

Joint User Identification, Channel Estimation and Data Detection for Grant-Free NOMA in LEO Satellite Communications

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Abstract— Satellite Internet of things (S-IoT) aims to provide globally covered network services. In this paper, we conceive an uplink grant-free random access scheme for S-IoT network, where ground devices transmit data packets to the low Earth orbit (LEO) satellite, reducing signaling cost and making efficient use of spectrum resources by employing the non-orthogonal multiple access scheme. The impact of high operational speed of the LEO satellite is also taken into account. We further propose an iterative Gaussian approximated message passing-aided sparse Bayesian learning (GAMP-SBL) algorithm to address the joint channel estimation (CE), active user identification (UID) and data detection (DD) problem, where the three steps interacts with each other during the iterative process. Simulation results have demonstrated that our proposed joint receiver design outperforms the existing AMP-based schemes in terms of bit error rate (BER), convergence speed, as well as false alarm rate (FAR).

Index Terms—Grant-free non-orthogonal multi access (GF-NOMA), low Earth orbit (LEO) satellite communications, message passing, sparse Bayesian learning (SBL).

I. INTRODUCTION

A. Background

The Internet of things (IoT) are revolutionizing social and economic industries, such as manufacturing, agriculture, transportation, medicine [1–3]. IoT is expected to provide high transmission rate and massive connection services due to its wide deployment of terminals, low duty cycle, and low power consumption [4]. Existing cellular communication networks deployed in densely populated areas are efficient for communications tasks in urban and regular workplaces [5]. However, based on the advancement of the Internet-of-everything (IoE), IoT terminals will be distributed in a

variety of application scenarios. A significant fraction of IoT terminals, for instance, may locate in remote areas that the traditional terrestrial cellular network cannot cover [6]. To address the remote coverage problem, the satellite IoT (S-IoT) is proposed to provide communication services for remote areas as a complement and extension of the terrestrial IoT [7, 8]. In fact, several companies and organizations, e.g., Starlink, OneWeb, and Kuiper, have launched a number of test LEO satellites to provide globally connected services [9]. The shorter orbit height, lower transmission delay, and lower path loss [10] of LEO satellite enables direct ground-space communications. A wider coverage area of a LEO satellite also brings challenges in multiple access design [11]. A massive number of users are supported by a single LEO satellite, resulting in resource insufficiency [12] in both the frequency and the time domain if orthogonal multiple access (OMA) is adopted. Fortunately, non-orthogonal multiple access (NOMA) allows multiple user signals to superimpose on the same time/frequency resource [13], and is recognized as a key technology of the next generation wireless network [14–18]. Due to the excellent spectrum efficiency of NOMA, it has been widely applied in LEO satellite communications to support massive connectivity [19–23].

However, in the satellite networks, the long distance between satellite and ground leads to extremely high round-trip signal propagation delay [24]. Traditional grant-based protocols need a request-grant procedure to achieve uplink access, which usually encounter complex control signaling exchange and high access latency [25]. The long distance between the LEO satellite and users will further exacerbate the transmission delay. Additionally, in the IoT scenarios, user devices are active in a sporadic manner, which means that only a small fraction of them require network access at a time [26]. In order to reduce the transmission latency and achieve efficient massive random access, grant-free random access (GF-RA) has emerged as a promising candidate [24–27]. In GF-RA, active devices send data and pilot sequences directly to the satellite receiver without the handshaking procedure [28]. In recent years, the GF non-orthogonal multi access (GF-NOMA) has been proposed [12, 26, 28], in which multiple devices share the limited spectrum resources in a non-orthogonal way. In this work, we consider the application of GF-NOMA in LEO satellite communications and propose a novel receiver design at the LEO satellite.

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B. Related Work

In response to the influx of IoT devices, combining different IoT technologies, such as narrow-band IoT (NB-IoT) and massive machine type communications (mMTC), with non-terrestrial networks (NTN) has become a research hotspot [29, 30]. In [31], a grant-free multiple access based on orthogonal time-frequency space (OTFS) system has been proposed for the realization of smart railways mMTC over LEO satellites. In order to reduce the impact of propagation delay between terrestrial equipment and LEO satellites, a grant-free age-optimal (GFAO) random access protocol was proposed in [32] to guarantee the information freshness in mMTC. LoRA is one of the most extensively researched protocols in the satellite scenario to establish long-distance communication [33]. In order to avoid the mutual interference of different LoRA users in the same time-frequency resource, Zhang *et al.* proposed an orthogonal multiple access method in [34] by taking advantage of LoRA's confidentiality in the fractional domain. In [35], a method for parallel demodulation of multiple concurrent intra-spreading factor transmissions has been presented, and the receiver has been enhanced to reduce the multiple access interference in LoRA via satellite. To improve scalability in the case of user overload in the range of satellite services, a novel Aloha variant was proposed in [36]. [33] showed an in-depth study on the influence of Doppler effect on the reliability of LoRA satellite link.

Different from the traditional grant-based protocols, GF-RA scheme faces an important challenge: active user identification (UID) and data detection (DD). So far, research works on receiver design for GF-NOMA can be divided into two categories: *joint UID and DD with perfect channel state information (CSI)*; and *joint UID, CE and DD without CSI*.

1) *Joint UID and DD with perfect CSI*: When CSI is available at the receiver, compressed sensing (CS)-based algorithms are developed for extracting non-zero elements from the received signal vector. Specifically, by converting the multiple measurement vector problem into several single measurement vector (SMV) problem, Yuan *et al.* developed a parallel adaptive subspace pursuit algorithm for multiuser detection and presented a proper information exchange strategy [37]. In [38], the multiuser detection (MUD) is transformed into several least absolute shrinkage and selection operator problems, which struck a good trade-off between complexity and detection performance. Additionally, the sparse Bayesian learning (SBL) architecture [39] was used in [40, 41] to address the MUD problem in GF-NOMA. To solve the MUD problem for single and multiple time slots, a pair of SBL-based algorithms have been proposed in [40]. To further reduce the high computational complexity of SBL, Zhang *et al.* has embed approximate message passing (AMP) structure to SBL [41].

2) *Joint UID, CE and DD without CSI*: Considering a more practical scenario, where CSI is normally unavailable at the receiver, many researchers proposed approaches to achieve UID, CE and further DD at the receiver. Specifically, by exploiting the characteristic of quasi-time-invariant channel tap delays as the prior information, [42] developed a CS-aided UID and CE algorithm, which achieved lower complexity

and higher accuracy than orthogonal matching pursuit (OMP). Similarly, the SBL method can be also used to address the joint UID and CE problem [25, 43]. [25] has formulated the joint UID and CE as a block sparse signal recovery problem by utilizing the low density signature (LDS) structure and investigated a message passing based block SBL algorithm. [43] has replaced the matrix inversion operation with a relaxed evidence lower bound to reduce the complexity of SBL. Since joint CE and signal detection involve continuous and discrete variables, Wei *et al.* approximated the intractable distributions to Gaussian distributions by expectation propagation, and a message passing receiver was proposed to solve the joint UID, CE and DD problem [12]. Through the addition of suitable auxiliary variables, [44] has divided the entire detection process into two parts: slot-wise MUD and joint CE and DD, which were solved by different message passing methods.

3) *GF-RA in LEO satellite scenario*: [27] has proposed an iterative Bernoulli-Rician message passing with expectation-maximization (BR-MP-EM) algorithm, where the inner iterations pass messages and the outer iterations update the hyperparameters, to address the joint UID and CE problem for the GF-RA scheme in S-IoT. Mapping the data with a predetermined and unique codebook, Guo *et al.* designed a structure of GF-RA in S-IoT and conceived the corresponding detector [45]. The authors in [46] proposed a novel framework for GF-RA S-IoT and converted signals to a tensor decomposition form. Utilizing the tensor structure of signals, [46] designed a low-complexity detector for its system. Applying GF-RA in orthogonal frequency division multiplexing (OFDM), Zuo *et al.* designed a grid-based parametric system [47]. Adopting the OFDM repetition method to identify the Doppler components, a modified variance state propagation (MVSP) algorithm was developed to address the joint UID and CE problem. Zhou *et al.* employed OTFS and proposed a GF-NOMA-OTFS paradigm in S-IoT [24]. Utilizing the time-domain training sequences to assist modulation and demodulation, a two-stage detector for successive UID, CE and DD was developed. Furthermore, Shen *et al.* exploited the input-output relationship of multiple-input multiple-output (MIMO)-OTFS system with a high latency and a high Doppler offset in LEO satellite communication networks [48]. Besides, a SBL-aided two-dimensional convolution detector for joint UID and CE was proposed in [48].

C. Contributions

The works of joint UID and DD mentioned above is based on the premise that the channel state information (CSI) is known at the receiver. However, the CSI in satellite-ground communications varies over time [25], and hence it is necessary to estimate the channel frequently before DD due to the high operational speed of the LEO satellite. Motivated by this, we focus on designing a novel strategy for addressing joint UID, CE and DD in uplink grant-free NOMA network. Besides, we adopt a code-domain NOMA scheme, LDS-OFDM, which may also be extended to other schemes, e.g., sparse code multiple access (SCMA) [25]. The contributions of this paper are summarized as follows:

- Due to the sporadic activity of the S-IoT, we conceive an uplink grant-free NOMA system for S-IoT, where ground devices transmit data packets directly to the satellite without the grant establishment process, reducing the signaling cost and making efficient use of spectrum resources with the sparse structure of LDS. The receiver identifies the active users via the received pilots, and performs the channel estimation and data detection jointly.
- Modeling the joint active UID and CE problem as a SMV problem, we propose a novel Gaussian approximated message passing (GAMP)-SBL algorithm, which ensures the false alarm rate (FAR), while attaining lower complexity, compared with the existing joint UID and CE algorithms, such as EM-based SBL and BR-MP-EM [27]. The GAMP algorithm approximates the posterior distribution of unknown channel as Gaussian-distributed, and transmits the mean and variance via the factor graph. The SBL architecture leverages the channel sparsity, and obtains the posterior information of channel from a Gaussian likelihood model.
- Considering the high velocity of the LEO satellite, we employ the time-varying channel model to account for Doppler frequency offsets, characterizing the time correlations. In order to improve the channel estimation accuracy in this high-speed scenario, we propose a joint CE, UID and DD scheme, where the highly reliable recovered data in the current time slot will be utilized later for channel estimation in the next slot, further enhancing the channel estimation performance.
- To further improve the system performance, we propose an iterative GAMP-SBL receiver structure to jointly perform the CE, UID and DD. Specifically, we first formulate a factor graph of our grant-free LDS-OFDM system to characterize the message passing process in UID, CE and DD. A pair of selection criteria is used to filter out reliable data symbols and the highly reliability data is reused to assist improving the CE accuracy. Finally, after the message passing in joint UID and CE stage, we utilize the sparse structure of LDS-OFDM to further optimize the results of UID. Simulation results have demonstrated that our proposed joint algorithm outperforms the existing AMP-based schemes in terms of bit error rate (BER), convergence speed, as well as false alarm rate (FAR).

The paper is structured as follows. Section II describes the system model of uplink grant-free NOMA system in S-IoT. The GAMP-SBL algorithm for joint UID and CE is developed in Section III. Then, the GAMP-SBL algorithm for joint UID, CE and DD is derived in Section IV, while the system performance is shown in Section V. Finally, our conclusions are drawn in Section VI.

II. SYSTEM MODEL

In this section, we introduce the system model of GF-NOMA in LEO satellite communications. The transmitter structure along with the pilot transmission is discussed in Section II-A, followed by the space-ground channel model

introduced in II-B. The receiver structure is discussed in Section II-C, and finally, Section II-D introduces the structure of pilot signal.

A. Transmitter

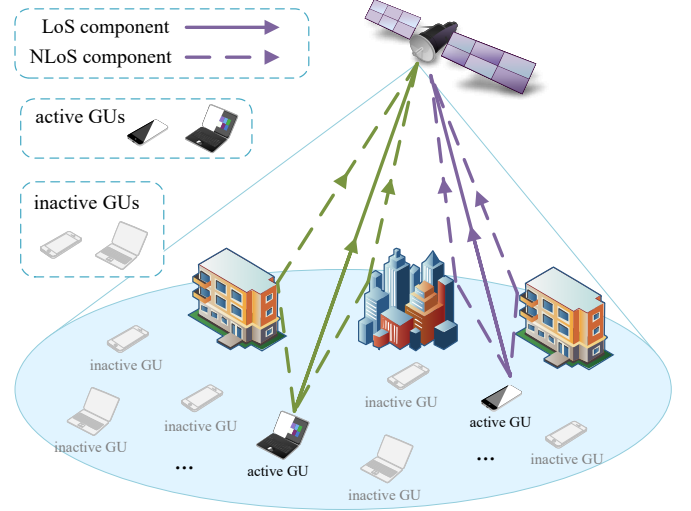


Fig. 1. System model.

We consider an uplink grant-free LDS-OFDM system in S-IoT, as shown in Fig. 1, where K potential single-antenna ground users (GUs) transmit data to the LEO satellite employing linear antenna array in the initial slot at an active probability of p_a . At the receiver, the LEO satellite is equipped with R receive antennas (RA). Following, The transmitter structure is illustrated in Fig. 2. The symbol A_k ($1 \leq k \leq K$) is used to indicate the user activity of device k , i.e., $A_k = 1$ if GU k is active. Otherwise, $A_k = 0$. We assume that the state of each GU (active or inactive) does not change over T time slots. For the active GU k , the binary bit stream is mapped to a L -length quadrature amplitude modulation (QAM) symbol sequence $\mathbf{x}_k^t = [A_k x_{k,1}^t, A_k x_{k,2}^t, \dots, A_k x_{k,L}^t] \in \mathbb{C}^{1 \times L}$ in time slot t by the QAM alphabet $\mathcal{A}$ and $|\mathcal{A}| = M$. For each inactive GU k , $\mathbf{x}_k^t$ is a sequence of all zeros. Due to the two states (active or inactive) of GUs, we further extend the QAM alphabet to $\mathcal{A}^+ = \mathcal{A} \cup \{0\}$ and $|\mathcal{A}^+| = M + 1$. With the low-density spreading sequence $\mathbf{s}_k = [s_{k,1}, s_{k,2}, \dots, s_{k,N}]^T \in \mathbb{C}^{N \times 1}$, the QAM symbol sequence is spread over N ($K > N$) orthogonal subcarriers. The relationship between K GUs and N subcarriers can be expressed in a sparse matrix $\mathbf{F} = (f_{nk})$ ($1 \leq n \leq N$), taking $K = 6, N = 4$ as an example, we have

$$\mathbf{F} = \begin{bmatrix} 0 & 1 & 1 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 & 0 & 1 \\ 0 & 1 & 0 & 1 & 0 & 1 \\ 1 & 0 & 0 & 1 & 1 & 0 \end{bmatrix}. \quad (1)$$

(1) indicates that $d_f = 3$ GUs share a single subcarrier and each GU occupies $d_v = 2$ subcarriers. Additionally, we define the set $\mathcal{K}_n$ to represent all the GUs that share the n -th

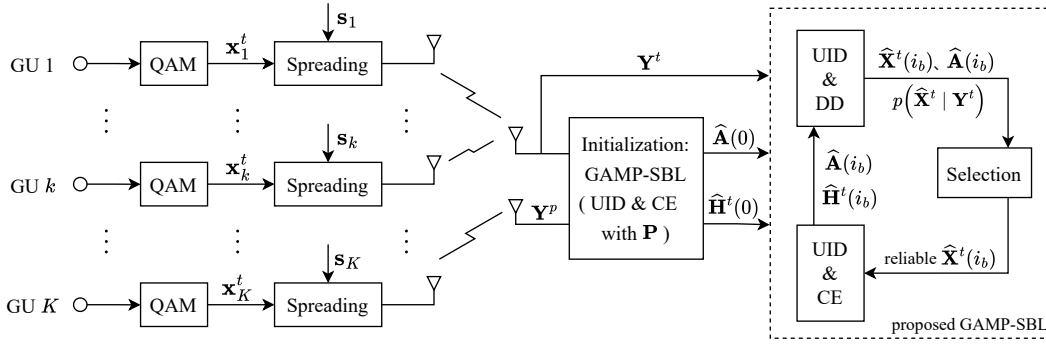


Fig. 2. The detailed transmitter and receiver structure of the grant-free LDS-OFDM system for the S-LoT scenario.

subcarrier and the set $\mathcal{N}_k$ to represent all the subcarriers which are occupied by the k -th GU, i.e.,

$$\begin{aligned}\mathcal{K}_n &= \{k | F_{n,k} = 1, \forall k\} \\ \mathcal{N}_k &= \{n | F_{n,k} = 1, \forall n\}.\end{aligned}\quad (2)$$

Obviously, $|\mathcal{K}_n| = d_f$ and $|\mathcal{N}_k| = d_v$.

B. Channel Model

In this paper, we follow the space-ground channel model proposed in [27, 49, 50]. Considering a multicarrier system, the channel between GU k and the satellite over the n -th subcarrier through the r -th ($1 \leq r \leq R$) RA in the first time slot can be expressed as

$$h_{c,k}^1 = h_s e^{j\varphi_\theta} (h_{c,k}^{\text{los}} e^{j\varphi_{c,k}^{\text{los}}} + h_{c,k}^{\text{los}} e^{j\varphi_{c,k}^{\text{los}}}), \quad (3)$$

where $c = (r-1) \times N + n$ and $1 \leq c \leq NR$. Let $h_{c,k}^{\text{los}} e^{j\varphi_{c,k}^{\text{los}}}$ denotes the Line-of-Sight (LoS) component and it is assumed to be a constant [27] because the stationary GUs communicate with satellite at fixed elevation angles. In addition, the Non-Line-of-Sight (NLoS) component, which is described as $h_{c,k}^{\text{nlos}} e^{j\varphi_{c,k}^{\text{nlos}}}$ with a Rayleigh-distributed amplitude $h_{c,k}^{\text{nlos}}$ and a uniformly random phase $e^{j\varphi_{c,k}^{\text{nlos}}}$, can be seen as following the complex Gaussian distribution $h_{c,k}^{\text{nlos}} e^{j\varphi_{c,k}^{\text{nlos}}} \sim \mathcal{CN}(0, v_{c,k}^{\text{nlos}})$ [27]. Besides, considering the channel impairments, e.g., Doppler shift, the weather condition and the atmospheric variation [51], the propagation fading h_s and the phase shift φ_θ are added. Specifically, we suppose h_s is log-normal-distributed [27] and φ_θ follows a Gaussian distribution $\varphi_\theta \sim \mathcal{N}(0, v_\theta)$. All GUs can be considered to be in a small area relative to the distance between the satellite and the earth, so their channel impairment component $h_s e^{j\varphi_\theta}$ is assumed to be the same [27].

Considering temporal correlation, we adopt the first-order Autoregressive (AR) model [52]. The channel of the first time slot is generated by formula (3), and the channel of time slot t ($1 < t \leq T$) is related to the channel of its previous slot,

which can be expressed as

$$h_{c,k}^t = \rho h_{c,k}^{t-1} + \sqrt{1 - \rho^2} \epsilon_{c,k}^t, \quad t = 2, 3, \dots, T, \quad (4)$$

where $\epsilon_{c,k}^t \sim \mathcal{CN}(0, v_\epsilon)$ and $\rho = J_0(2\pi f_d \tau) \in [-1, 1]$. More specifically, $J_0(\cdot)$ is the zeroth-order Bessel function of the first kind, τ is the time slot duration and f_d is the maximum Doppler frequency. We employ Ku-band for our system, f_c represents the carrier frequency and v denotes the mobile speed, then, we can derive that $f_d = v f_c / c$.

C. Receiver

The receiver is shown in Fig. 2. The l -th ($1 < l \leq L$) symbol $y_{c,l}^t$ received by the satellite over the n -th subcarrier at the r -th RA in the t -th time slot can be described as

$$y_{c,l}^t = \sum_{k=1}^K h_{c,k}^t s_{n,k} x_{k,l}^t A_k + n_{c,l}^t, \quad (5)$$

where $n_{c,l}^t \sim \mathcal{CN}(0, \sigma^2)$ denotes the Gaussian noise. Let $\mathbf{y}_l^t = [y_{1,l}^t, \dots, y_{N,l}^t, y_{N+1,l}^t, \dots, y_{NR,l}^t]^T \in \mathbb{C}^{NR \times 1}$ represent the l -th symbol received in the t -th time slot; $\mathbf{n}_l^t = [n_{1,l}^t, \dots, n_{N,l}^t, n_{N+1,l}^t, \dots, n_{NR,l}^t]^T \in \mathbb{C}^{NR \times 1}$ be the noise vector; $\mathbf{x}_l^t = [A_1 x_{1,l}^t, A_2 x_{2,l}^t, \dots, A_K x_{K,l}^t]^T \in \mathbb{C}^{K \times 1}$ be the l -th symbol transmitted by all GUs, $\mathbf{h}_k^t = [A_k h_{1,k}^t, \dots, A_k h_{N,k}^t, A_k h_{N+1,k}^t, \dots, A_k h_{NR,k}^t]^T \in \mathbb{C}^{NR \times 1}$ be the channel vector of GU k ; and $\mathbf{H}^t = [\mathbf{h}_1^t, \mathbf{h}_2^t, \dots, \mathbf{h}_K^t] \in \mathbb{C}^{NR \times K}$ be the channel matrix. Then, the vector form of (5) can be given as

$$\mathbf{y}_l^t = \tilde{\mathbf{H}}^t \mathbf{x}_l^t + \mathbf{n}_l^t, \quad (6)$$

where we define $\tilde{\mathbf{h}}_k^t \triangleq \mathbf{h}_k^t \odot (\mathbf{1} \otimes \mathbf{s}_k)$, $\mathbf{1}$ represents a R -dimensional vector whose elements is all 1 and $\tilde{\mathbf{H}}^t \in \mathbb{C}^{NR \times K}$ is the matrix form of $\tilde{\mathbf{h}}_k^t$. Furthermore, formula (6) can be written in matrix form

$$\mathbf{Y}^t = \tilde{\mathbf{H}}^t \mathbf{X}^t + \mathbf{N}^t, \quad (7)$$

where the received signal $\mathbf{Y}^t = [\mathbf{y}_1^t, \mathbf{y}_2^t, \dots, \mathbf{y}_L^t]$ is a $NR \times L$ matrix, the transmitted signal is $\mathbf{X}^t = [\mathbf{x}_1^t, \mathbf{x}_2^t, \dots, \mathbf{x}_L^t] \in$

$\mathbb{C}^{K \times L}$ and the noise matrix is $\mathbf{N}^t = [\mathbf{n}_1^t, \mathbf{n}_2^t, \dots, \mathbf{n}_L^t] \in \mathbb{C}^{NR \times L}$. As shown in Fig. 2, UID, DD and CE are iteratively performed at receiver, which will be introduced in detail in Section IV.

D. Pilot signal

In order to obtain the channel state information, we assume that each GU k has a L_p -length pilot sequence $\mathbf{P}_k = [P_{1,k}, P_{2,k}, \dots, P_{L_p,k}]^T \in \mathbb{C}^{L_p \times 1}$ and the satellite receiver has the knowledge of $\mathbf{P}_k$. We assume that $\mathbf{P}_k$ is non-orthogonal Gaussian sequence [27] and each symbol $P_{l_p,k} \sim \mathcal{CN}(0, 1)$ ($1 < l_p \leq L_p$) is independent. The active GUs of the set $\mathcal{K}_n$ transmit their pilot sequence together with data information on subcarrier n at the first time slot and if GU k is inactive, the sequence is not sent. Then, the l_p -th pilot symbol y_{c,l_p}^p received by the the satellite over subcarrier n through the r -th RA is

$$y_{c,l_p}^p = \sum_{k \in \mathcal{K}_n} P_{l_p,k} h_{c,k}^1 A_k + n_{c,l_p}^p. \quad (8)$$

Furthermore, the vector form of (8) can be expressed as

$$\mathbf{y}_c^p = \mathbf{P} \mathbf{h}_c^1 + \mathbf{n}_c^p, \quad (9)$$

where $\mathbf{y}_c^p = [y_{c,1}^p, y_{c,2}^p, \dots, y_{c,L_p}^p]^T \in \mathbb{C}^{L_p \times 1}$ is the pilot symbols received on the n -th subcarrier through the r -th RA, $\mathbf{P} = [\mathbf{P}_1, \mathbf{P}_2, \dots, \mathbf{P}_K] \in \mathbb{C}^{L_p \times K}$ is the pilot sequence transmitted by all GUs, $\mathbf{n}_c^p = [n_{c,1}^p, n_{c,2}^p, \dots, n_{c,L_p}^p]^T \in \mathbb{C}^{L_p \times 1}$ is the Gaussian noise vector and its variance is σ^2 , $\mathbf{h}_c^1 = [A_1 h_{c,1}^1, A_2 h_{c,2}^1, \dots, A_K h_{c,K}^1]^T \in \mathbb{C}^{K \times 1}$ is the channel vector over subcarrier n through the r -th RA at the first time slot and it is also the transposition of the c -th row vector of the matrix $\mathbf{H}^1$.

Considering all the subcarriers and all the RAs of our system, let $\mathbf{Y}^p = [\mathbf{y}_1^p, \dots, \mathbf{y}_N^p, \mathbf{y}_{N+1}^p, \dots, \mathbf{y}_{NR}^p] \in \mathbb{C}^{L_p \times NR}$ and $\mathbf{N}^p = [\mathbf{n}_1^p, \dots, \mathbf{n}_N^p, \mathbf{n}_{N+1}^p, \dots, \mathbf{n}_{NR}^p] \in \mathbb{C}^{L_p \times NR}$, the matrix form of (9) can be written as

$$\mathbf{Y}^p = \mathbf{P}(\mathbf{H}^1)^T + \mathbf{N}^p. \quad (10)$$

III. JOINT CE AND UID ALGORITHM

In this section, we first review the basics of the SBL method in Section III-A. Due to the high complexity of the SBL algorithm, we embed the efficient GAMP method into the structure of SBL and develop the GAMP-SBL algorithm for joint UID and CE in Section III-B.

A. Overview of Sparse Bayesian Learning

Due to the spodic pattern of GUs, the corresponding channel for the inactive GU is 0, indicating the channel sparsity. Moreover, the SBL method does not need to know the active GU indices. Taking joint UID and CE as an example and

assuming the noise variance σ^2 is known, we give a brief introduction to SBL. Since the channel of each subcarrier and each RA is independent, the joint detection problem of each subcarrier and each RA in the first time slot is modeled as a SMV model and the channel in the first time slot can be obtained by traversing the subcarriers and RAs. SBL assumes a Gaussian likelihood model of

$$p(\mathbf{y}_c^p | \mathbf{h}_c^1, \sigma^2) = (2\pi\sigma^2)^{-\frac{L_p}{2}} \exp(-\frac{1}{2\sigma^2} \|\mathbf{y}_c^p - \mathbf{P} \mathbf{h}_c^1\|^2). \quad (11)$$

SBL estimates the hyperparameters α_c^p from the data, which controls the prior variance of $\mathbf{h}_c^1$. Then, the prior of $\mathbf{h}_c^1$ is

$$p(\mathbf{h}_c^1 | \alpha_c^p) = \prod_k^K \mathcal{CN}(h_{c,k}^1 | 0, (\alpha_{c,k}^p)^{-1}). \quad (12)$$

where $\alpha_{c,k}^p$ is positive and these priors are non-informative. We follow the assumptions in [53] and define a Gamma prior distribution for $\alpha_{c,k}^p$,

$$\begin{aligned} p(\alpha_{c,k}^p | a^p, b^p) &= \prod_k^K \text{Gamma}(\alpha_{c,k}^p | a^p, b^p) \\ &= \prod_k^K \Gamma(a^p)^{-1} (b^p)^{a^p} (\alpha_{c,k}^p)^{a^p-1} e^{-b^p \alpha_{c,k}^p}. \end{aligned} \quad (13)$$

The *a posteriori* distribution will be learned after the correction of known data in the process of sparse Bayesian learning. In order to eliminate the influence of the prior information on the posterior distribution, we assign some special values to the parameters a^p and b^p so that $\mathbf{h}_c^1$ has an improper prior and ensure these priors are non-informative. As discussed in [54], the values of these hyperparameters are not very critical to the performance, as long as the hyperparameters are set within a reasonable range, the performance of the algorithm can remain stable.

The expectation-maximization (EM) algorithm can be adopted to update the channel $\mathbf{h}_c^1$ as well as the hyperparameters α_c^p , where $\mathbf{h}_c^1$ is treated as hidden variables. Let I_a represents the total number of iterations for joint UID and CE, and i_a ($1 \leq i_a \leq I_a$) represents the i_a -th iteration. and we iteratively estimate the parameters α_c^p by

$$\begin{aligned} \alpha_c^p(i_a) &= \arg \max_{\alpha_c^p} Q(\alpha_c^p | \alpha_c^p(i_a - 1)) \\ &\triangleq \arg \max_{\alpha_c^p} E_{\mathbf{h}_c^1 | \mathbf{y}_c^p, \alpha_c^p(i_a - 1)} [\log p(\alpha_c^p | \mathbf{h}_c^1, \mathbf{y}_c^p)], \end{aligned} \quad (14)$$

where the operator $E_{\mathbf{h}_c^1 | \mathbf{y}_c^p, \alpha_c^p(i_a - 1)}[\cdot]$ denotes the expectation with respect to the posterior distribution $p(\mathbf{h}_c^1 | \mathbf{y}_c^p, \alpha_c^p(i_a - 1))$. EM algorithm is an iterative algorithm with alternating E-step and M-step. In each iteration, we need to use the parameters estimated in the last iteration to calculate the expectation (Q-function) and estimate parameters by maximizing the Q-function. The details are as follows:

1) *E-step*: According to the Bayesian formula, we insert

(11) (12), and the posterior distribution needed for the E-step of channel $\mathbf{h}_c^1$ can be derived as

$$p(\mathbf{h}_c^1 | \mathbf{y}_c^p, \boldsymbol{\alpha}_c^p, \sigma^2) \propto p(\mathbf{y}_c^p | \mathbf{h}_c^1, \sigma^2) p(\mathbf{h}_c^1 | \boldsymbol{\alpha}_c^p) = \mathcal{CN}(\mathbf{h}_c^1 | \boldsymbol{\mu}, \boldsymbol{\Sigma}), \quad (15)$$

where the covariance and mean are respectively expressed as

$$\boldsymbol{\Sigma} = (\sigma^{-2} \mathbf{P}^T \mathbf{P} + \mathbf{A}_c)^{-1}, \quad (16)$$

$$\boldsymbol{\mu} = \sigma^{-2} \boldsymbol{\Sigma} \mathbf{P}^T \mathbf{y}_c^p, \quad (17)$$

with $\mathbf{A}_c = \text{diag}(\alpha_{c,1}^p, \alpha_{c,2}^p, \dots, \alpha_{c,K}^p)$. Then the Q-function can be calculated.

2) *M-step*: Update $\boldsymbol{\alpha}_c^p(i_a + 1)$ by (14).

The EM algorithm needs to calculate the posterior probability with matrix inversion and the complexity of EM-based SBL algorithm for joint UID and CE is $\mathcal{O}(NRK^3)$. With the number of GUs, the complexity of the whole system grows rapidly. Thus, the EM-based SBL algorithm is not suitable for satellite scenarios with multiuser requirement. To reduce the complexity of SBL method, we adopt the efficient GAMP technique in SBL to reduce the complexity in the following section.

B. GAMP-SBL for joint UID and CE

Generalized approximate message passing algorithm is a low-complexity algorithm which is developed in [55] by analyzing and summarizing a large class of message passing algorithms. The details of GAMP algorithm can be seen in [55]. In this section, we embed GAMP method into SBL framework and develop the GAMP-SBL algorithm for joint UID and CE. Specifically, according to the central limit theorem and Taylor theorem, the approximate posterior distribution $p(\mathbf{h}_c^1 | \mathbf{y}_c^p, \boldsymbol{\alpha}_c^p)$ can be obtained with GAMP method. Based on the approximate posterior distribution, the hyperparameters $\boldsymbol{\alpha}_c^p$ can be derived in the M-step by maximizing the Q-function. Next, the estimated hyperparameters $\boldsymbol{\alpha}_c^p$ is used to approximate posterior distribution and repeat the iteration until the final convergence.

We still use I_a to denote the total number of iterations for joint UID and CE, and i_a represents the i_a -th iteration. Assuming the estimated hyperparameters $\boldsymbol{\alpha}_c^p$ in the last iteration is known, the approximate posterior distribution of $\mathbf{h}_c^1$ can be expressed as

$$\begin{aligned} & p(h_{c,k}^1 | \mathbf{y}_c^p, \zeta_{c,k}(i_a), r_{c,k}(i_a), \boldsymbol{\alpha}_c^p(i_a - 1)) \\ &= \frac{p(h_{c,k}^1 | \boldsymbol{\alpha}_c^p(i_a - 1)) \mathcal{CN}(h_{c,k}^1 | \zeta_{c,k}(i_a), r_{c,k}(i_a))}{\int p(h_{c,k}^1 | \boldsymbol{\alpha}_c^p(i_a - 1)) \mathcal{CN}(h_{c,k}^1 | \zeta_{c,k}(i_a), r_{c,k}(i_a)) dh_{c,k}^1} \\ &= \mathcal{CN}(h_{c,k}^1 | \hat{h}_{c,k}^p(i_a), \phi_{c,k}(i_a)), \end{aligned} \quad (18)$$

where $\zeta_{c,k}(i_a)$ and $r_{c,k}(i_a)$ are variables in the GAMP algorithm, and $\hat{h}_{c,k}^p(i_a)$ is the estimated value of $A_k h_{c,k}^1$ for the i -th iteration and the final vector form of it can be given as $\hat{\mathbf{h}}_k^p = [\hat{h}_{1,k}^p(I), \dots, \hat{h}_{N,k}^p(I), \dots, \hat{h}_{NR,k}^p(I)]^T \in \mathbb{C}^{NR \times 1}$. The

Algorithm 1 GAMP-SBL algorithm for joint UID and CE

Input:

The received pilot signal $\mathbf{Y}^p$, pilot symbols $\mathbf{P}$;

Output:

The estimated channel in the first time slot $\hat{\mathbf{h}}_k^p$ for $k = 1, 2, \dots, K$;

Initialization:

$\hat{h}_{c,k}^p(0) > 0$, $\phi_{c,k}(0) > 0$, $s_{c,l_p}(0) = 0$ and $\alpha_{c,k}^p(0)$, $c = 1, 2, \dots, NR$, $k = 1, 2, \dots, K$, $l_p = 1, 2, \dots, L_p$.

Iteration:

```

1: for  $i_a = 1, \dots, I$  do
2:   for  $c = 1, \dots, NR$  do
3:     for  $l_p = 1, \dots, L_p$  do
4:        $u_{c,l_p}(i_a) = \sum_{k \in \mathcal{K}_n} P_{l_p,k} \hat{h}_{c,k}^p(i_a - 1)$ ;
5:        $\tau_{c,l_p}(i_a) = \sum_{k \in \mathcal{K}_n} |P_{l_p,k}|^2 \phi_{c,k}(i_a - 1)$ ;
6:        $p_{c,l_p}(i_a) = u_{c,l_p}(i_a) - \tau_{c,l_p}(i_a) s_{c,l_p}(i_a - 1)$ ;
7:     end for
8:     for  $l_p = 1, \dots, L_p$  do
9:        $s_{c,l_p}(i_a) = \frac{1}{\tau_{c,l_p}(i_a)} \left( \frac{\tau_{c,l_p}(i_a) \gamma y_{c,l_p}^p + \vartheta_{c,l_p}(i_a)}{\gamma \tau_{c,l_p}(i_a) + 1} - \vartheta_{c,l_p}(i_a) \right)$ ;
10:       $z_{c,l_p}(i) = \frac{\gamma}{\gamma \tau_{c,l_p}(i_a) + 1}$ ;
11:    end for
12:    for  $k = 1, \dots, K$  do
13:       $\zeta_{c,k}(i_a) = (\sum_{l_p}^L |P_{l_p,k}|^2 z_{n,l_p}(i_a))^{-1}$ ;
14:       $r_{c,k}(i_a) = \hat{h}_{c,k}^p(i_a - 1) + \zeta_{c,k}(i_a) \sum_{l_p}^L (P_{l_p,k})^* s_{n,l_p}(i_a)$ ;
15:    end for
16:    for  $k = 1, \dots, K$  do
17:       $\hat{h}_{c,k}^p(i_a) = \frac{r_{c,k}(i_a)}{\alpha_{c,k}^p(i_a - 1) \zeta_{c,k}(i_a) + 1}$ ;
18:       $\phi_{c,k}(i) = \frac{\zeta_{c,k}(i_a)}{\alpha_{c,k}^p(i_a - 1) \zeta_{c,k}(i_a) + 1}$ ;
19:    end for
20:    for  $k = 1, \dots, K$  do
21:       $\alpha_{c,k}^p(i_a) = \frac{2a^p - 1}{|\hat{h}_{c,k}^p(i_a)|^2 + \phi_{c,k}(i_a) + 2b^p}$ ;
22:    end for
23:  end for
24: end for
25: if  $\hat{h}_{c,k}^p(I) < \eta$  then
26:    $\hat{h}_{c,k}^p(I) = 0$ .
27: end if

```

other approximation is made to the noiseless output $\mathbf{z}_c^p \triangleq \mathbf{P} \mathbf{h}_c^1$ and $\mathbf{z}_c^p = [z_{c,1}^p, z_{c,2}^p, \dots, z_{c,L_p}^p]^T \in \mathbb{C}^{L_p \times 1}$. The approximate posterior distribution of $\mathbf{z}_c^p$ is

$$\begin{aligned} & p(\mathbf{z}_{c,l_p}^p | \mathbf{y}_c^p, \vartheta_{c,l_p}(i_a), \tau_{c,l_p}(i_a), \boldsymbol{\alpha}_c^p(i_a - 1)) \\ &= \frac{p(y_{c,l_p}^p | z_{c,l_p}^p, \boldsymbol{\alpha}_c^p(i_a - 1)) \mathcal{CN}(z_{c,l_p}^p | \vartheta_{c,l_p}(i_a), \tau_{c,l_p}(i_a))}{\int p(y_{c,l_p}^p | z_{c,l_p}^p, \boldsymbol{\alpha}_c^p(i_a - 1)) \mathcal{CN}(z_{c,l_p}^p | \vartheta_{c,l_p}(i_a), \tau_{c,l_p}(i_a)) dz_{c,l_p}^p} \\ &= \mathcal{CN}(z_{c,l_p}^p | \xi_{c,l_p}(i_a), v_{c,l_p}(i_a)), \end{aligned} \quad (19)$$

where $\vartheta_{c,l_p}(i_a)$ and $\tau_{c,l_p}(i_a)$ are variables in the GAMP algorithm.

There are two functions $g_{in}(\cdot)$ and $g_{out}(\cdot)$ of GAMP in [55]. Actually, the input function $g_{in}(\cdot)$ can be defined as the posteriori mean $\hat{h}_{c,k}^1(i)$, that is

$$g_{in}(r_{c,k}(i_a), \alpha_{c,k}^p(i_a - 1), \zeta_{c,k}(i_a)) \\ = \hat{h}_{c,k}^p(i_a) = \frac{r_{c,k}(i_a)}{\alpha_{c,k}^p(i_a - 1)\zeta_{c,k}(i_a) + 1}. \quad (20)$$

Moreover, the output function $g_{out}(\cdot)$ has to do with another posterior mean $\xi_{c,l_p}(i_a)$, which is expressed as

$$g_{out}(\vartheta_{c,l_p}(i_a), y_{c,l_p}^p, \tau_{c,l_p}(i_a)) \\ = \frac{1}{\tau_{c,l_p}(i_a)}(\xi_{c,l_p}(i_a) - \vartheta_{c,l_p}(i_a)) \\ = \frac{1}{\tau_{c,l_p}(i_a)}\left(\frac{\tau_{c,l_p}(i_a)\gamma y_{c,l_p}^p + \vartheta_{c,l_p}(i_a)}{\gamma\tau_{c,l_p}(i_a) + 1} - \vartheta_{c,l_p}(i_a)\right). \quad (21)$$

Based on the derivation above, the approximate posterior probability has been obtained by GAMP algorithm, and the next step is to update the hyperparameters α_c^p by maximizing the Q-function which is defined in (14). We take the partial derivative of the Q-function with respect to $\alpha_{c,k}^p(i_a)$ and set the partial derivative to zero, the parameter $\alpha_{c,k}^p(i_a)$ can be updated as

$$\alpha_{c,k}^p(i_a) = \frac{2a^p - 1}{|\hat{h}_{c,k}^1(i_a)|^2 + \phi_{c,k}(i_a) + 2b^p}. \quad (22)$$

The detailed derivation process can be referred to [39, 41, 56].

Note that we introduce the threshold η , and if $\hat{h}_{c,k}^p(I) < \eta$, we set $\hat{h}_{c,k}^p(I) = 0$. We summarize the GAMP-SBL algorithm for joint CE and UID in Algorithm 1.

IV. JOINT CE, UID AND DD FOR GF-NOMA IN S-IoT

In this section, we describe the joint UID, CE and DD in detail. Specifically, according to the Bayesian formula of the posterior distribution, we first formulate the factor graph of our grant-free LDS-OFDM system to characterize the process of message passing, as will be discussed in Section IV-A. We then divide the joint problem into two stages and messages are passed across these two stages along the factor graph in each iteration by performing GAMP-SBL. Utilizing the results of Algorithm 1 to initialize the channel and the active GUs, we further developed an iterative joint GAMP-SBL algorithm in Section IV-B. Following the joint UID and DD stage, a pair of selection criteria are used to filter out reliable data symbols and the high-reliability data is reused to assist improving the accuracy of CE. Finally, after message passing in joint UID and CE stage, we utilize the sparse structure of LDS-OFDM to further optimize the results of UID.

A. Factor Graph Representation of the Proposed GAMP-SBL

According to the Bayesian formula of the posterior distribution, the message passing process of the proposed GAMP-SBL algorithm for joint UID, CE and DD is illustrated on the factor graph in Fig. 3, where the circles represent variable nodes and the squares represent function nodes. The entire factor graph is divided into two parts, with the left part representing joint UID and CE processes as well as the right part representing UID and DD processes. When a function is associated with a variable, the corresponding square and circle nodes are connected. In particular, the received signal is related to the transmitted signal and the channel according to (7). One function node $y_{c,l}^t$ is connected to K variable nodes $\tilde{h}_{c,k}^t$ and one variable node $\tilde{h}_{c,k}^t$ is connected to L function nodes $y_{c,l}^t$, whereas one function node $y_{c,l}^t$ is connected to d_f variable nodes $\tilde{x}_{k,l}^t$ and one variable node $\tilde{x}_{k,l}^t$ is connected to Rd_v function nodes $y_{c,l}^t$ due to the sparse structure of LDS-OFDM.

B. Joint CE, UID and DD with proposed GAMP-SBL

Noticing that the CSI changes over time in many scenarios, we propose an efficient iterative detector to address the joint CE, UID and DD problem as shown in Fig. 2. To be more specific, we use the results of the GAMP-SBL algorithm to initialize the channel and active GUs. Splitting the joint UID, CE, and DD problem into two sub-processes, joint UID and DD stage as well as joint UID and CE stage, we develop an iterative joint GAMP-SBL algorithm. In each iteration, messages are passed through two stages along the factor graph in Fig. 3 with the GAMP-SBL method. After the message delivery in joint UID and DD stage is completed, a pair of selection criteria are used to filter out reliable data signal and the related message is passed to joint UID and CE stage to achieve the data-aided CE. Besides, after joint UID and CE stage, we further improve the accuracy of UID by utilizing the sparse structure of LDS-OFDM and update the sparse matrix which represents the relationship of GUs and subcarriers.

In the previous subsection, we have estimated the channel and detected the active users of the first time slot $\hat{\mathbf{h}}_k^p$ with the pilot symbols. According to the formula (4), the channel of each time slot is related to the channel of its previous time slot, i.e., the channel of each time slot is related to the channel of the first time slot. Therefore, we initialize the estimated channel value of the first time slot $\hat{\mathbf{h}}_k^p$ to all time slots. Then, the transmitted signal can be estimated based on the initialized channel. Obviously, the estimated value of both the transmitted signal and channel is inaccurate.

In order to reduce the deviation above, we reuse the estimated transmitted signal and the known received signal for CE, combined with the results of previous estimation, to improve the accuracy of CE. Meanwhile, the estimated channel which is more accurate is used to detect the transmitted signal, thus reducing the bit error rate (BER). After continuous iteration, the error is gradually reduced. Since the GUs are randomly accessed, we still employed the framework of GAMP-SBL, a low-complexity algorithm that doesn't know whether the user

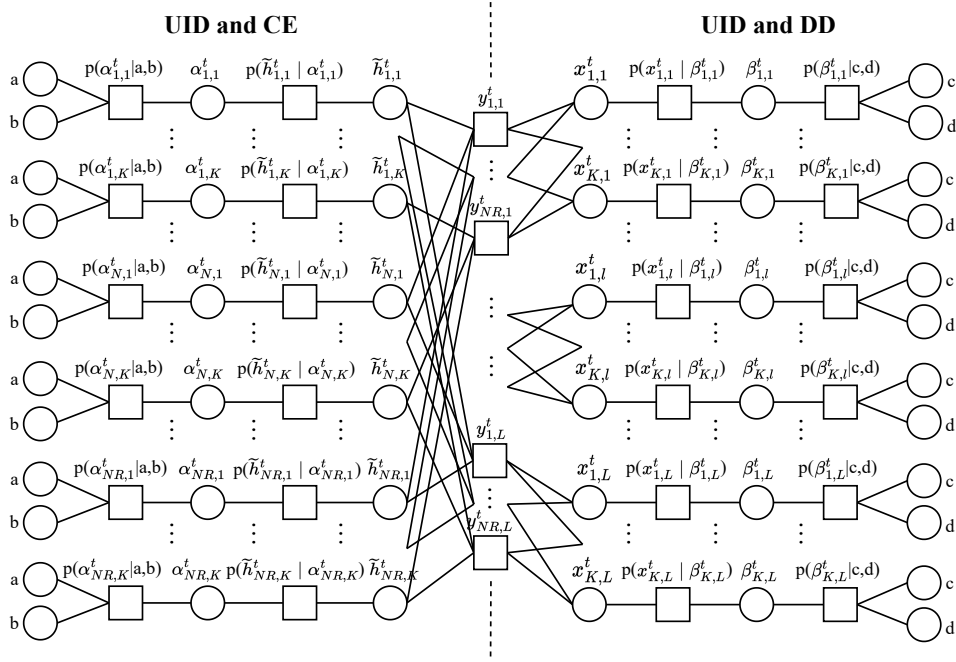


Fig. 3. Factor graph of the proposed GAMP-SBL algorithm for joint UID, CE and DD.

is active, to achieve the above process. Furthermore, the results of CE and DD can be used for UID.

1) *Initialization*: We initialize the channel of all time slots with the result $\hat{\mathbf{h}}_k^p$ of Algorithm 1, i.e.,

$$\hat{\mathbf{h}}_k^t(0) = \hat{\mathbf{h}}_k^p \odot (\mathbf{1} \otimes \mathbf{s}_k), t = 1, 2, \dots, T, \quad (23)$$

where $\mathbf{1}$ represents a R -dimensional vector whose elements are all 1. Based on the assumption in Section II, if GU k is inactive, $A_k h_{c,k}^1 = 0$. This is one of the basis for UID. Using $\hat{A}_{c,k}(0)$ to represent the estimate of A_k over the n -th subcarrier through the r -th RA and $\hat{A}_k(0)$ to represent the estimate of A_k during initialization, we assume if $\hat{h}_{c,k}^p = 0$, $\hat{A}_{c,k}(0) = 0$ and if $\hat{h}_{c,k}^p \neq 0$, $\hat{A}_{c,k}(0) = 1$. However, $\hat{h}_{c,k}^p = 0$ does not necessarily mean that GU k is not active because of the possibility of miscalculation. Therefore, if we simply assign $\hat{A}_{c,k}(0)$ based on the above assumption, errors will occur and affect the subsequent process. The sparse structure of LDS-OFDM can help us to further improve the accuracy of UID, thus reducing the interference caused by misjudgment and reducing the error rate of DD. Taking the sparse matrix $\mathbf{F}$ in (1) as an example, if GU 1 and GU 2 are not active, then the actual sparse matrix $\mathbf{F}^{\text{act}} = (f_{nk}^{\text{act}}) = (f_{nk} A_k)$ can be given as:

$$\mathbf{F}^{\text{act}} = \begin{bmatrix} 0 & 0 & 1 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 1 & 1 & 0 \end{bmatrix}, \quad (24)$$

where the sum of the column elements corresponding to inactive GUs is no longer d_v , but 0. According to the above discussion, we introduce threshold θ and if $1/d_v/R \sum_c \hat{A}_{c,k}(0) \leq$

θ , we consider GU k is not active and set the corresponding $\hat{A}_k(0)$ is equal to 0. Considering the multiple antennas, we first extend the sparse matrix, i.e., $\mathbf{F}^{\text{ex}} = \mathbf{1} \otimes \mathbf{F} \in \mathbb{C}^{NR \times K}$, $\mathbf{1}$ represents a R -dimensional vector whose elements are all 1. Then, the sparse matrix $\mathbf{F}^{\text{new}}$ for the following detection can be updated as

$$\mathbf{F}^{\text{new}} = (f_{ck}^{\text{new}}) = (f_{ck}^{\text{ex}} \hat{A}_k(0)). \quad (25)$$

Furthermore, the set $\mathcal{K}_n$ and $\mathcal{N}_k$ in 2 can be updated as

$$\begin{aligned} \mathcal{K}_c^{\text{new}} &= \{k | F_{c,k}^{\text{new}} = 1, \forall k\} \\ \mathcal{N}_k^{\text{new}} &= \{c | F_{c,k}^{\text{new}} = 1, \forall c\}. \end{aligned} \quad (26)$$

2) *Joint UID and DD*: Similar to CE process, the transmitted signal from the user is sparse. Due to each symbol sent by each user in each time slot is independent of each other, we modeled the DD problem for each time slot in (6) as a SMV model. We adopt the GAMP-SBL algorithm to detect the transmitted signal. The Gaussian likelihood model is given as

$$p(\mathbf{y}_l^t | \mathbf{x}_l^t, \sigma^2) = (2\pi\sigma^2)^{-\frac{NR}{2}} \exp(-\frac{1}{2\sigma^2} \|\mathbf{y}_l^t - \tilde{\mathbf{H}}^t \mathbf{x}_l^t\|^2). \quad (27)$$

SBL estimates the hyperparameters β_l^t from the data, which controls the prior variance of $\mathbf{x}_l^t$. And the prior of $\mathbf{x}_l^t$ is:

$$p(\mathbf{x}_l^t | \beta_l^t) = \prod_k \mathcal{CN}(x_{k,l}^t | 0, (\beta_{k,l}^t)^{-1}). \quad (28)$$

where $\beta_{k,l}^t$ is positive and we define a Gamma prior distribution for it,

$$p(\beta_l^t|c, d) = \prod_k^K \text{Gamma}(\beta_{k,l}^t|c, d) \\ = \prod_k^K \Gamma(c)^{-1} d^c (\beta_{k,l}^t)^{c-1} e^{-d\beta_{k,l}^t}. \quad (29)$$

Let I_b presents the total number of iterations for Joint CE, UID and DD problem, and i_b ($1 \leq i_b \leq I_b$) represents the i_b -th iteration. The hyperparameter β_l^t can be updated with EM algorithm as:

$$\beta_l^t(i_b) = \arg \max_{\beta_l^t} Q(\beta_l^t|\beta_l^t(i_b - 1)) \\ \triangleq \arg \max_{\beta_l^t} E_{\mathbf{x}_l^t|\mathbf{y}_l^t, \beta_l^t(i_b - 1)}[\log p(\beta_l^t|\mathbf{x}_l^t, \mathbf{y}_l^t)], \quad (30)$$

where the operator $E_{\mathbf{x}_l^t|\mathbf{y}_l^t, \beta_l^t(i_b - 1)}[\cdot]$ denotes the expectation with respect to the posterior distribution $p(\mathbf{x}_l^t|\mathbf{y}_l^t, \beta_l^t(i_b - 1))$. And the posterior distribution can be approximated with GAMP method, i.e., $p(x_{k,l}^t|\mathbf{y}_l^t, \zeta_{c,k,t}^x(i_b), r_{c,k,t}^x(i_b), \beta_l^t(i_b - 1)) = \mathcal{CN}(x_{k,l}^t|\hat{x}_{k,l}^t(i_b), \phi_{c,k,t}^x(i_b))$, where $\hat{x}_{k,l}^t(i_b)$ is the estimated value of $x_{k,l}^t$ for the i_b -th iteration. Another approximation is made to the noiseless output $\mathbf{z}_{l,t}^x \triangleq \tilde{\mathbf{H}}^t \mathbf{x}_l^t$ and $\mathbf{z}_{l,t}^x = [z_{1,l,t}^x, \dots, z_{N,l,t}^x, \dots, z_{NR,l,t}^x]^T$. Similarly, the approximate posterior distribution of $\mathbf{z}_{l,t}^x$ follows a complex Gaussian distribution $p(z_{c,l,t}^x|\mathbf{y}_l^t, \vartheta_{c,l,t}^x(i_b), \tau_{c,l,t}^x(i_b), \beta_l^t(i_b - 1)) = \mathcal{CN}(z_{c,l,t}^x|\zeta_{c,l,t}^x(i_b), v_{c,l,t}^x(i_b))$. The rest of the formula derivation of GAMP-SBL algorithm can be derived by referring to Section III-B.

When we obtain the estimated $\hat{x}_{k,l}^t(i_b)$, the related $\hat{A}_k(i_b)$ can be updated. If $\hat{x}_{k,l}^t(i_b) = 0$ for all of l and t , we assume GU k is inactive and set $\hat{A}_k(i_b) = 0$.

3) *Joint UID and CE with the transmitted signal*: We have got the rough estimation of the channel before, now we use the estimated value of the transmitted signal to improve the result of CE. Moreover, only the transmitted signal which is considered reliable is used for CE, not all. In this paper, we take a pair of selection conditions to filter out reliable transmitted signal.

Firstly, we take the approximate posterior probability $p(x_{k,l}^t|\mathbf{y}_l^t, \zeta_{c,k,t}^x(i_b), r_{c,k,t}^x(i_b), \beta_l^t(i_b - 1))$ as the basis of reliability and introduce the threshold p_{th} . If $p(x_{k,l}^t|\mathbf{y}_l^t, \zeta_{c,k,t}^x(i_b), r_{c,k,t}^x(i_b), \beta_l^t(i_b - 1)) \geq p_{th}$, we think the symbol $x_{k,l}^t$ is reliable. Besides, as we assumed in Section II-A, the symbols sent by the active GU are selected from the QAM alphabet, and the alphabet does not contain 0. That is to say, if the transmitted symbol $x_{k,l}^t$ of active GU is detected to be 0, we consider this symbol unreliable. Suppose the number of reliable GUs after filtering is K_a , the length of the reliable symbols is L_a .

In addition to formula (6), there is another vector representation of formula (7), i.e.,

$$\mathbf{y}_c^t = \mathbf{X}^t \tilde{\mathbf{h}}_c^t + \mathbf{n}_c^t, \quad (31)$$

Algorithm 2 proposed GAMP-SBL algorithm for joint CE, UID and DD

Input:

The received pilot signal $\mathbf{Y}^p$, pilot symbols $\mathbf{P}$, the received signal $\mathbf{Y}^t$ for $t = 1, 2, \dots, T$;

Output:

The estimated transmitted signal $\hat{\mathbf{X}}^t$ and channel $\hat{\mathbf{H}}^t$ for $t = 1, 2, \dots, T$;

Initialization:

Perform Algorithm 1, $\hat{\mathbf{h}}_k^t(0) = \hat{\mathbf{h}}_k^p \odot (\mathbf{1} \otimes \mathbf{s}_k)$, update $\mathbf{F}^{\text{new}}$, $\mathcal{K}_c^{\text{new}}$ and $\mathcal{N}_k^{\text{new}}$, $\hat{x}_{k,l}^t(0) > 0$, $\phi_{c,k,t}^x(0) > 0$, $\phi_{c,k,t}^h(0) > 0$, $s_{c,l,t}^x(0) = 0$, $s_{c,l,t}^h(0) = 0$, $\beta_{k,l}^t(0)$ and $\alpha_{c,k}^t(0)$

1: **for** $i_b = 1, \dots, I_b$; $t = 1, \dots, T$ **do**

2: **joint UID and DD:**

3: **for** $l = 1, \dots, L$ **do**

4: **for** $c = 1, \dots, NR$ **do**

5: $u_{c,l,t}^x(i_b) = \sum_{k \in \mathcal{K}_c^{\text{new}}} \hat{h}_{c,k}^t(i_b - 1) \hat{x}_{k,l}^t(i_b - 1)$;

6: $\tau_{c,l,t}^x(i_b) = \sum_{k \in \mathcal{K}_c^{\text{new}}} |\hat{h}_{c,k}^t(i_b - 1)|^2 \phi_{k,l,t}^x(i_b - 1)$;

7: $\vartheta_{c,l,t}^x(i_b) = u_{c,l,t}^x(i_b) - \tau_{c,l,t}^x(i_b) s_{c,l,t}^x(i_b - 1)$;

8: $s_{c,l,t}^x(i_b) = \frac{1}{\tau_{c,l,t}^x(i_b)} [\frac{\tau_{c,l,t}^x(i_b) \gamma y_{c,l,t}^t + \vartheta_{c,l,t}^x(i_b)}{\gamma \tau_{c,l,t}^x(i_b) + 1} - \vartheta_{c,l,t}^x(i_b)]$;

9: $z_{c,l,t}^x(i_b) = \frac{\gamma}{\gamma \tau_{c,l,t}^x(i_b) + 1}$;

10: **end for**

11: **for** $k = 1, \dots, K$ **do**

12: $\zeta_{k,l,t}^x(i_b) = (\sum_{c \in \mathcal{N}_k^{\text{new}}} |\hat{h}_{c,k}^t(i_b - 1)|^2 z_{c,l,t}^x(i_b))^{-1}$;

13: $r_{k,l,t}^x(i_b) = \hat{x}_{k,l}^t(i_b - 1) + \zeta_{k,l,t}^x(i_b) \sum_{c \in \mathcal{N}_k^{\text{new}}} (\hat{h}_{c,k}^t(i_b - 1))^* s_{c,l,t}^x(i_b)$;

14: $\hat{x}_{k,l}^t(i_b) = \frac{r_{k,l,t}^x(i_b)}{\beta_{k,l}^t(i_b - 1) \zeta_{k,l,t}^x(i_b) + 1}$ and update $\hat{A}_k(i_b)$;

15: $\phi_{k,l,t}^x(i_b) = \frac{s_{k,l,t}^x(i_b)}{\beta_{k,l}^t(i_b - 1) \zeta_{k,l,t}^x(i_b) + 1}$; $\beta_{k,l}^t(i_b) =$

16: $\frac{2c-1}{|\hat{x}_{k,l}^t(i_b)|^2 + \phi_{k,l,t}^x(i_b) + 2d}$;

17: **end for**

18: **end for**

19: Filter out reliable transmitted signal with a pair of selection conditions;

20: **joint UID and CE with the transmitted signal:**

21: **for** $c = 1, \dots, NR$ **do**

22: **for** $l = 1, \dots, L_a$ **do**

23: $u_{c,l,t}^h(i_b) = \sum_{k \in K_a} \hat{x}_{k,l}^t(i_b) \hat{h}_{c,k}^t(i_b - 1)$; $\tau_{c,l,t}^h(i_b) = \sum_{k \in K_a} |\hat{x}_{k,l}^t(i_b)|^2 \phi_{c,k,t}^h(i_b - 1)$;

24: $\vartheta_{c,l,t}^h(i_b) = u_{c,l,t}^h(i_b) - \tau_{c,l,t}^h(i_b) s_{c,l,t}^h(i_b - 1)$;

25: $s_{c,l,t}^h(i_b) = \frac{1}{\tau_{c,l,t}^h(i_b)} [\frac{\tau_{c,l,t}^h(i_b) \gamma y_{c,l,t}^t + \vartheta_{c,l,t}^h(i_b)}{\gamma \tau_{c,l,t}^h(i_b) + 1} - \vartheta_{c,l,t}^h(i_b)]$;

26: $z_{c,l,t}^h(i_b) = \frac{\gamma}{\gamma \tau_{c,l,t}^h(i_b) + 1}$;

27: **end for**

28: **for** $k = 1, \dots, K_a$ **do**

29: $\zeta_{c,k,t}^h(i_b) = (\sum_{l=1}^{L_a} |\hat{x}_{k,l}^t(i_b)|^2 z_{c,l,t}^h(i_b))^{-1}$;

30: $r_{c,k,t}^h(i_b) = \zeta_{c,k,t}^h(i_b) \sum_{l=1}^{L_a} (\hat{x}_{k,l}^t(i_b))^* s_{c,l,t}^h(i_b) + \hat{h}_{c,k}^t(i_b - 1)$;

31: $\hat{h}_{c,k}^t(i_b) = \frac{\delta r_{c,k,t}^h(i_b)}{\alpha_{c,k}^t(i_b - 1) \zeta_{c,k,t}^h(i_b) + 1} + (1 - \delta) \hat{h}_{c,k}^t(i_b - 1)$;

32: $\phi_{c,k,t}^h(i_b) = \frac{\zeta_{c,k,t}^h(i_b)}{\alpha_{c,k}^t(i_b - 1) \zeta_{c,k,t}^h(i_b) + 1}$; $\alpha_{c,k}^t(i_b) =$

33: $\frac{2a-1}{|\hat{x}_{k,l}^t(i_b)|^2 + \phi_{c,k,t}^h(i_b) + 2b}$;

34: **end for**

35: **end for**

36: Update $\hat{A}_k(i_b)$, $\mathbf{F}^{\text{new}}$, $\mathcal{K}_c^{\text{new}}$ and $\mathcal{N}_k^{\text{new}}$;

37: **end for**

where $\mathbf{y}_c^t = [y_{c,1}^t, y_{c,2}^t, \dots, y_{c,L}^t]^T \in \mathbb{C}^{L \times 1}$ is the received signal on subcarrier n in t -th time slot, $\mathbf{X}^t = [(\mathbf{x}_1^t)^T, (\mathbf{x}_2^t)^T, \dots, (\mathbf{x}_L^t)^T] \in \mathbb{C}^{L \times K}$ is the transmitted signal in t -th time slot, $\mathbf{h}_c^t$ is the c -th row of the matrix $\tilde{\mathbf{H}}^t$ and $\mathbf{n}_c^t$ is the noise vector. Consistent with the above description, we modeled the CE problem for each subcarrier per time slot as a SMV model and we adopt GAMP-SBL algorithm to solve this problem.

The Gaussian likelihood model can be expressed as

$$p(\mathbf{y}_c^t | \tilde{\mathbf{h}}_c^t, \sigma^2) = (2\pi\sigma^2)^{-\frac{L}{2}} \exp(-\frac{1}{2\sigma^2} \|\mathbf{y}_c^t - \mathbf{X}^t \tilde{\mathbf{h}}_c^t\|^2). \quad (32)$$

The hyperparameters α_c^t controls the prior variance of $\tilde{\mathbf{h}}_c^t$, i.e.,

$$p(\tilde{\mathbf{h}}_c^t | \alpha_c^t) = \prod_k^K \mathcal{CN}(\tilde{h}_{c,k}^t | 0, (\alpha_{c,k}^t)^{-1}), \quad (33)$$

and

$$\begin{aligned} p(\alpha_c^t | a, b) &= \prod_k^K \text{Gamma}(\alpha_{c,k}^t | a, b) \\ &= \prod_k^K \Gamma(a)^{-1} b^a (\alpha_{c,k}^t)^{a-1} e^{-b\alpha_{c,k}^t}. \end{aligned} \quad (34)$$

The rest of the formula derivation of GAMP-SBL algorithm can be derived by referring to Section III-B.

In particular, we need to combine the estimated channel of data signal with the estimated channel of pilot signal. Introducing parameter δ , the channel can be updated as

$$\hat{h}_{c,k}^t(i_b) = \frac{\delta r_{c,k,t}^h(i_b)}{\alpha_{c,k}^t(i_b - 1) \zeta_{c,k,t}^h(i_b) + 1} + (1 - \delta) \hat{h}_{c,k}^t(i_b - 1). \quad (35)$$

Similarly, we adopt the threshold η as a measure of whether $\hat{h}_{c,k}^t(i_b)$ is 0, i.e., if $\hat{h}_{c,k}^t(i_b) < \eta$, we set $\hat{h}_{c,k}^t(i_b) = 0$. Consistent with the update process of $\hat{A}_k(0)$ in Section IV-B1, we first update $\hat{A}_{c,k}(i_b)$ as follows:

$$\hat{A}_{c,k}(i_b) = \begin{cases} 1, & \hat{h}_{c,k}^t(i_b) \neq 0 \\ 0, & \hat{h}_{c,k}^t(i_b) = 0 \end{cases} \quad (36)$$

Making use of the sparse structure of LDS-OFDM, if $1/d_v/R \sum_c^{NR} \hat{A}_{c,k}(i_b) \leq \theta$, $\hat{A}_k(i_b) = 0$. Then, the sparse matrix $\mathbf{F}_c^{\text{new}}$, set $\mathcal{K}_c^{\text{new}}$ and $\mathcal{N}_k^{\text{new}}$ can be updated according to (25) and (26). And the whole algorithm is summarized in Algorithm 2.

C. Asymptotic Analysis

The asymptotic analysis of the proposed GAMP-SBL algorithm is performed in two steps: the first step is to analyze

the convergence of the GAMP algorithm embedded in E-step, and the second step is to analyze the integration of GAMP algorithm and SBL.

As a message passing-based algorithm, the convergence performance of the GAMP algorithm can be characterized by state evolution (SE) under the assumption of the large system limit [57]. [55] has proved that the asymptotic behavior of the GAMP algorithm with i.i.d Gaussian transform matrices can be simplified as a set of SE equations which is given below.

For all l, c and k , we have the limits

$$\lim_{K \rightarrow \infty} \zeta_{k,l,t}^x(i_b) = \bar{\zeta}_{l,t}^x(i_b), \quad \lim_{K \rightarrow \infty} \tau_{c,l,t}^x(i_b) = \bar{\tau}_{l,t}^x(i_b), \quad (37)$$

where $\bar{\zeta}_{l,t}^x(i_b) = -\mathbf{E}^{-1}[\frac{\partial g_{out}}{\partial \theta}]$ and $\bar{\tau}_{l,t}^x(i_b) = \bar{\zeta}_{l,t}^x(i_b) \mathbf{E}[\frac{\partial g_{in}}{\partial r}]$ as well as the limits

$$\lim_{K \rightarrow \infty} \zeta_{c,k,t}^h(i_b) = \bar{\zeta}_{c,t}^h(i_b), \quad \lim_{K \rightarrow \infty} \tau_{c,l,t}^h(i_b) = \bar{\tau}_{c,t}^h(i_b), \quad (38)$$

where $\bar{\zeta}_{c,t}^h(i_b) = -\mathbf{E}^{-1}[\frac{\partial g_{out}}{\partial \theta}]$ and $\bar{\tau}_{c,t}^h(i_b) = \bar{\zeta}_{c,t}^h(i_b) \mathbf{E}[\frac{\partial g_{in}}{\partial r}]$. The components of the vector $\mathbf{x}_l^t$ empirically converge with bounded moments of order k as

$$\begin{aligned} \lim_{K \rightarrow \infty} \hat{x}_{k,l}^t(i_b) &= X; \\ \lim_{K \rightarrow \infty} \hat{h}_{c,k}^t(i_b) &= H; \end{aligned} \quad (39)$$

where $X \sim p(x_l^t | \beta_l^t)$ and $H \sim p(\tilde{h}_c^t | \alpha_c^t)$ are random variables. The detailed proof derivation can be found in [58].

According to the analysis of [59], the introduction of damping factor δ in (35) can ensure the global convergence of GAMP algorithm.

The convergence of the GAMP algorithm guarantees that the mean and variance in E-step of the SBL can converge to $\hat{x}_{k,l}^t(i_b)$ and $\hat{A}_k(i_b)$ as well as $\hat{h}_{c,k}^t(i_b)$ and $\phi_{c,k,t}^h(i_b)$. However, there is no guarantee that it can converge to the value required by SBL and this convergence depends on the quality of the GAMP detector. Based on the conclusion in [60], for any transform matrix, the mean obtained by the GAMP algorithm is equal to the true average of the mean required by SBL. If the variance obtained by GAMP detector is equal to the true variance required by SBL, the transmission matrix needs to be large and independent with Gaussian distribution, and in other cases, it is close to the true value. In summary, the mean and variance obtained by the proposed algorithm can approximately converge to the values required by SBL, thus achieving the superior performance of EM-SBL almost.

D. Complexity Analysis

For SBL, the conventional EM algorithm [27] needs to calculate an $K \times K$ matrix inversion of Σ in (16) and the corresponding computational complexity is $\mathcal{O}(K^3)$. Thus, the computational complexity of EM-based SBL algorithm for joint UID and CE becomes $\mathcal{O}(NRK^3)$ and the complexity of joint UID and DD with EM-based SBL algorithm is $\mathcal{O}(LTK^3)$. Obviously, the complexity of the whole system

TABLE I
COMPLEXITY OF DIFFERENT DETECTORS

Detector	Complexity
EM-based SBL	$\mathcal{O}(NRK^3 + LTK^3)$
EM [27]+AMP [62]	$\mathcal{O}(NRKL + LTNK)$
EM [27]+SBL-AMP [61]	$\mathcal{O}(NRKL + LTNr + LTK)$
Proposed joint GAMP-SBL	$\mathcal{O}(N^2RK + LTNK)$

grows rapidly with the number of GUs. By embedding GAMP method into SBL framework, proposed GAMP-SBL algorithm no longer needs to compute matrix inversion, and the corresponding algorithm complexity is reduced to $\mathcal{O}(NK)$. Considering the whole process of the system, the complexity of proposed joint GAMP-SBL is $\mathcal{O}(N^2RK + LTNK)$.

In addition, according to [27], the complexity of the BR-MP-EM algorithm is $\mathcal{O}(NRKL)$. The complexity of the SBL-AMP detector in [61] and AMP algorithm is $\mathcal{O}(LTNR + LTK)$ and $\mathcal{O}(LTNK)$ respectively. The complexity of each algorithm is summarized in [62] the Table I. Compared with EM-based SBL method, the other three algorithms greatly reduce the computational complexity.

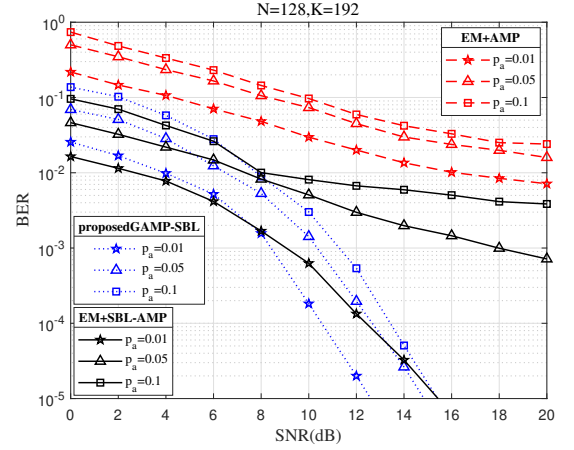
V. NUMERICAL RESULTS

In this section, we carried out a number of simulation experiments to prove the performance of our proposed GAMP-SBL algorithm. To test the performance of the proposed GAMP-SBL algorithm, we compare it with several existing message passing-based algorithms, i.e., the BR-MP-EM algorithm in [27] which performs well against channel impairments, AMP algorithm [62] which is the common variation of the traditional MPA algorithm as well as AMP-SBL algorithm [61] which embed AMP method into SBL framework. Specifically, we combine BR-MP-EM [27] with AMP algorithm [62] and AMP-SBL algorithm [61] respectively as comparison algorithms, where the channel as well as active GUs estimated by BR-MP-EM algorithm are provided for AMP algorithm and AMP-SBL algorithm to detect data. For simplicity, EM [27]+SBL-AMP [61] is used to represent the combination of BR-MP-EM and AMP-SBL algorithms, while EM [27]+AMP [62] is used to represent the combination of BR-MP-EM and AMP algorithms. The simulation parameters are listed in Table II.

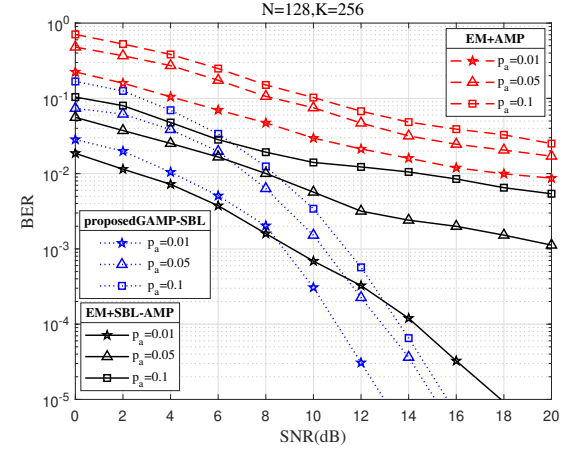
A. BER Results

First, we verify the performance of the three algorithms under different active probability and different user load as shown in Fig. 4(a) and Fig. 4(b) correspond to user load of 150%, and 200%, respectively, i.e., $K = 192$ and $K = 256$.

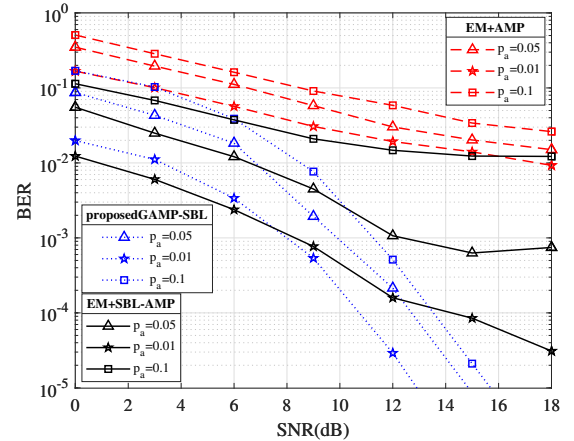
From these two subgraphs, we can find that EM [27]+AMP [62] has the worst performance among the three algorithms with the same number of users and active probability, and the bit error rate of EM [27]+AMP [62] does not reach 10^{-3} . This is because the AMP algorithm needs to know which users are active, and although the BR-MP-EM algorithm can detect active users for it, there is



(a) $N = 128, K = 192$



(b) $N = 128, K = 256$



(c) $N = 512, K = 1024$

Fig. 4. BER performance of EM [27]+AMP [62], EM [27]+SBL-AMP [61] and our proposed GAMP-SBL algorithm when $p_a = 0.01$, $p_a = 0.05$ and $p_a = 0.1$ respectively.

TABLE II
SIMULATION PARAMETERS

Parameters	Notation	Value
Number of antennas	R	2
Modulation order	M	4
Number of users	K	128, 192, 256
Number of subcarriers	N	128
Number of time slots	T	5
Pilot sequence length	L_p	8
Threshold	p_{th}	0.9
Channel update parameter	δ	0.9
LOS amplitude	$ h_{c,k}^{los} ^2$	[0.6, 0.7]
LOS phase	$\varphi_{c,k}^{los}$	$[-\pi, \pi]$
NLOS variance	$v_{c,k}^{nlos}$	[0.2, 0.25]
Phase shift variance	v_θ	$\pi/8$
carrier frequency	f_c	15GHz
sub-carrier spacing	Δf	300kHz
hyperparameter	a^p, a, c	1
hyperparameter	b^p, b, d	10^{-8}

also the possibility of error. If users which are inactive but are detected active, unnecessary inter-user interference (IUI) is introduced. As for the comparison between EM [27]+SBL-AMP [61] and our proposed GAMP-SBL, the performance of EM [27]+SBL-AMP [61] is slightly better than that of proposed GAMP-SBL at low SNR while the performance of proposed GAMP-SBL obviously performs better than EM [27]+SBL-AMP [61] with SNR increase. Furthermore, the error floor occurs in EM [27]+SBL-AMP [61] when $p_a = 0.05$ and $p_a = 0.1$ in Fig. 4(a) and 4(b). When the user overload rate and active probability are low, the difference between EM [27]+SBL-AMP [61] and proposed GAMP-SBL algorithm is not obvious, e.g., EM [27]+SBL-AMP [61] has almost 0.5dB loss compared to the proposed GAMP-SBL algorithm when $BER=10^{-3}$ with $p_a = 0.01$ in Fig. 4(a). As the user overload rate and active probability increase, EM [27]+SBL-AMP [61] can not achieve excellent BER performance but our proposed GAMP-SBL algorithm can.

Besides, because users sharing the same sub-carrier can interfere with each other, as the active probability increases with the same number of users, and as the number of users increases with the same active probability, the BER performance of these three algorithms deteriorates. For instance, EM [27]+AMP [62] with $p_a = 0.05$ has almost 4dB loss compared to $p_a = 0.01$ when $BER=10^{-1}$ and EM [27]+AMP [62] with $p_a = 0.1$ has almost 2dB loss compared to $p_a = 0.05$ in Fig. 4(a). EM [27]+SBL-AMP [61] with $p_a = 0.05$ has almost 5dB loss compared to $p_a = 0.01$ when $BER=10^{-2}$ and EM [27]+AMP [62] with $p_a = 0.1$ has almost 1dB loss compared to $p_a = 0.05$ in Fig. 4(a). proposed GAMP-SBL algorithm with $p_a = 0.05$ has almost 2.5dB loss compared to $p_a = 0.01$ when $BER=10^{-2}$ and EM [27]+AMP [62] with $p_a = 0.1$ has almost 0.5dB loss compared to $p_a = 0.05$ in Fig. 4(a).

Moreover, in order to verify the scalability of the proposed

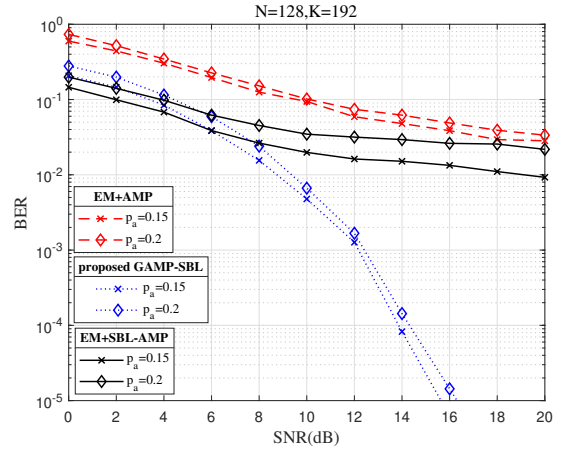


Fig. 5. BER performance of EM [27]+AMP [62], EM [27]+SBL-AMP [61] and our proposed GAMP-SBL algorithm when $p_a = 0.15$ and $p_a = 0.2$ respectively.

GAMP-SBL algorithm in the large-scale satellite network scenario, we simulate the case with 1024 users as well as 512 subcarriers, and the result is shown in Fig. 4(c). Compared with Figure 4(b), the increase of the number of users does not degrade the performance of proposed GAMP-SBL algorithm at the same 200% user load, showing the potential in the mMTC scenarios of future wireless communication networks. By contrast, although the BER performance of EM [27]+SBL-AMP [61] algorithm is improved when the active probability is 0.05, the error floor still appears, and the BER performance deteriorates when $p_a = 0.01$ due to inter-user interference. The BER performance of the EM [27]+AMP [62] algorithm has not changed much.

To further verify the performance of our proposed GAMP-SBL algorithm, we simulate the activate probability of 0.15 and 0.2 with $N = 128$ and $K = 192$, as shown in Fig. 5. Compared with Figure 4(a), the BER performance of all three algorithms is decreased and when $p_a = 0.2$, three algorithms perform worst among all of p_a . EM [27]+AMP [62] still performs worst among three algorithms. The bit error rate of EM [27]+SBL-AMP [61] does not reach 10^{-3} and the error floor appears in EM [27]+SBL-AMP [61], while our proposed GAMP-SBL still performs well. The proposed GAMP-SBL algorithm with $p_a = 0.2$ has almost 0.5dB loss compared to $p_a = 0.15$ when $BER=10^{-2}$.

Different message passing algorithms are adopted in the above comparison. In order to further observe the performance of proposed GAMP-SBL algorithms, Algorithm 1 is uniformly adopted for joint UID and CE, and according to the description in Section IV-B, the property of LDS is utilized to further improve the accuracy of UID. For joint UID and DD, a variety of message passing-based algorithm are compared in Fig. 6 as well as the 100%-loading OMA scheme. Both MPA and AMP [62] detectors cannot complete joint UID and DD when the active user is unknown, and both need a good UID result to achieve good BER performance. For example, we can see a significant BER degradation of the AMP [62] algorithm in Fig. 4(b), when comparing with Fig. 6, as a result of the non-

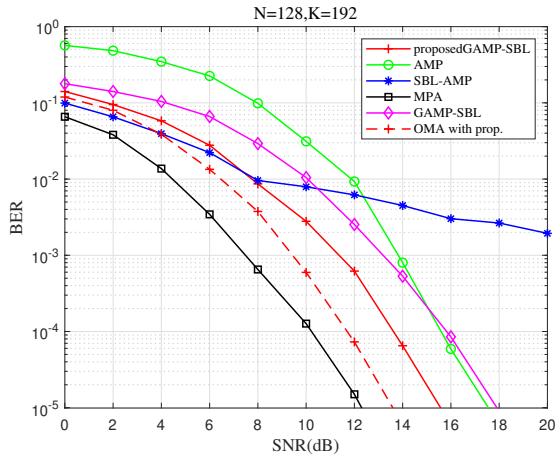


Fig. 6. BER performance of message passing-based detectors when $p_a = 0.1$ with the channel estimated by GAMP-SBL algorithm.

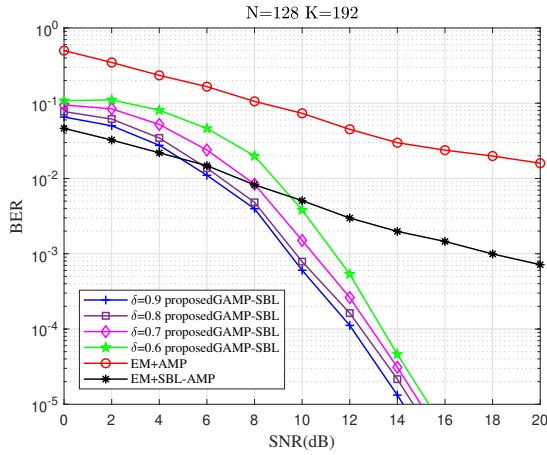


Fig. 7. BER performance of our proposed GAMP-SBL algorithm with different δ when $p_a = 0.05$.

ideal UID results in Fig. 4(b). The MPA algorithm achieves the most superior performance in Fig. 6, also because of the good results of UID at the cost of extremely high computational complexity. The rest of the algorithms are embedded in the SBL framework, which enables detection without the need to know the active GUs. The AMP-SBL [61] algorithm has better BER performance when SNR is relatively small, but error floor occurs. Because the proposed GAMP-SBL algorithm uses data-assisted channel estimation and positively feedbacks the results of DD, its BER performance is always better than that of GAMP-SBL which only performs DD once. In addition, we compare the OMA scheme supporting 128 users in Fig. 6. As we expected, when using the same GAMP-SBL algorithm, the OMA scheme achieves a better BER than 150%-loading LDS-OFDM, but achieves a lower spectrum efficiency.

Fig. 7 compares the BER performance of our proposed GAMP-SBL algorithm with different δ , as well as the EM [27]+AMP [62] and EM [27]+SBL-AMP [61] algorithms. Due to AMP algorithm need to know the active users, the performance of the EM [27]+AMP [62] is always the worst, regardless of δ value. Although the BER performance of our

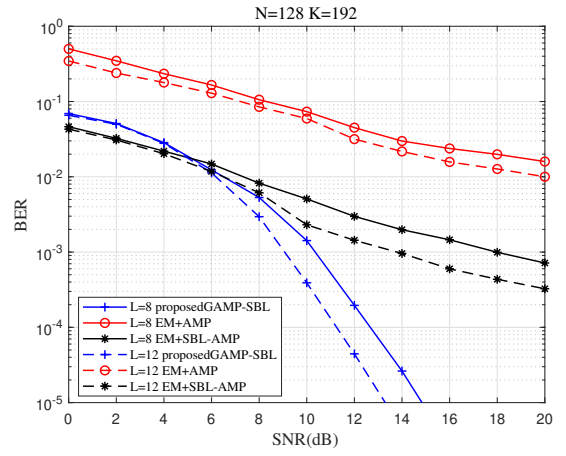


Fig. 8. BER performance of EM [27]+AMP [62], EM [27]+SBL-AMP [61] and our proposed GAMP-SBL algorithm with different length of pilot signal ($L_p = 8$ and $L_p = 12$) when $p_a = 0.05$.

proposed GAMP-SBL algorithm with different δ are worse than that of EM [27]+SBL-AMP [61] when SNR is less than 10 dB, the error floor occurs in EM [27]+SBL-AMP [61] with the increase of SNR while the BER of proposed GAMP-SBL with different δ decrease rapidly. Among all the value of δ , when $\delta = 0.9$ proposed GAMP-SBL algorithm performs best and when $\delta = 0.6$ proposed GAMP-SBL algorithm performs worst.

In order to explore the effect of pilot length on BER performance, we simulate the case of $L = 8$ and $L = 12$ respectively, as shown in Fig. 8. The BER of these three algorithms in Fig. 8 is lower when $L = 12$ than that when $L = 8$. The longer the pilot signal is, the better the performance of CE and UID is, and the better the performance of subsequent signal detection is, that is to say, the lower the bit error rate is. On the other hand, the pilot length is related to access efficiency [27] and the longer the pilot length, the higher the access delay. Therefore, when choosing pilot length, a balance needs to be struck between performance and access latency.

B. Convergence Behavior

Fig. 9 shows the convergence rate of EM [27]+AMP [62], EM [27]+SBL-AMP [61] and our proposed GAMP-SBL algorithm with different threshold p_{th} when SNR=10dB. With the number of iterations increases, the BER of all three algorithms tend to be stable. After about the sixth iteration, all the algorithms tend to be stable except for the proposed GAMP-SBL algorithm with $p_{th} = 0.7$. Comparing these three algorithms, our proposed GAMP-SBL algorithm always has the lowest BER regardless of the p_{th} value. Among all the values of p_{th} , the proposed GAMP-SBL algorithm has the lowest BER when $p_{th} = 0.7$, while the proposed GAMP-SBL algorithm has the highest BER when $p_{th} = 0$. This also proves that if we do not set the threshold to filter the estimated signal, but use all the estimated signal for CE, it will make the error accumulation, thus reducing the bit error rate.

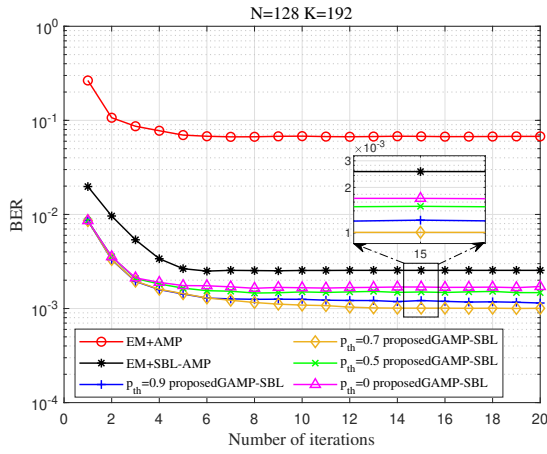


Fig. 9. Convergence rate of our proposed GAMP-SBL algorithm with different threshold p_{th} when $p_a = 0.05$, SNR=10dB.

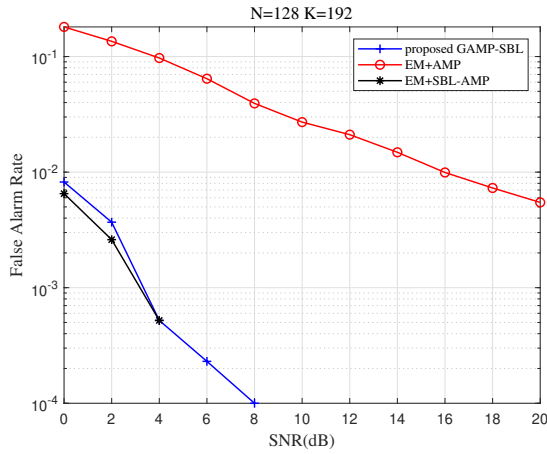


Fig. 10. False Alarm Rate (FAR) of EM [27]+AMP [62], EM [27]+SBL-AMP [61] and our proposed GAMP-SBL algorithm when $p_a = 0.1$.

C. UID Results

To characterize the performance of the proposed GAMP-SBL algorithm, the results of UID is given in Fig. 10, where FAR denotes the proportion of GUs whose status is incorrect in the total number of GUs. FAR of EM [27]+AMP [62] performs worst and it doesn't reach 10^{-3} . The UID results of EM [27]+AMP [62] is consistent with the BER results, because great UID results could not be obtained in CE and UID, introducing redundant IUI, and thus BER results is poor. This also confirms the effectiveness of using the sparse structure of LDS-OFDM to improve the precision of UID. Similarly, the proposed GAMP-SBL algorithm has excellent BER performance as well as UID performance. However, the UID performance of EM [27]+SBL-AMP [61] algorithm is excellent, which shows that the error floor in BER results is not caused by UID, but by AMP-SBL algorithm in signal detection.

VI. CONCLUSION

In this paper, the GAMP-SBL algorithm was proposed for CE and UID of the uplink grant-free NOMA of S-IoT, where the GAMP algorithm was embedded to the SBL framework. Furthermore, we develop an iterative GAMP-SBL algorithm-based receiver to address joint UID, CE and DD. The simulation results demonstrated that our algorithm has superior BER performance as well as FAR, and mitigates the error-floor problem that occurred in benchmark schemes.

In the future, we will extend our research to study the multiple access schemes for the LEO satellite constellation, investigating the impact of multiple satellites on the system performance, and modelling the LEO movement to investigate the influence of the constellation movement.

REFERENCES

- [1] Y. Zuo, M. Yue, M. Zhang, S. Li, S. Ni, and X. Yuan, "OFDM-based massive connectivity for LEO satellite internet of things," *IEEE Transactions on Wireless Communications*, pp. 1–1, 2023.
- [2] W. U. Khan, J. Liu, F. Jameel, V. Sharma, R. Jäntti, and Z. Han, "Spectral efficiency optimization for next generation NOMA-enabled IoT networks," *IEEE Transactions on Vehicular Technology*, vol. 69, pp. 15284–15297, Dec. 2020.
- [3] S. Khairy, P. Balaprakash, L. X. Cai, and H. V. Poor, "Data-driven random access optimization in multi-cell IoT networks using NOMA," *IEEE Transactions on Wireless Communications*, vol. 21, pp. 4938–4953, July 2022.
- [4] Y. Qian, L. Ma, and X. Liang, "Symmetry chirp spread spectrum modulation used in LEO satellite internet of things," *IEEE Communications Letters*, vol. 22, pp. 2230–2233, Nov. 2018.
- [5] J. Chu, X. Chen, C. Zhong, and Z. Zhang, "Robust design for NOMA-based multibeam LEO satellite internet of things," *IEEE Internet of Things Journal*, vol. 8, pp. 1959–1970, Feb. 2021.
- [6] A. K. Dwivedi, S. Praneeth Chokkarapu, S. Chaudhari, and N. Varshney, "Performance analysis of novel direct access schemes for LEO satellites based IoT network," in *2020 IEEE 31st Annual International Symposium on Personal, Indoor and Mobile Radio Communications*, pp. 1–6, Aug. 2020.
- [7] Z. Yin, N. Cheng, Y. Hui, W. Wang, L. Zhao, K. Aldubaikhy, and A. Alqasir, "Multi-domain resource multiplexing based secure transmission for satellite-assisted IoT: AO-SCA approach," *IEEE Transactions on Wireless Communications*, pp. 1–1, 2023.
- [8] Z. Qu, G. Zhang, H. Cao, and J. Xie, "LEO satellite constellation for internet of things," *IEEE Access*, vol. 5, pp. 18391–18401, 2017.
- [9] Y. Lyu, Z. Liu, R. Fan, C. Zhan, H. Hu, and J. An, "Optimal computation offloading in collaborative LEO-IoT enabled MEC: A multiagent deep reinforcement learning approach," *IEEE Transactions on Green Communications and Networking*, vol. 7, pp. 996–1011, June 2023.
- [10] X. Liu, H. Zhang, K. Long, A. Nallanathan, and V. C. M. Leung, "Deep dyna-reinforcement learning based on random access control in LEO satellite IoT networks," *IEEE Internet of Things Journal*, vol. 9, pp. 14818–14828, Aug. 2022.
- [11] J. Jeong and D. Hong, "Two-stage preamble detector for LEO satellite-based NTN IoT random access," *IEEE Transactions on Vehicular Technology*, pp. 1–14, 2023.
- [12] F. Wei, W. Chen, Y. Wu, J. Ma, and T. A. Tsiftsis, "Message-passing receiver design for joint channel estimation and data decoding in uplink grant-free SCMA systems," *IEEE Transactions on Wireless Communications*, vol. 18, pp. 167–181, Jan. 2019.
- [13] J. Son, H. Lee, I. Jung, and D. Hong, "Exploiting intentional frequency offset in NOMA-OFDM systems: From basic to practical," *IEEE Transactions on Wireless Communications*, vol. 22, no. 10, pp. 7087–7097, 2023.
- [14] A. Chauhan, S. Ghosh, and A. Jaiswal, "RIS partition-assisted non-orthogonal multiple access (NOMA) and quadrature-NOMA with imperfect SIC," *IEEE Transactions on Wireless Communications*, vol. 22, no. 7, pp. 4371–4386, 2023.
- [15] M. A. Arfaoui, A. Ghayeb, C. Assi, and M. Qaraqe, "Comp-assisted NOMA and cooperative NOMA in indoor VLC cellular systems," *IEEE Transactions on Communications*, vol. 70, no. 9, pp. 6020–6034, 2022.

- [16] S. Wu, C. Guo, Z. Deng, J. Jiao, N. Zhang, and Q. Zhang, "Optimizing age of information in adaptive NOMA/OMA/cooperative-SWIPT-NOMA system," *IEEE Transactions on Wireless Communications*, vol. 21, no. 12, pp. 11125–11138, 2022.
- [17] A. Krishnamoorthy and R. Schober, "Uplink and downlink MIMO-NOMA with simultaneous triangularization," *IEEE Transactions on Wireless Communications*, vol. 20, no. 6, pp. 3381–3396, 2021.
- [18] Y. Sun, Z. Ding, and X. Dai, "On the outage performance of network NOMA (N-NOMA) modeled by poisson line cox point process," *IEEE Transactions on Vehicular Technology*, vol. 70, no. 8, pp. 7936–7950, 2021.
- [19] Z. Gao, A. Liu, C. Han, and X. Liang, "Sum rate maximization of massive MIMO NOMA in LEO satellite communication system," *IEEE Wireless Communications Letters*, vol. 10, no. 8, pp. 1667–1671, 2021.
- [20] F. Zheng, Z. Pi, Z. Zhou, M. Ye, and H. Qiu, "NOMA-based collaborative beam hopping frequency allocation mechanism for future LEO satellite systems," *China Communications*, vol. 20, no. 6, pp. 321–338, 2023.
- [21] A. Wang, L. Lei, X. Hu, E. Lagunas, A. I. Pérez-Neira, and S. Chatzinotas, "Adaptive beam pattern selection and resource allocation for NOMA-based LEO satellite systems," in *GLOBECOM 2022 - 2022 IEEE Global Communications Conference*, pp. 674–679, 2022.
- [22] H. Yu, H. Zhao, Z. Fei, J. Wang, Z. Chen, and Y. Gong, "Deep-reinforcement-learning-based NOMA-aided slotted ALOHA for LEO satellite IoT networks," *IEEE Internet of Things Journal*, vol. 10, no. 20, pp. 17772–17784, 2023.
- [23] Q. Hu, J. Jiao, S. Wu, R. Lu, and Q. Zhang, "Los-aware handover uplink NOMA transmissions for multi-layer LEO satellite constellation," in *GLOBECOM 2022 - 2022 IEEE Global Communications Conference*, pp. 1187–1192, 2022.
- [24] X. Zhou, K. Ying, Z. Gao, Y. Wu, Z. Xiao, S. Chatzinotas, J. Yuan, and B. Ottersten, "Active terminal identification, channel estimation, and signal detection for grant-free NOMA-OTFS in LEO satellite internet-of-things," *IEEE Transactions on Wireless Communications*, vol. 22, pp. 2847–2866, Apr. 2023.
- [25] Y. Zhang, Q. Guo, Z. Wang, J. Xi, and N. Wu, "Block sparse Bayesian learning based joint user activity detection and channel estimation for grant-free NOMA systems," *IEEE Transactions on Vehicular Technology*, vol. 67, pp. 9631–9640, Oct. 2018.
- [26] Y. Mei, Z. Gao, Y. Wu, W. Chen, J. Zhang, D. W. K. Ng, and M. Di Renzo, "Compressive sensing-based joint activity and data detection for grant-free massive IoT access," *IEEE Transactions on Wireless Communications*, vol. 21, pp. 1851–1869, Mar. 2022.
- [27] Z. Zhang, Y. Li, C. Huang, Q. Guo, L. Liu, C. Yuen, and Y. L. Guan, "User activity detection and channel estimation for grant-free random access in LEO satellite-enabled internet of things," *IEEE Internet of Things Journal*, vol. 7, pp. 8811–8825, Sept. 2020.
- [28] P. Gao, Z. Liu, P. Xiao, C. H. Foh, and J. Zhang, "Low-complexity channel estimation and multi-user detection for uplink grant-free NOMA systems," *IEEE Wireless Communications Letters*, vol. 11, pp. 263–267, Feb. 2022.
- [29] A. Guidotti, A. Vanelli-Coralli, M. Conti, S. Andrenacci, S. Chatzinotas, N. Maturo, B. Evans, A. Awoseyila, A. Ugolini, T. Foggi, L. Gaudio, N. Alagha, and S. Cioni, "Architectures and key technical challenges for 5G systems incorporating satellites," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 3, pp. 2624–2639, 2019.
- [30] C. Amatetti, M. Alsenwi, H. Chougrani, A. Vanelli-Coralli, and M. R. Palattella, "A novel twofold approach to enhance NB-IoT MAC procedure in NTN," *IEEE Journal on Selected Areas in Communications*, vol. 42, no. 5, pp. 1453–1464, 2024.
- [31] Y. Ma, G. Ma, N. Wang, Z. Zhong, J. Yuan, and B. Ai, "Enabling OTFS-TSMA for smart railways mMTC over LEO satellite: A differential doppler shift perspective," *IEEE Internet of Things Journal*, vol. 10, no. 6, pp. 4799–4814, 2023.
- [32] T. Yang, J. Jiao, S. Wu, R. Lu, and Q. Zhang, "Grant free age-optimal random access protocol for satellite-based internet of things," *IEEE Transactions on Communications*, vol. 70, no. 6, pp. 3947–3961, 2022.
- [33] M. Asad Ullah, G. Pasolini, K. Mikhaylov, and H. Alves, "Understanding the limits of LoRa direct-to-satellite: The Doppler perspectives," *IEEE Open Journal of the Communications Society*, vol. 5, pp. 51–63, 2024.
- [34] C. Zhang, L. Wang, L. Jiao, S. Wang, J. Shi, and J. Yue, "A novel orthogonal LoRa multiple access algorithm for satellite internet of things," *China Communications*, vol. 19, pp. 279–289, Mar. 2022.
- [35] T. Petermann, F. Clazzer, A. Munari, and M. Gardill, "Internet of things via satellite: A multiple-access performance study of LoRa and its enhancements," in *2022 11th Advanced Satellite Multimedia Systems Conference and the 17th Signal Processing for Space Communications Workshop (ASMS/SPSC)*, (Graz, Austria), pp. 1–8, IEEE, Sept. 2022.
- [36] S. Herrería-Alonso, M. Rodríguez-Pérez, R. F. Rodríguez-Rubio, and F. Pérez-Fontán, "Improving uplink scalability of LoRa-based direct-to-satellite IoT networks," *IEEE Internet of Things Journal*, vol. 11, pp. 12526–12535, Apr. 2024.
- [37] R. Yuan and J. Zheng, "Parallel adaptive subspace pursuit algorithm for multiuser detection of uplink grant-free NOMA," in *2021 IEEE Wireless Communications and Networking Conference (WCNC)*, pp. 1–5, Mar. 2021.
- [38] P. Gao, Z. Liu, P. Xiao, C. H. Foh, and J. Zhang, "Low-complexity block coordinate descend based multiuser detection for uplink grant-free NOMA," *IEEE Transactions on Vehicular Technology*, vol. 71, pp. 9532–9543, Sept. 2022.
- [39] X. Zou, F. Li, J. Fang, and H. Li, "Computationally efficient sparse Bayesian learning via generalized approximate message passing," in *2016 IEEE International Conference on Ubiquitous Wireless Broadband (ICUWB)*, pp. 1–4, Oct. 2016.
- [40] X. Zhang, P. Fan, J. Liu, and L. Hao, "Bayesian learning-based multiuser detection for grant-free NOMA systems," *IEEE Transactions on Wireless Communications*, vol. 21, pp. 6317–6328, Aug. 2022.
- [41] X. Zhang, P. Fan, L. Hao, and X. Quan, "Generalized approximate message passing based Bayesian learning detectors for uplink grant-free NOMA," *IEEE Transactions on Vehicular Technology*, pp. 1–6, 2023.
- [42] Y. Wang, X. Zhu, E. G. Lim, Z. Wei, Y. Liu, and Y. Jiang, "Compressive sensing based user activity detection and channel estimation in uplink NOMA systems," in *2020 IEEE Wireless Communications and Networking Conference (WCNC)*, pp. 1–6, May 2020.
- [43] X. Zhang, F. Labeau, L. Hao, and J. Liu, "Joint active user detection and channel estimation via Bayesian learning approaches in MTC communications," *IEEE Transactions on Vehicular Technology*, vol. 70, pp. 6222–6226, June 2021.
- [44] S. Jiang, X. Yuan, X. Wang, C. Xu, and W. Yu, "Joint user identification, channel estimation, and signal detection for grant-free NOMA," *IEEE Transactions on Wireless Communications*, vol. 19, pp. 6960–6976, Oct. 2020.
- [45] C. Guo, X. Chen, J. Yu, and Z. Xu, "Design of joint device and data detection for massive grant-free random access in LEO satellite internet of things," *IEEE Internet of Things Journal*, vol. 10, pp. 7090–7099, Apr. 2023.
- [46] M. Ying, X. Chen, and X. Shao, "Exploiting tensor-based Bayesian learning for massive grant-free random access in LEO satellite internet of things," *IEEE Transactions on Communications*, vol. 71, pp. 1141–1152, Feb. 2023.
- [47] Y. Zuo, M. Yue, M. Zhang, S. Li, S. Ni, and X. Yuan, "OFDM-based massive connectivity for LEO satellite internet of things," *IEEE Transactions on Wireless Communications*, vol. 22, no. 11, pp. 8244–8258, 2023.
- [48] B. Shen, Y. Wu, J. An, C. Xing, L. Zhao, and W. Zhang, "Random access with massive MIMO-OTFS in LEO satellite communications," *IEEE Journal on Selected Areas in Communications*, vol. 40, pp. 2865–2881, Oct. 2022.
- [49] A. Abdi, W. Lau, M. Alouini, and M. Kaveh, "A new simple model for land mobile satellite channels: First- and second-order statistics," *IEEE Transactions on Wireless Communications*, vol. 2, pp. 519–528, May 2003.
- [50] M. R. Bhatnagar, "Making two-way satellite relaying feasible: A differential modulation based approach," *IEEE Transactions on Communications*, vol. 63, pp. 2836–2847, Aug. 2015.
- [51] M. Karaliopoulos and F.-N. Pavlidou, "Modelling the land mobile satellite channel: A review," *Electronics & Communication Engineering Journal*, vol. 11, pp. 235–248, Oct. 1999.
- [52] K. Baddour and N. Beaulieu, "Autoregressive modeling for fading channel simulation," *IEEE Transactions on Wireless Communications*, vol. 4, pp. 1650–1662, July 2005.
- [53] M. E. Tipping, "Sparse Bayesian learning and the relevance vector machine," *Journal of machine learning research*, vol. 1, no. Jun, pp. 211–244, 2001.
- [54] J. Fang, Y. Shen, H. Li, and P. Wang, "Pattern-coupled sparse Bayesian learning for recovery of block-sparse signals," *IEEE Transactions on Signal Processing*, vol. 63, no. 2, pp. 360–372, 2015.
- [55] S. Rangan, "Generalized approximate message passing for estimation with random linear mixing," in *2011 IEEE International Symposium on Information Theory Proceedings*, (St. Petersburg, Russia), pp. 2168–2172, IEEE, July 2011.

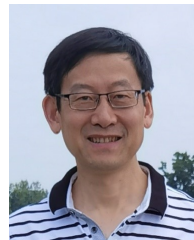
- [56] J. Fang, L. Zhang, and H. Li, "Two-dimensional pattern-coupled sparse Bayesian learning via generalized approximate message passing," *IEEE Transactions on Image Processing*, vol. 25, pp. 2920–2930, June 2016.
- [57] M. Luo, Q. Guo, M. Jin, Y. C. Eldar, D. Huang, and X. Meng, "Unitary approximate message passing for sparse Bayesian learning," *IEEE Transactions on Signal Processing*, vol. 69, pp. 6023–6039, 2021.
- [58] S. Rangan, "Generalized approximate message passing for estimation with random linear mixing," 2012.
- [59] S. Rangan, P. Schniter, and A. Fletcher, "On the convergence of approximate message passing with arbitrary matrices," in *2014 IEEE International Symposium on Information Theory*, (Honolulu, HI, USA), pp. 236–240, IEEE, 2014.
- [60] S. Rangan, P. Schniter, E. Riegler, A. K. Fletcher, and V. Cevher, "Fixed points of generalized approximate message passing with arbitrary matrices," *IEEE Transactions on Information Theory*, vol. 62, no. 12, pp. 7464–7474, 2016.
- [61] M. Al-Shoukairi and B. Rao, "Sparse Bayesian learning using approximate message passing," in *2014 48th Asilomar Conference on Signals, Systems and Computers*, pp. 1957–1961, Nov. 2014.
- [62] J. Dai, K. Niu, and J. Lin, "Iterative Gaussian-approximated message passing receiver for MIMO-SCMA system," *IEEE Journal of Selected Topics in Signal Processing*, vol. 13, no. 3, pp. 753–765, 2019.



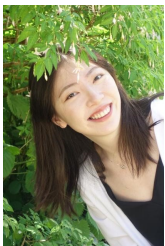
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