach to a threshold and reduce the number of outer-loop iterations and computational complexity greatly.

INDEX TERMS Industrial Internet of Things, massive data communication, iterative multiuser receiver, JS-divergence, low-complexity detection.

I. INTRODUCTION

In the era of Internet of Everything, Industrial Internet of Things (IIOT) has attracted considerable interest over the past years, due to real time, reliability, high-efficiency and cost-effectiveness. The IIOT integrates various sensors, cloud computing, big data and real-time communication technologies into the whole process of industrial production [1]. The sensors are employed to sense, identify, process and analyze data as well as to communicate in the industrial process. They allow industrial devices to be monitored and controlled remotely across existing network infrastructures. Massive data communication among the sensors is a fundamental problem in IIOT, on which extensive studies have been conducted [2]–[5].

Due to stringent bandwidth constraints, traditional orthogonal multiple access schemes cannot satisfy massive data communication. However non-orthogonal multiple access (NOMA) gains more and more attention. It is able to improve spectrum efficiency and allow more users access to networks. Non-orthogonal multiple access schemes mainly include Sparse Code Multiple Access (SCMA) [6], Multi-User Shared Access (MUSA) [7] and Pattern Division Multiple Access (PDMA) [8]. A lot of studies have been represented. Reference [9] shows that SCMA, combining sparse codewords design and Message Passing (MP) decoding algorithm, outperforms MUSA and PDMA at the same overloading factor.

In [10], an iterative multiuser receiver (IMR) is developed for SCMA system, and soft information is exchanged iteratively between the SCMA detector and the channel decoder. Making full use of shaping gains [11], [12] of SCMA and coding gains of the decoder, the performance is greatly improved. However, Papke *et al.* [13] indicate the iterative detection system suffers from a distortion that the output reliability information is too "optimistic" for bad channels. Furthermore, the negative impact of reliability overestimation will be accumulated during the iterations. The scaling factor, which extrinsic information of the SCMA detector is multiplied by, is employed to reduce the overestimation of reliability values in [14]. But the factor cannot be adjusted dynamically according to the extrinsic information, which changes in every iteration and also needs to be restructured in different channels. Clearly, while the iterative multiuser receiver provides a substantial performance improvement, the main challenge lies in the high computational complexity.

Low-complexity detection algorithms for the iterative multiuser receiver have been investigated in a multitude of studies [10], [15]–[18]. In order to reduce the computational complexity, max-log approximation is applied in [10], and the performance degradation caused by the approximation is negligible. Mu *et al.* [15] propose a low-complexity iterative detection algorithm based on partial marginalization (PM). After a fixed number of outer-loop iterations, the PM-MPA randomly selects t users to determine their codewords, and information of the other users continues to be updated with the determined codewords, until the maximum number of iterations. Improved PM-MPA (IPM-MPA) is proposed in [16]. The algorithm chooses t users intentionally on the basis of reliability information of the codewords. It improves the BER performance without increasing the computational burden. As stated in the above algorithms, all receivers will detect and decode under a fixed number of iterations, and just determine codewords of a part of users after a predetermined number of iterations. They reduce the number of users involving in residual iterations and the computational complexity. However, termination condition of iterations before reaching to the maximum is not given in the case that all users have successfully decoded.

In this work, we mainly focus on reducing the overestimation of reliability values to improve the performance of the iterative multiuser receiver in SCMA system. The paper develops an iterative multiuser receiver with independent channel information denoted by L_c, and LDPC is adopted as channel code. The correlation of information exchanged between the detector and the decoder is measured by JS-divergence, and the performance of iterative multiuser receiver is analyzed in theory. Firstly, L_c is the output Log likelihood Ratio (LLR) of SCMA detector in the first iteration. The soft information is delivered to the channel decoder with the extrinsic information from the SCMA detector. Due to L_c, the input LLR of channel decoder has higher correlation with channel information than that of channel decoder without L_c, also the large mutual information (MI) of the former and channel information L_c is conducive to decode. Meanwhile, the MI of the input LLR and extrinsic information LLR of the detector is smaller than that of the input LLR without L_c, and it is equivalent to multiply the extrinsic information by a scaling factor. The effect of the distortion on the performance of the iterative multiuser receiver is reduced, because the overestimation of reliability values is reduced as well. Second, low-complexity iterative detection algorithm based on JS-divergence between input and extrinsic information LLR of LDPC decoder is proposed in this paper. When JS-divergence values reach to a threshold, codewords of the users are determined, so as to reduce the number of users who participate in the remaining iterations. More specifically, the iterative detection algorithm can terminate in advance when JS-divergence values of all users reach to the threshold and reduce the number of outer-loop iterations. It not only provides a promising performance, but also achieves the low computational complexity.

The rest of the paper is organized as follows. Section2 introduces the iterative multiuser receiver model in SCMA system briefly. Then we develop an improved iterative multiuser receiver with channel information in Section 3, and low-complexity iterative detection algorithm based on JS-divergence is proposed. Numerical results are analyzed in Section 4. Finally, we conclude this paper in Section 5.

II. SYSTEM MODEL

SCMA is a non-orthogonal multiple access scheme which combines modulation and spread spectrum. Input bits are mapped to multi-dimensional complex codewords selected from predetermined codebooks, and the codewords of different users are transmitted synchronously through the channel to accomplish resources (e.g. subcarriers) multiplexing. Due to sparsity of codebooks, the SCMA receiver resorts to MP algorithm to achieve multiuser detection under the acceptable implementation complexity.

Given the received signal $\boldsymbol{r}$ and the estimated channel h_j, the codewords are detected using Maximum a posteriori (MAP) rules. It is expressed as

$$\hat{\boldsymbol{x}} = \arg\max P(\boldsymbol{x} \,|\boldsymbol{r}). \tag{1}$$

It can be rewritten as

$$\hat{x}_j = \arg\max_a P(x_j = a \,|\boldsymbol{r}). \tag{2}$$

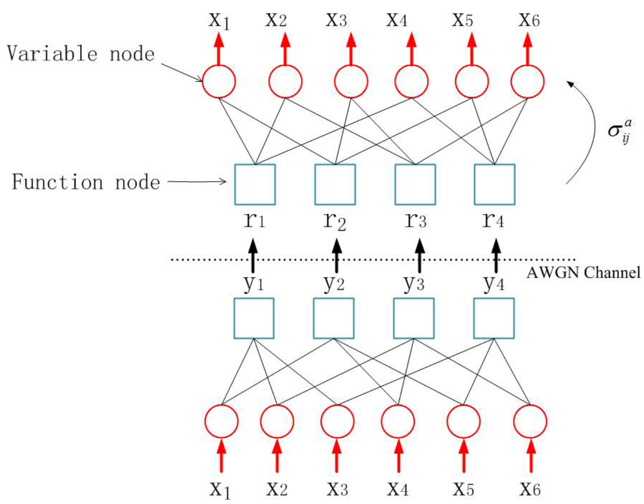

FIGURE 1. Factor graph representation of an SCMA system.

As shown in Fig. 1, the codewords from the predetermined codebooks are transmitted through AWGN channel, and the signals $\boldsymbol{r} = [r_1, \cdots, r_K]^T$ are received. At the receiver, the belief messages are exchanged iteratively between the user nodes and the resource nodes. The message from Function node (FN) to Variable node (VN) is

$$\begin{aligned}\sigma_{ij}^{a} &= \Pr(x_j = a\,|\boldsymbol{r}) \\ &= \sum_{\boldsymbol{x},x_j=a} \exp(-\frac{\|r_k - y_n\|^2}{2\sigma^2}) \cdot \prod_{j'} P(x_l), \end{aligned} \tag{3}$$

where r_k is the received signal on the k-th resource, and $y_n = \sum_{\boldsymbol{x},x_j=a} h_{ij} \cdot x_{ij}$ is the superimposed signal of different $\boldsymbol{x}$ combinations in which $x_j = a$.

The message from Function node VN to FN is

$$P(x_j = a) = P(x_0 = a) \cdot \prod_{i'} \sigma_{ij}^{a}, \tag{4}$$

where $P(x_0 = a)$ is the initial value of $P(x_j = a)$.

According to factor graph, nodes update the information of the codewords with the extrinsic information. After several iterations, the soft information delivered to the decoder converges to a reliable value and the detection is finished.

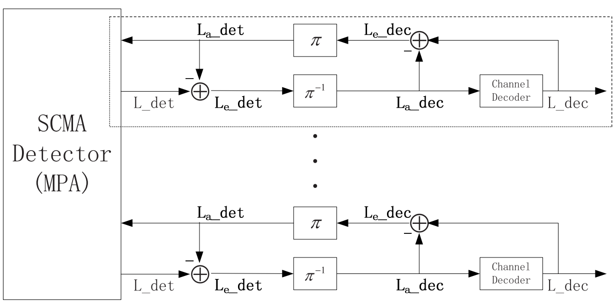

FIGURE 2. Structure of the iterative multiuser receiver for SCMA system.

Iterative multiuser receiver, as depicted in Fig. 2, consists of SCMA detector and J parallel channel decoders. Output of SCMA detector is a posterior probability LLR value of information bit of user j. It can be expressed as

$$L\_det\left(b_j\right) = \ln \frac{P\left(b_j = 0\,|\boldsymbol{r}\right)}{P\left(b_j = 1\,|\boldsymbol{r}\right)}. \tag{5}$$

Using Bayes rules, it is rewritten as

$$\begin{aligned} L\_det\left(b_j\right) &= \ln \frac{P\left(\boldsymbol{r}\,|b_j = 0\right)}{P\left(\boldsymbol{r}\,|b_j = 1\right)} + \ln \frac{P\left(b_j = 0\right)}{P\left(b_j = 1\right)} \\ &= L_e\_det\left(b_j\right) + L_a\_det\left(b_j\right), \end{aligned} \tag{6}$$

where SCMA detector has no LLR value of a priori probability as input in the first iteration, so we define $L_a\_det\left(b_j\right) = 0$.

After deinterleaving, the extrinsic information L_e_det of SCMA detector is delivered to the channel decoder as its initial value L_a_dec. The output LLR of decoder is also described as

$$L\_dec\left(b_j\right) = L_e\_dec\left(b_j\right) + L_a\_dec\left(b_j\right). \tag{7}$$

The extrinsic information L_e_dec is interleaved and delivered to the SCMA detector as its initial value. Like this, one iteration is finished. The output of decoder will not be judged until meeting the termination condition.

Without loss of generality, the output information LLR in iterative decoders can be written as

$$L\left(\hat{b}\right) = L_c\left(x\right) + L_a\left(b\right) + L_e\left(b\right), \tag{8}$$

where $L_c\left(x\right)$ denotes the measure of the channel at the receiver, $L_a\left(b\right)$ is the prior LLR of data bit, and $L_e\left(b\right)$ is the extrinsic information obtained from the decoder. According to formula (6) and (8), it is shown that $L_e\_det\left(b_j\right)$ involves the extrinsic information of SCMA detector, as well as channel information, and the correlation exists among them. Otherwise, because of the overestimated reliability values of $L_e\_det\left(b_j\right)$, it will result in decoding inaccurately. Similarly, the problem of overestimation exists in the output of the decoder. Furthermore, the negative impact will be accumulated during the iterations, resulting in a decline in performance.

III. LOW-COMPLEXITY ITERATIVE DETECTION ALGORITHM

In this section, we develop an improved iterative multiuser receiver in SCMA system. JS-divergence is used to measure the correlation between exchanged information, so as to analyze the reasons for the performance improvement. Low-complexity iterative detection algorithm based on JS-divergence is proposed.

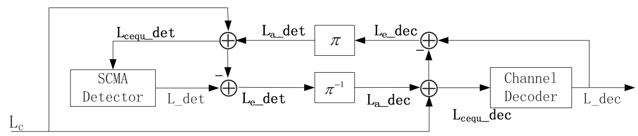

FIGURE 3. Structure of the improved iterative multiuser receiver with channel information L_c.

Inspired by turbo principle, this paper develops an iterative multiuser receiver with soft channel information L_c. As shown in Fig. 3, unlike the traditional iterative multiuser receiver marked with dashed lines in Fig. 2, channel information L_c is delivered into SCMA detector and the channel decoder with the extrinsic information. It is expressed as

$$L_e\_det\left(x_j\right) = \ln \frac{P\left(\boldsymbol{r}\,|x_j = a_0\right)}{P\left(\boldsymbol{r}\,|x_j = a_1\right)}. \tag{9}$$

Formula (3) is inserted into formula (9), and it is written as

$$L_e\_det\left(x_j\right) = \ln \frac{\sum\limits_{\boldsymbol{x},x_j=a_0} \exp(-\frac{\|r_k-y_n\|^2}{2\sigma^2}) \cdot \prod\limits_{j'} P(x_l)}{\sum\limits_{\boldsymbol{x},x_j=a_1} \exp(-\frac{\|r_k-y_n\|^2}{2\sigma^2}) \cdot \prod\limits_{j'} P(x_l)}. \tag{10}$$

In formula (10), $L_e\_det\left(x_j\right)$ contains not only the received signal r_k through AWGN channel, but also the values of $\boldsymbol{x}$ except x_j and their probability. Therefore it is relate to channel information as well as the extrinsic information generated by iterations. Nevertheless, in the first iteration of SCMA detector, $L_a^{(1)}\_det\left(b_j\right) = 0$ and (10) is calculated as

$$L_c\left(x_j\right) = \ln \frac{\prod\limits_{j'} P(x_l) \sum\limits_{\boldsymbol{x}, x_j = a_0} \exp(-\frac{\|r_k - y_n\|^2}{2\sigma^2})}{\prod\limits_{j'} P(x_l) \sum\limits_{\boldsymbol{x}, x_j = a_1} \exp(-\frac{\|r_k - y_n\|^2}{2\sigma^2})} = \ln \frac{\sum\limits_{\boldsymbol{x}, x_j = a_0} \exp(-\frac{\|r_k - y_n\|^2}{2\sigma^2})}{\sum\limits_{\boldsymbol{x}, x_j = a_1} \exp(-\frac{\|r_k - y_n\|^2}{2\sigma^2})}. \quad (11)$$

At this point, $L_c\left(x_j\right)$ is only related to the received signal r_k, rather than the probability values of $\boldsymbol{x} \backslash x_j$, so $L_c\left(x_j\right)$ is considered as the measure of the channel. Next, in order to analyze the effect of channel information L_c on the performance of iterative multiuser receiver, we resort to JS-divergence to measure the correlation between delivered information. The change of each delivered information LLR is observed in the presence of L_c and without L_c. First, we record the related delivered information LLRs. Then, we run Monte-Carlo simulation method to get the distribution of LLR, and the relevant JS-divergence values are also obtained on each iteration. Therefore, the correlation of delivered information can be analyzed.

According to (10), it is observed that $L_e\_det\left(x_j\right)$ contains the received signal r_k through AWGN channel, and the values of $\boldsymbol{x}$ except x_j and their probability. Hence, $L_e\_det\left(x_j\right)$ is related with L_c and L_e. It can be defined as

$$I\left(X; L_e\_det\right) = I\left(L_c; L_e\_det\right) + I\left(L_e; L_e\_det\right), \quad (12)$$

where the mutual information $I\left(X; L_e\_det\right)$ denotes the amount of data bit information X in L_e_det. The amount of information is generated by L_c and L_e, where L_e is the measure of extrinsic information. The mutual information $I\left(L_c; L_e\_det\right)$ and $I\left(L_e; L_e\_det\right)$ denote the amount of information L_c and L_e in L_e_det respectively. Similarly in the proposed iterative multiuser receiver, it is formulated as

$$\begin{aligned} I\left(X; L_{cequ}\_dec\right) &= I\left(L_c; L_{cequ}\_dec\right) \\ &\quad + I\left(L_e; L_{cequ}\_dec\right), \end{aligned} \quad (13)$$

where $L_{cequ}\_dec\left(x_j\right) = L_a\_dec\left(x_j\right) + L_c\left(x_j\right)$ is the input LLR of the decoder, and $L_a\_dec\left(x_j\right) = L_e\_det\left(x_j\right)$.

The difference between $I\left(L_c; L_{cequ}\_dec\right)$ and $I\left(L_c; L_e\_det\right)$ is expressed as

$$\begin{aligned} \Delta I_c &= I\left(L_c; L_{cequ}\_dec\right) - I\left(L_c; L_e\_det\right) \\ &= \left(H\left(L_c\right) - H\left(L_c | L_{cequ}\_dec\right)\right) \\ &\quad - \left(H\left(L_c\right) - H\left(L_c | L_e\_det\right)\right) \\ &= H\left(L_c | L_e\_det\right) - H\left(L_c | L_{cequ}\_dec\right). \end{aligned} \quad (14)$$

In order to measure the correlation between delivered information, Kullback-Leibler divergence is employed to calculate the difference between probability distributions. It is defined as

$$D\left(L_c \| L_e\_det\right) = \sum P\left(L_c\right) \cdot \log \frac{P\left(L_c\right)}{Q\left(L_e\_det\right)}. \quad (15)$$

However, there are two problems with KL divergence: (1) it is not symmetric, i.e., $D\left(P||Q\right) \neq D\left(Q||P\right)$; (2) the results are not finite, so that they cannot be compared. For example, there are three distributions, P, Q, R. If $D\left(P||Q\right) > D\left(R||Q\right)$, it will not mean that distribution P is closer to Q than R. Therefore, improved Jensen-Shannon divergence is adopted. It is defined as

$$JS(P||Q) = \frac{1}{2}D(P||M) + \frac{1}{2}D(Q||M), \quad (16)$$

where $M = \frac{P+Q}{2}$. The results are symmetric and the calculation of distance is a value between 0 and 1. It is easy to find out the similarity of two probability distributions. Therefore, the correlation of delivered information can be analyzed. The larger the JS-divergence value is, the greater the distance between the two probability distributions is. That means the correlation between two information variables is smaller, and vice versa.

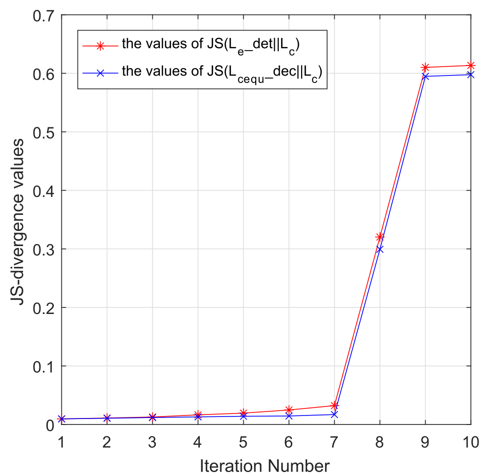

FIGURE 4. **Comparison the values of $JS\left(L_{cequ}\_dec \| L_c\right)$ and $JS\left(L_e\_det \| L_c\right)$ at different iteration number.**

In Fig. 4, it is shown that the value of $JS\left(L_e\_det \| L_c\right)$ is larger than that of $JS\left(L_{cequ}\_dec \| L_c\right)$. Therefore L_{cequ}_dec is correlated with L_c more highly than L_e_det, and the uncertainty $H\left(L_c | L_{cequ}\_dec\right)$ is less. As a result, $\Delta I_c > 0$, and $I\left(L_c; L_{cequ}\_dec\right) > I\left(L_c; L_e\_det\right)$. It reveals that the amount of channel information in L_{cequ}_dec is greater than that in L_e_det. In Fig. 5, the Extrinsic Information Transfer (EXIT) chart plotted in Monte-Carlo simulation method indicates the amount of mutual information $I\left(X; L_{cequ}\_dec\right)$ with L_c is smaller than that of $I\left(X; L_e\_det\right)$ without L_c .

According to formula (12) and (13), it is seen that the value of $I\left(L_e; L_{cequ}\_dec\right)$ is smaller than that of $I\left(L_e; L_e\_det\right)$, and the amount of extrinsic information in L_{cequ}_dec is small as well. That is equivalent to multiply $I\left(L_e; L_e\_det\right)$ by a scaling factor. It is expressed as

$$I\left(L_e; L_{cequ}\_dec\right) = \alpha \cdot I\left(L_e; L_e\_det\right), \quad (17)$$

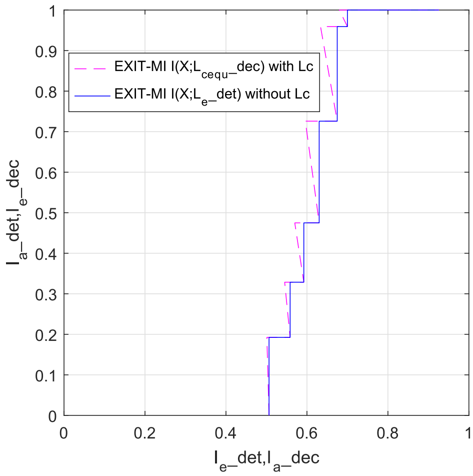

FIGURE 5. EXIT chart analysis of an SCMA system over AWGN channel with Eb/N0 = 1.7dB. Users adpot the LDPC code with code rate = 1/2.

where $0 < \alpha < 1$. The overestimation of reliability values is reduced, meanwhile the large $I\left(L_c; L_{cequ}\_dec\right)$ values are conducive to decode as well. These are the reasons that the iterative multiuser receiver with L_c improves the performance.

Similarly, due to BP iterative decoding, the extrinsic information L_e_dec of channel decoder is correlated with the input L_{cequ}_dec. The difference between the amount of channel information in L_{cequ}_dec on i-th and (i+1)-th iteration is expressed as

$$\begin{aligned}\Delta I'_c &= I\left(L_c; L_{cequ}^{(i+1)}\_dec\right) - I\left(L_c; L_{cequ}^{(i)}\_dec\right) \\ &= H\left(L_c | L_{cequ}^{(i)}\_dec\right) - H\left(L_c | L_{cequ}^{(i+1)}\_dec\right). \quad (18)\end{aligned}$$

In Fig. 4, it is shown that, as the number of iterations increases, the value of $JS\left(L_{cequ}\_dec \,\|L_c\right)$ gets larger, and $L_{cequ}^{(i+1)}\_dec$ is less correlated with L_c than $L_{cequ}^{(i)}\_dec$. So the uncertainty $H\left(L_c | L_{cequ}^{(i+1)}\_dec\right)$ is smaller than $H\left(L_c | L_{cequ}^{(i)}\_dec\right)$. As a result, $\Delta I'_c < 0$. The amount of channel information in L_{cequ}_dec becomes smaller in every iteration. Fig. 5 illustrates that the value of $I\left(X; L_{cequ}^{(i+1)}\_dec\right)$ is larger than that of $I\left(X; L_{cequ}^{(i)}\_dec\right)$. Therefore, according to (13), it is observed that, as iterations going on, $I\left(L_e; L_{cequ}\_dec\right)$ becomes larger, and more extrinsic information inputs LDPC decoder. When the amount of extrinsic information is large enough to decode correctly, the iterative detection algorithm terminates and the iterative multiuser detection is achieved.

As stated previous, this paper proposes a low-complexity iterative detection algorithm based on JS-divergence. In the algorithm, step 1 is the initialization, and it is the iterative process from step 2 to step 4. The specific algorithm steps are described as follow,

Step 1, initialize $P\left(x_j\right) = \frac{1}{M}$ of each user, and calculate $L_c\left(x_j\right)$ according to (11);

Step 2, exchange information between SCMA detector and the channel decoder to update $P\left(x_j\right)$ iteratively;

Step 3, choose the user whose $JS\left(L_{cequ}\_dec \,\|L_e\_dec\right)$ value reaches to α^* and determine its $P\left(\hat{x}_j\right)$ and the corresponding $\hat{x}_j$;

Step 4, insert $P\left(\hat{x}_j\right)$ into $P\left(x_j\right)$, and repeat Step 2 and Step 3 until $JS\left(L_{cequ}\_dec \,\|L_e\_dec\right)$ values of all users reach to α^*, or the number of iterations reaches to maximum.

During the iterations, if $\Delta JS\left(L_{cequ}\_dec \,\|L_e\_dec\right) \neq 0$, it demonstrates the extrinsic information is still generated. The iterations terminate when $\Delta JS\left(L_{cequ}\_dec \,\|L_e\_dec\right) = 0$ that shows there is no extrinsic information.

The whole iterative detection procedures are summarized in Algorithm 1.

Algorithm 1 Low-Complexity Iterative Detection Algorithm Based on JS-divergence

Input: $\boldsymbol{r}$
Output: $P(x_j)$
Initialize: $\boldsymbol{x}$, $P_0\left(x_j\right) = \frac{1}{M}$, $\alpha^* = 0.5$, calculate L_c;
repeat
a. calculate σ_{ij}^a, according to formula (3);
b. utilize σ_{ij}^a to update $P(x_j = a)$ as input of channel decoder;
c. calculate L_{cequ}_dec and decode;
d. **If** the $\Delta JS\left(L_{cequ}\_dec \,\|L_e\_dec\right) > \alpha^*$, output $P\left(x_j\right)$ and the corresponding x_j.
else the iterations continue;
until $JS\left(L_{cequ}\_dec \,\|L_e\_dec\right)$ *values of all users reach to* α^*, *or* $\Delta JS\left(L_{cequ}\_dec \,\|L_e\_dec\right) \neq 0$;

IV. SIMULATION RESULTS

In this section, numerical simulations are conducted to illustrate the performance of the proposed iterative detection algorithm. In the simulations, the codebooks are predetermined and LDPC are chosen as the channel code. We assume code rate = 1/2 and length N = 1000. The factor graph matrix corresponding to Fig. 1 is

$$F = \begin{bmatrix} 1 & 1 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 1 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 & 1 & 1 \end{bmatrix}.$$

Six layers transmit on four resources, and overloading factor is defined as $\lambda = \frac{J}{K} = \frac{6}{4} = 150\%$.

Fig. 6 compares the performance of different iterative detection algorithms, including the proposed Iterative Detection Algorithm with L_c (IDAC), SF-IMR algorithm [14], Standard IMR without L_c [10] and IPM-MPA [16]. The simulation results demonstrate IDAC outperforms others by 0.75dB at most when Eb/N0 is less than 3dB, because the IDAC not only reduces the overestimation reliability values of extrinsic information as SF-IMR does, but also the large

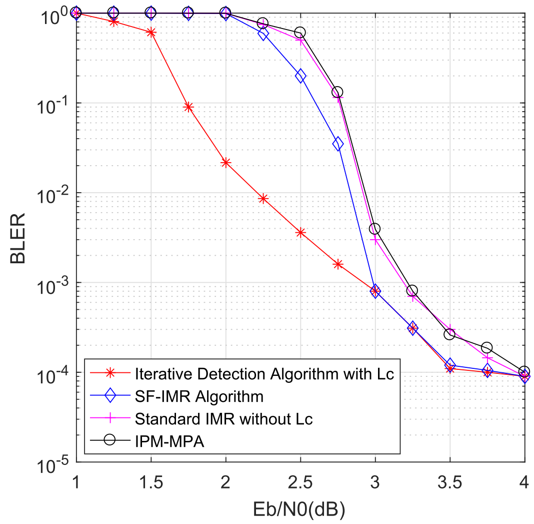

FIGURE 6. **Comparison the BLER performance of four iterative detection algorithms, including the proposed Iterative Detection Algorithm with L_c, SF-IMR algorithm, Standard IMR without L_c and IPM-MPA at different Eb/N0.**

amount of channel information in $I\left(L_c; L_{cequ}\_dec\right)$ is conducive to decode. As Eb/N0 increases, the advantage becomes less obvious. When Eb/N0 reaches to 3dB, the two curves coincide and converge to the same error floor at 3.5dB. Moreover the two algorithms behave better than the other two until Eb/N0 reaches to 4dB. The performance of IPM-MPA is close to that of Standard IMR without L_c, but its computational complexity is low.

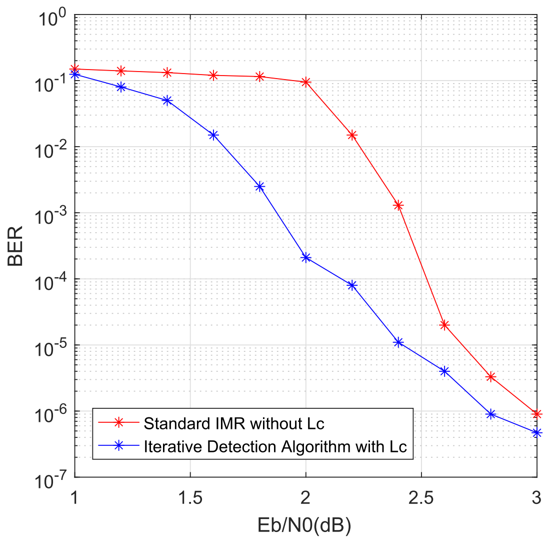

FIGURE 7. **Comparison the BER performance between the iterative detection algorithms with Lc and without Lc at different Eb/N0.**

The performance of bit error ratio (BER) is depicted in Fig. 7. The IDAC outperforms Standard IMR without L_c by 0.5dB at most. And the curves of Fig. 6 and Fig. 7 are in accordance with the trend. That is the gap which gets smaller at first, and then larger when Eb/N0 reaches to a certain value.

We assume the maximum iteration number $N_{\max}$ is 10. In Fig. 8, it is observed that the number of outer-loop

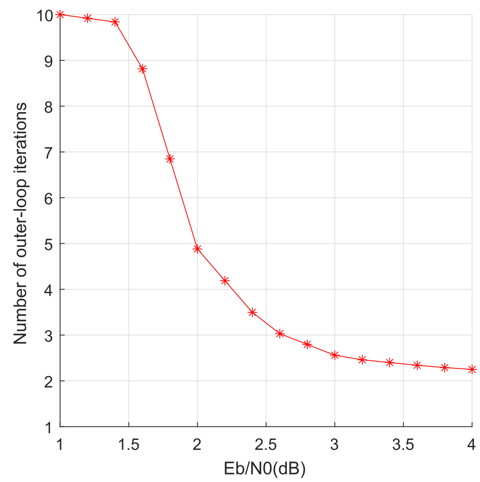

FIGURE 8. **Number of outer-loop iterations is required to complete the multiuser detection in IDAC at different Eb/N0.**

iterations is approximately 10 at the low Eb/N0 region. Then the iteration number, achieving detecting and decoding, decreases rapidly as the waterfall region does, and tends to converge to 2.2 at about 3dB. The trend is in accordance with the trajectory of the corresponding curve in Fig. 6 as well. More importantly, the number of outer-loop iterations is greatly reduced for employing the iteration termination condition based on JS-divergence values. However, IPM-MPA only reduces the number of users who participate in the remaining inner-loop iterations, and the number of outer-loop iterations is still the maximum iteration number $N_{\max}$. Therefore IDAC reduces the computational complexity of iterative multiuser receiver highly.

V. CONCLUSION

In this paper, we develop the iterative multiuser receiver with L_c in SCMA system. It reduces the overestimated reliability values of extrinsic information as SF-IMR does, while the large amount of mutual information between channel information and the input information of the decoder is conducive to decode. In order to analyze the performance of the proposed iterative multiuser receiver, JS-divergence is introduced to measure the correlation of exchanged information between the detector and the decoder. Low-complexity iterative detection algorithm based on JS-divergence is proposed. It provides a promising performance with the low computational complexity. The simulation results demonstrate IDAC outperforms others by 0.75dB at most at low Eb/N0 region. Furthermore, because of the termination condition based on JS-divergence values, the number of outer-loop iterations is greatly reduced, and it tends to converge to 2.2 at about 3dB. Therefore IDAC reduces the computational complexity of iterative multiuser receiver.

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