Grant-Free MIMO-NOMA With Differential Modulation for Machine-Type Communications

Yuanyuan Zhang, Zhengdao Yuan, Qinghua Guo, Senior Member, IEEE, Zhongyong Wang, Senior Member, IEEE, Jiangtao Xi, Senior Member, IEEE, Yanguang Yu, Senior Member, IEEE, and Yonghui Li, Fellow, IEEE

Abstract—This article considers a challenging scenario of machine-type communications, where we assume Internet of Things (IoT) devices send short packets sporadically to an access point (AP) and the devices are not synchronized in the packet level. High-transmission efficiency and low latency are concerned. Motivated by the great potential of multiple-input–multiple-output nonorthogonal multiple access (MIMO-NOMA) in massive access, we design a grant-free MIMO-NOMA scheme, and in particular differential modulation is used so that expensive channel estimation at the receiver (AP) can be bypassed. The receiver at AP needs to carry out active device detection and multidevice data detection. The active user detection is formulated as the estimation of the common support of sparse signals, and a message-passing-based sparse Bayesian learning (SBL) algorithm is designed to solve the problem. Due to the use of differential modulation, we investigate the problem of noncoherent multidevice data detection, and develop a message-passing-based Bayesian data detector, where the constraint of differential modulation is exploited to drastically improve the detection performance, compared to the conventional noncoherent detection scheme. Simulation results demonstrate the effectiveness of the proposed active device detector and noncoherent multidevice data detector.

Index Terms—Grant free, Internet of Things (IoT), machine-type communications, message passing, multiple-input–multiple-output (MIMO), nonorthogonal multiple access (NOMA).

I. INTRODUCTION

As an enabler for the Internet of Things (IoT), massive machine-type communications have attracted much attention, which is characterized by massive connections and sporadic short-burst transmissions [1], [2]. Various IoT communication transmission scheduling mechanism have been studied in [3], [4], [5], and [6]. Due to the limited spectral resource, it is difficult to use the orthogonal multiple access (OMA) scheme to provide connectivity for a massive number of IoT devices. Nonorthogonal multiple access (NOMA), where a resource block is used to serve multiple users [7], [8], [9], is considered to meet the demands on low latency and massive connectivity. The existing NOMA schemes can be mainly divided into two categories, i.e., power domain multiplexing, such as basic power-domain NOMA [10], [11], [12], [13], [14], and code domain multiplexing which includes low-density spreading (LDS) multiple access [15], sparse code multiple access (SCMA) [16], [17], etc. Moreover, in grant-based network, the handshaking between the receiver and the transmitter must be processed before the data transmission, i.e., data transmission requires a “Grant” [18]. Due to the handshaking procedure, the conventional grant-based transmission schemes may incur uncertain latency and excessive signaling overhead, which makes the communications inefficient, especially in the case that IoT devices have only a small amount of payload data, e.g., a few bits for each transmission [19], [20]. Therefore, grant-free transmission without handshaking procedure, where users can randomly transmit data at any time instant, is highly desirable, which can save a huge amount of signaling overhead and reduce the communication latency to ensure the real-time communication of IoT, and that is very attractive for dynamic scenarios, e.g., in Internet of Vehicles (IoV). The grant-free NOMA [21], [22], [23], [24], [25], which uses a resource block to serve multiple users and does not need the handshaking procedure, is a very promising technique for machine-type communications.

A. Recent Works and Motivation

Recently, to further enhance the spectrum efficiency, multiuser access and/or communication reliability, NOMA has been combined with multiple-input–multiple-output (MIMO), leading to MIMO-NOMA [26], [27], [28]. The performance of MIMO-NOMA schemes have been studied...
in [29], [30], and [31]. With the assumption that the channel state information (CSI) is available to the receiver, various signal processing techniques, such as those based on Karush–Kuhn–Tucker (KKT) conditions [32], Gaussian message passing (GMP) [33], and improved Bayesian learning [34], have been studied. For practical applications, the CSI has to be acquired via training signals for coherent detection [35], [36], and a MIMO-NOMA receiver based on deep learning is proposed in [37], where a deep neural network is implemented for the joint estimation of channel parameters and the detection of signals. However, due to the large number of variables to be estimated, the acquisition of accurate instantaneous CSI for (massive) MIMO leads to significant training overhead, and channel estimation is a challenging task, especially in the scenarios that wireless channels are fast time varying. The implementation of grant-free MIMO-NOMA systems is even more challenging, but it has great potential for massive machine-type communications.

This article deals with the design of grant-free MIMO-NOMA for machine-type communications, where each device is equipped with a single antenna and the access point (AP) is equipped with a (massive) number of antennas. We assume that the data payload of the devices is small (e.g., a few bits), and the devices send information to an AP randomly. In addition, the data packet length of the devices is not fixed, so the devices are not synchronized in the packet level, i.e., any device is allowed to freely access the channel whenever it has information to transmit, and it becomes inactive when its packet is delivered. Due to the high flexibility of the transmission and the consideration of high-transmission efficiency, the realization of the system is very challenging, especially the implementation of the receiver at the AP, as it needs to identify the active devices and perform multidevice data detection. The conventional grant-free NOMA strategy is to first perform active user identification and channel estimation, followed by coherent data detection. However, due to a large number of antennas at the AP and the data packet of the devices is very short, the conventional strategy will render the transmissions highly inefficient due to the requirement of long training signals for active user identification and channel estimation. Even the large training overhead is not an issue, it is unknown how to use the conventional strategy to handle the asynchronous transmissions of the IoT devices, where the devices have different packet lengths and are allowed to access and leave the channel freely.

**B. Contributions**

The main contributions of this work are summarized below.

1) We propose to solve the challenge by adopting differential modulation at the devices and designing noncoherent multidevice data detection at the AP. Such design can bypass channel estimation. The implementation of the transmitters is very simple, where each device is assigned a spreading sequence and transmits information with differential modulation. The receiver needs to first identify active users without the assistance of any training signals, and then perform multidevice data detection for the active users.

2) We assume that the channels remain constant over two consecutive symbol intervals. The active user detection and multidevice data detection are performed symbol by symbol, so that the devices are allowed to access and leave the channel freely without packet level synchronization and channel estimation, which are the key to achieve high flexibility and high efficiency. To this end, the design of efficient active user detector and multidevice data detector is crucial.

3) We use the factor graph and message passing techniques to address the problem. With the sparsity of active users, the active device detection is formulated as common support estimation of sparse signals, and we develop a message-passing-based sparse Bayesian learning (SBL) algorithm to solve it, where belief propagation (BP) [38] and mean field (MF) [39], [40] are combined to implement the SBL. After active users are identified, noncoherent data detection needs to be performed. For this, we investigate the problem of noncoherent multidevice detection problem and design a BP-MF message-passing-based data detector, which treats the differential modulation as a constraint and encodes it into a probabilistic form as a local function in the factor graph representation. We show that exploiting the constraint can improve the detection performance remarkably, compared to the conventional detection scheme. Simulation results are provided to demonstrate the effectiveness of the proposed scheme and superior performance of the developed algorithms.

The remainder of this article is organized as follows. In Section II, the grant free MIMO-NOMA system is designed and the problems of active device detection and noncoherent multidevice data detection are formulated. Message passing-based noncoherent receiver is developed in Section III. Numerical simulation results are provided in Section IV, followed by conclusions in Section V.

**Notation:** Lowercase and uppercase letters denote scalars. Boldface lowercase and uppercase letters denote column vectors and matrices, respectively. The superscriptions (·)T and (·)H denote the transpose and conjugate transpose operations, respectively, and ∝ denotes equality of functions up to a scale factor. The function CN(x; ̄x, σ2) stands for a complex Gaussian distribution with mean ̄x and variance σ2. As the convention, ∫∫f(x, y, z)g(x, y, z)dxdydz is used to denote the marginalization operator. The expectation operator with respect to a scaled probability density function (PDF) g(x) is expressed by <x>g(x) = ∫fxg(x)dxdydz g(x)dx, and Var[x]g(x) = ∫x2g(x)dxdydz g(x)dx − <x>g(x)2 stands for the variance of x.

**II. GRANT FREE MIMO-NOMA SYSTEM MODEL AND PROBLEM FORMULATION**

**A. Grant Free MIMO-NOMA With Differential Modulation**

The grant free MIMO-NOMA system is illustrated in Fig. 1. The key notations are listed in Table I. We assume an
IoT communication system, where an AP equipped with \( N \) antennas is used to serve \( U \) IoT devices, each equipped with a single antenna. In particular, we consider uplink transmission, i.e., the IoT devices send information to the AP. As the transmissions of the IoT devices are sporadic, i.e., not all devices are active at the same time, we use \( K \) to denote the number of active devices served by the AP.

Due to the small payload of the IoT devices, the requirement of low latency and (larger) number of antennas used at the AP, the use of training symbols for channel estimation and active device detection is not preferable. In this work, we design a noncoherent scheme and differential modulation is employed by the IoT devices, so that the use of training symbols can be avoided. As show in Fig. 1(b), the input bit stream \( b_u \) of device \( u \) is mapped to a symbol sequence \( s_u = [s_{u,0}, s_{u,1}, \ldots, s_{u,T-1}] \) with differential modulation, e.g., M-ary differential phase shift keying (DPSK), where \( T \) is the length of the symbol sequence and \( s_{u,0} \) is a known reference symbol that is drawn from the M-ary DPSK constellation set \( \mathcal{X} \). Then, each symbol in \( s_u \) is spread onto \( L \) chips using a unique spreading sequence \( \mathbf{h}_u \in \mathbb{C}^{L \times 1} \) for device \( u \), which is a column of the spreading matrix \( \mathbf{H} = [\mathbf{h}_1, \mathbf{h}_2, \ldots, \mathbf{h}_U] \). To support a large number of users with spreading sequences of limited length, the spreading sequences are not orthogonal. In this article, the Zadoff–Chu (ZC) sequences with different roots and shifts are employed as the spreading sequences. As not all users are active, we define \( A_u \) as the activity indicator for device \( u \), which takes 1 if the device is active, and 0 otherwise. The \( t \)-th equivalent transmitted symbol of device \( u \) is denoted as

\[
\tilde{\mathbf{s}}^{(t)}_u = A_u s_{u,t}.
\]

Then, the received signal at the \( n \)-th antenna can be expressed as

\[
\mathbf{y}^{(n)} = \mathbf{P} \mathbf{H}_n \tilde{\mathbf{s}}^{(t)} + \mathbf{w}_n^{(n)}
\]

where \( \mathbf{y}^{(n)} \in \mathbb{C}^{L \times 1} \), \( \mathbf{H}_n = \text{diag}(\mathbf{h}_n) \) is a diagonal matrix, whose diagonal elements are given by \( \mathbf{h}_n = [h_{1,n}, h_{2,n}, \ldots, h_{U,n}] \), \( h_{u,n} \) is the channel coefficient between device \( u \) and the \( n \)-th antenna, which is complex Gaussian distributed with zero mean, \( \tilde{\mathbf{s}}^{(t)} = [s^{(t)}_1, s^{(t)}_2, \ldots, s^{(t)}_L]^\top \) is the \( t \)-th transmitted equivalent symbol vector of length \( U \), whose element \( s^{(t)}_u \) takes a value from the complex-constellation set \( \mathcal{X} \approx \{ |X| \} \), and the noise vector on the \( n \)-th antenna \( \mathbf{w}_n^{(n)} \sim \mathcal{CN}(\mathbf{w}_n^{(n)}, 0, \sigma^2_n \mathbf{I}_L) \).

The received signals by \( N \) antennas can be expressed in a matrix form as

\[
\mathbf{Y}^{(t)} = \mathbf{P} \mathbf{H}_1 \mathbf{s}^{(t)} + \vdots + \mathbf{H}_U \mathbf{s}^{(t)} + \mathbf{W}^{(t)}
\]

where \( \mathbf{Y}^{(t)} = [\mathbf{y}_1^{(t)}, \mathbf{y}_2^{(t)}, \ldots, \mathbf{y}_N^{(t)}] \) is a matrix of size \( L \times N \), and \( \mathbf{W}^{(t)} \in \mathbb{C}^{L \times N} \) is a matrix of white Gaussian noise whose power is unknown.

As mentioned before, the IoT devices are allowed to access and leave the channel freely as they may need to transmit their data to the AP randomly with varying packet length. By taking advantage of differential modulation, our aim is to obtain the transmitted information of active devices, while avoiding the estimation of the channel coefficients. To achieve this, both active device detection and data detection need to be carried out based on two consecutive received matrices \( \mathbf{Y}^{(t)} \) and \( \mathbf{Y}^{(t-1)} \), corresponding to two consecutive symbol intervals.

### B. Problem Formulation

Define \( \mathbf{X}_u^{(t)} = \mathbf{H}_u \mathbf{s}_u^{(t)} \), where \( \mathbf{s}_u^{(t)} = [s^{(t)}_{u,1}, s^{(t)}_{u,2}, \ldots, s^{(t)}_{u,T}]^\top \) is a vector of length \( U \) and \( A_{u,n} = A_u h_{u,n} a_{u,t} \). From (3), we have

\[
\mathbf{Y}^{(t)} = \mathbf{P} \mathbf{X}^{(t)} + \mathbf{W}^{(t)}
\]

where \( \mathbf{X}^{(t)} = [\mathbf{x}_1^{(t)}, \mathbf{x}_2^{(t)}, \ldots, \mathbf{x}_N^{(t)}] \) is a \( U \times N \) matrix. As joint active device detection and data detection (multidevice detection) will lead to high complexity, we adopt a two-stage strategy, i.e., performing active device identification followed by data detection.

#### 1) Active Device Detection

As only \( K \) out of \( U \) users are active, according to the definition of \( \mathbf{X}^{(t)} \), we can see that each column of the matrix is a sparse vector, and all the columns share a common support. We need to find the nonzero rows of \( \mathbf{X}^{(t)} \), then identify the spreading sequences of active users according to the indices of the nonzero rows (thereby active devices are detected). We define the common support of \( \mathbf{X}^{(t)} \) as a set \( \mathcal{U}_d \) whose elements are the indices of the nonzero rows of \( \mathbf{X}^{(t)} \). Note that the cardinality of \( \mathcal{U}_d \) is the number of active users, i.e., \( K = |\mathcal{U}_d| \). Hence, active device detection can be formulated as a problem of recovering sparse vectors with

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**Table I**

| Notation | Description |
|----------|-------------|
| \( N \)  | Number of antennas at AP |
| \( n \)  | Antenna index |
| \( U \)  | Total number of devices |
| \( u \)  | Device index |
| \( K \)  | Number of active devices |
| \( k \)  | Active device index |
| \( T \)  | Length of the symbol sequence |
| \( t \)  | Symbol index |
| \( L \)  | Length of spreading sequences (i.e. Number of subcarriers) |
| \( l \)  | Subcarrier index |
| \( N_d \) | DPSK demodulation symbol set |
a common support, and we will design a SBL algorithm to solve it.

Based on the states of the devices over two consecutive symbol intervals, we can decide their activities. If a device is active at time $t-1$ while inactive at time $t$, the device finishes transmission. If a device is inactive at time $t-1$ while active at time $t$, the device just starts data transmission. If a device is active at both time $t-1$ and time $t$, the device is transmitting data, and we need to perform data detection for the device.

2) Noncoherent Multidevice Data Detection: To facilitate multidevice data detection, we pick out the nonzero rows (whose indices belong to the support set $\mathcal{U}_d$) of $X^{(t)}$ and $X^{(t-1)}$, and the corresponding columns of $P$. Then (4) can be reduced to

$$
Y^{(t)} = \tilde{P} \tilde{X}^{(t)} + W^{(t)}
$$

(5)

where $\tilde{P}$ is an $L \times K$ matrix, whose columns are drawn from $P$ based on the support set $\mathcal{U}_d$. $\tilde{X}^{(t)}$ is a $K \times N$ matrix, whose rows are drawn from $X^{(t)}$ based on the support set $\mathcal{U}_d$.

Assuming that DPSK is used, we define $\psi_k^{(t)} = s_{k,l}/s_{k,l-1}$ to denote the $r$th symbol of device $k$. Then, we have

$$
\begin{align*}
\psi_k^{(t)} &= \frac{s_{k,l}}{s_{k,l-1}} \\
&= \frac{h_{k,1}s_{k,l}}{h_{k,1}s_{k,l-1}} \\
&= \cdots \\
&= \frac{h_{k,N}s_{k,l}}{h_{k,N}s_{k,l-1}}.
\end{align*}
$$

(6)

In a vector form, the $r$th symbol vector $\psi^{(t)} = [\psi_1^{(t)}, \psi_2^{(t)}, \ldots, \psi_K^{(t)}]^T$ over $N$ antennas can be expressed as

$$
\begin{bmatrix}
\psi_1^{(t)} \\
\psi_2^{(t)} \\
\vdots \\
\psi_K^{(t)}
\end{bmatrix}
= \tilde{X}^{(t)} \odot \tilde{X}^{(t-1)}
$$

(7)

where $\odot$ is the operation of element-wise division.

The multidevice data detection is formulated as the estimation of $\psi^{(t)}$ based on $Y^{(t)}$ and $Y^{(t-1)}$. The conventional demodulation method carries out two steps: first estimate $\tilde{X}^{(t-1)}$ and $\tilde{X}^{(t)}$ based on $Y^{(t-1)}$ and $Y^{(t)}$, respectively, then use (7) to estimate $[\psi_k^{(t)}]$, based on which hard decision for the information bits can be performed. In this article, we propose a new method, where the decision on $[\psi_k^{(t)}]$ is obtained directly based on $Y^{(t-1)}$ and $Y^{(t)}$ (instead of the intermediate results $\tilde{X}^{(t-1)}$ and $\tilde{X}^{(t)}$ as in the conventional two step approach), leading to remarkable performance gain as demonstrated later.

In this article, both active device detection and multidevice data detection are solved with Bayesian methods. In particular, we use the factor graph techniques and design efficient message passing algorithms to solve the problems, which are elaborated in next section.

III. MESSAGE-PASSING-BASED BAYESIAN APPROACHES FOR ACTIVE DEVICE DETECTION AND NONCOHERENT MULTIDEVICE DATA DETECTION

In this section, factor graph representations for the formulated problems are developed, based on which message-passing-based Bayesian algorithms are designed for active device detection and multidevice data detection.

A. Graph Representation for Block SBL-Based Active Device Detection

To identify the active devices, we develop a block SBL method to estimate the common support of the row sparse matrix $X^{(t)}$ in (4). Here, a two-layer hierarchical prior is employed, where the prior of the $(n,u)$th element in $X^{(t)}$ is

$$
p(x_{u,n}^{(t)}) = \int p(x_{u,n}^{(t)}|y_u)p(y_u)dy_u
$$

(8)

where $p(x_{u,n}^{(t)}|y_u) = \mathcal{CN}(x_{u,n}^{(t)}; 0, \gamma_u^{-1})$, and $p(y_u) = \mathcal{G}(y_u; \epsilon, \eta)$ with hyperparameters $\epsilon$ and $\eta$. Due to the common support of the columns of $X^{(t)}$, the elements of the $r$th row in $X^{(t)}$ share a single hyperparameter precision $\gamma_u$, as shown in (8). The elements of $X^{(t)}$ are conditionally independent, and we have

$$
p(X^{(t)}|y) = \prod_{n=1}^{N} \prod_{u=1}^{U} p(x_{u,n}^{(t)}|y_u)
$$

(9)

where $y = [y_1, y_2, \ldots, y_U]^T$. We assume that the noise precision at the $n$th antenna $\lambda_n$ is unknown, and an improper prior $p(\lambda_n) \propto 1/\lambda_n$ is assumed.

Then the joint distribution of $X^{(t)}$, $y$ and $\lambda$ can be expressed as

$$
p(X^{(t)}, y, \lambda|Y^{(t)}) \propto p(Y^{(t)}|X^{(t)}, \lambda)p(X^{(t)}|y)p(\lambda)p(y)
$$

$$
= \prod_{u=1}^{U} p(y_u) \prod_{n=1}^{N} \left( \prod_{l=1}^{L} p(y_{l,n}^{(t)}|x_{l,n}^{(t)}, \lambda_n) \right) p(\lambda_n) p(x_{u,n}^{(t)}|y_u)
$$

(10)

where $p(y_{l,n}^{(t)}|x_{l,n}^{(t)}, \lambda_n) = \mathcal{CN}(y_{l,n}^{(t)}; p_l^T x_{l,n}^{(t)}, \lambda_n^{-1})$ with $p_l^T$ being the $l$th row of $P$ and $x_{l,n}^{(t)}$ being the $n$th column of $X^{(t)}$ in (4), and $\lambda = [\lambda_1, \ldots, \lambda_N]^T$.

To facilitate the factor graph representation of the factorization in (10), we introduce the notations in Table II, showing the correspondence between the factor labels and the underlying distributions they represent. In addition, to combine BP and MF message passing [41], we introduce the auxiliary variable $z_{l,n}^{(t)} = p_l^T x_{l,n}^{(t)}$ in Table II, inducing
TABLE II
FACTORS INVOLVED IN THE FACTORIZATION IN (10)

| Factor       | Distribution       | Functional Form |
|--------------|--------------------|-----------------|
| $f_{la}(\lambda_a)$ | $p(\lambda_a)$ | $1/\lambda_a$ |
| $f_{la}(\lambda_a)$ | $p(z_{la}^0) \cdot p(\lambda_a)$ | $CN(z_{la}^0, \lambda_a^{-1})$ |
| $f_{la}(\lambda_a)$ | $p(z_{la}^0) \cdot \delta(z_{la}^0 - p^T x_{la}^0)$ | $\delta(z_{la}^0 - p^T x_{la}^0)$ |
| $f_{la}(\lambda_a)$ | $p(x_{la}^0) \cdot p(y_{la})$ | $CN(y_{la}, \kappa_{la}, \gamma_{la}^0)$ |
| $f_{la}(\lambda_a)$ | $p(y_{la})$ | $\Gamma(\kappa_{la}, \eta)$ |

Fig. 2. Factor graph representation of (10).

extra hard constrains $\delta(z_{la}^0 - p^T x_{la}^0)$, which is denoted by $f_{la}(\lambda_a)$.

TABLE III
FACTORS INVOLVED IN THE FACTORIZATION IN (12)

| Factor       | Distribution       | Functional Form |
|--------------|--------------------|-----------------|
| $f_{la}(\lambda_a)$ | $p(\lambda_a)$ | $1/\lambda_a$ |
| $f_{la}(\lambda_a)$ | $p(z_{la}^0) \cdot p(\lambda_a)$ | $CN(z_{la}^0, \lambda_a^{-1})$ |
| $f_{la}(\lambda_a)$ | $p(z_{la}^0) \cdot \delta(z_{la}^0 - p^T x_{la}^0)$ | $\delta(z_{la}^0 - p^T x_{la}^0)$ |
| $f_{la}(\lambda_a)$ | $p(x_{la}^0) \cdot p(y_{la})$ | $CN(y_{la}, \kappa_{la}, \gamma_{la}^0)$ |
| $f_{la}(\lambda_a)$ | $p(y_{la})$ | $\Gamma(\kappa_{la}, \eta)$ |

Fig. 3. Factor graph representation of (12).

B. Graph Representation for Bayesian Approach for Noncoherent Multidevice Data Detection

With the results of active device detection, multidevice data detection is then carried out based on (5).

To transform the factor graph into a probabilistic form, and then the joint distribution of $x^{(t)}$, $x^{(t-1)}$, and $\psi^{(t)}$ can be expressed as

$$p(x^{(t)}, x^{(t-1)}, \psi^{(t)}) = \prod_{k=1}^{K} p(\psi_k^{(t)}) \prod_{n=1}^{N} p(z_{kn}^{(t)}, z_{kn}^{(t-1)} | \psi_k^{(t)})$$

where $p(z_{kn}^{(t)}, z_{kn}^{(t-1)} | \psi_k^{(t)})$ represents a hard constraint, i.e., $\delta(x_{kn}^{(t)} - \psi_k^{(t-1)})$, and $p(\psi_k^{(t)})$ is the prior of $\psi_k^{(t)}$. As $\psi_k^{(t)}$ is discrete valued, we have $p(\psi_k^{(t)}) = \sum_{q \in \chi_q} (1/Q) \delta(\psi_k^{(t)} - q)$, and $Q$ is the cardinality of the demodulation symbol set $\chi_q$, i.e., $Q = |\chi_q|$. Given $y^{(t)}$ and $y^{(t-1)}$, the joint a posteriori distribution of $x^{(t)}$, $x^{(t-1)}$, $\psi^{(t)}$, and $\lambda$ can be expressed as

$$p(x^{(t)}, x^{(t-1)}, \psi, \lambda | y^{(t)}, y^{(t-1)})$$

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use $I_{A \rightarrow B}(x)$ to denote a message passed from a variable node (function node) $A$ to a function node (variable node) $B$, which is a function of $x$. The notations $m$ and $v$ are used to denote the mean and variance of a Gaussian message specified by their subscripts. The arrows over $m$ and $v$ represent the directions of Gaussian massage passing. Note that, if a forward message computation requires backward messages, we use the messages in previous iteration by default.

In Fig. 2, combined BP and MF-based message passing is used to realize the estimation of $\{\gamma_u \forall u\}$, where the function nodes $\{f_{z_{l,n}}^{(l)}(\lambda_n) \ \forall l,n\}, \{f_{z_{l,n}}^{(l)}(\lambda_n) \ \forall l,n\}, \{f_{x_{l,n},u}(x_{l,n},\gamma_u) \ \forall u,n\}$ and $\{f_{z_{l,n}}^{(l)}(\lambda_n) \ \forall l,n\}$ are handled by the MF rule, and the function nodes $\{f_{z_{l,n}}^{(l)} \ \forall l,n\}$ and $\{f_{z_{l,n}}^{(l-1)} \ \forall l,n\}$ are handled by the BP rules. We note that some proper message approximations are used to reduce the computational complexity.

1) Forward Message Computations: With the belief $b(\lambda_n)$ whose computation is delayed to (41), the outgoing forward message at $f_{z_{l,n}}^{(l)}$ can be expressed as

$$ I_{f_{z_{l,n}}^{(l)} ightarrow \gamma_u}^{(l)}(\gamma_u) \propto \exp \left\{ \int \ln \left[ f_{z_{l,n}}^{(l)}(\lambda_n) \right] b(\lambda_n) d\lambda_n \right\} \propto \mathcal{CN} \left( \frac{\gamma_u}{\lambda_n}, \frac{\lambda_n}{\gamma_u} \right) $$

where $\gamma_u$ is calculated in (42). With $I_{f_{z_{l,n}}^{(l)} ightarrow x_{l,n}^{(l)}(\gamma_u)} = I_{f_{z_{l,n}}^{(l)} ightarrow \gamma_u}^{(l)}(\gamma_u)$ and $[I_{f_{z_{l,n}}^{(l)} ightarrow \gamma_u}^{(l)}(\gamma_u) \ \forall u' \neq u]$ computed in (31), the outgoing forward message at $f_{x_{l,n}}^{(l)}$ can be expressed as

$$ I_{f_{x_{l,n}}^{(l)} ightarrow \gamma_u}^{(l)}(\gamma_u) = \int f_{z_{l,n}}^{(l)}(\gamma_u) \prod_{u' \neq u} I_{f_{z_{l,n}}^{(l)} ightarrow \gamma_u}^{(l)}(\gamma_u) dz_{l,n}^{(l)} dx_{l,n}^{(l)} \propto \mathcal{CN} \left( \gamma_u, m_{z_{l,n}}, v_{z_{l,n}}^{(l)} \right) $$

where

$$ m_{z_{l,n}} = \gamma_u / \lambda_n + P_{m_{z_{l,n}}} m_{x_{l,n}}, $$

$$ v_{z_{l,n}}^{(l)} = \left[ \frac{1}{\lambda_n^2} \right] $$

and

$$ m_{z_{l,n}} = \frac{U}{P_{z_{l,n}}} m_{z_{l,n}}^{(l)}, $$

$$ v_{z_{l,n}}^{(l)} = \frac{U}{P_{z_{l,n}}} v_{z_{l,n}}^{(l)}. $$

Thus, with $\{I_{f_{z_{l,n}}^{(l)} ightarrow \gamma_u}^{(l)}(\gamma_u) \ \forall l\}$, the outgoing forward message at $x_{l,n}$ reads

$$ I_{x_{l,n} ightarrow \gamma_u}^{(l)}(\gamma_u) = \prod_{l=1}^{L} I_{f_{z_{l,n}}^{(l)} ightarrow \gamma_u}^{(l)}(\gamma_u) $$

and the derivation of (21) is provided in Appendix-A. With $I_{f_{z_{l,n}}^{(l)} ightarrow x_{l,n}^{(l)}(\gamma_u)}$ and $I_{f_{z_{l,n}}^{(l)} ightarrow x_{l,n}^{(l)}(\gamma_u)}$ given in (30), the belief of $x_{l,n}$ can be updated as

$$ b(x_{l,n}) = I_{f_{z_{l,n}}^{(l)} ightarrow x_{l,n}^{(l)}(\gamma_u)} I_{f_{z_{l,n}}^{(l)} ightarrow x_{l,n}^{(l)}(\gamma_u)} \propto \mathcal{CN} \left( x_{l,n}, m_{x_{l,n}}, v_{x_{l,n}}^{(l)} \right) $$

where

$$ m_{x_{l,n}} = \frac{m_{x_{l,n}}}{1 + \gamma_u v_{x_{l,n}}^{(l)}} $$

and $\gamma_u$ is given by (27). Thus, the outgoing forward message at $f_{x_{l,n}}^{(l)}$ can be computed as

$$ I_{f_{x_{l,n}}^{(l)} ightarrow \gamma_u}^{(l)}(\gamma_u) = \prod_{u' \neq u} I_{f_{x_{l,n}}^{(l)} ightarrow \gamma_u}^{(l)}(\gamma_u) dz_{l,n}^{(l)} dx_{l,n}^{(l)} \propto \mathcal{CN} \left( \gamma_u, m_{z_{l,n}}^{(l)}, v_{z_{l,n}}^{(l)} \right) $$

With $\{I_{f_{z_{l,n}}^{(l)} ightarrow \gamma_u}^{(l)} \ \forall u,n\}$ and $I_{f_{x_{l,n}}^{(l)} ightarrow \gamma_u}^{(l)}$ computed in (29), the belief of $\gamma_u$ can be updated as

$$ b(\gamma_u) = I_{f_{x_{l,n}}^{(l)} ightarrow \gamma_u}^{(l)}(\gamma_u) \prod_{n=1}^{N} I_{f_{z_{l,n}}^{(l)} ightarrow \gamma_u}^{(l)}(\gamma_u) \propto \mathcal{CN} \left( \gamma_u, m_{x_{l,n}}^{(l)}, v_{x_{l,n}}^{(l)} \right) $$

Thus, the estimation of $\gamma_u$ can be updated by

$$ \hat{\gamma}_u = \left\{ \gamma_u \right\}_b = \frac{\hat{c} + N}{\eta + \sum_{n=1}^{N} \left( m_{x_{l,n}}^{(l)} \right)^2 + v_{x_{l,n}}^{(l)}}. $$

According to the results in [42], to enhance the performance of SBL, we can set $\eta = 0$, and update $\epsilon$ automatically, i.e.,

$$ \hat{\epsilon} = \frac{1}{2} \sqrt{\log \left( \frac{1}{U} \sum_u \hat{\gamma}_u \right) - \frac{1}{U} \sum_u \log \hat{\gamma}_u}. $$
2) **Backward Message Computations:** According to the MF rule, the outgoing backward message at \( f_{t,u} \) can be calculated by

\[
I_{f_{t,u} \rightarrow y_u}(\gamma_u) \propto Ga(\gamma_u; \hat{\epsilon}, n).
\]  

With \( b(\gamma_u) \), the outgoing backward message at \( f_{x,0,u} \) can be computed as

\[
I_{f_{x,0,u} \rightarrow f_{x,0,u}}(x_{0,u,n}) \propto \exp \left\{ \int \ln \left[ f_{x,0,u}(x_{0,u,n}, y_u) \right] b(\gamma_u) dy_u \right\} \propto CN \left( x_{0,u,n} ; 0, \hat{\gamma}_u^{-1} \right).
\]

With the calculated \( I_{f_{y,n} \rightarrow f_{x,0,u}}(x_{0,u,n}) \) in (14) and \( b(x_{0,u,n}) \) in (22), the outgoing backward message at \( x_{0,u,n} \) is given as

\[
I_{f_{x,0,u} \rightarrow f_{x,0,u}}(x_{0,u,n}) = \frac{b(x_{0,u,n})}{I_{f_{y,n} \rightarrow f_{x,0,u}}(x_{0,u,n})} \propto CN \left( x_{0,u,n} ; m_{x,0,u,n}^{\rightarrow}, v_{x,0,u,n}^{\rightarrow} \right)
\]

where

\[
v_{x,0,u,n,l} = \left( \frac{1}{v_{x,0,u,n,l}} - \frac{1}{v_{x,0,u,n,l}} \right)^{-1} \approx v_{x,0,u,n,l}^{\rightarrow} \tag{32}
\]

and

\[
m_{x,0,u,n,l}^{\rightarrow} = v_{x,0,u,n,l}^{\rightarrow} \left( m_{x,0,u,n,l} - v_{x,0,u,n,l}^{\rightarrow} \right)
\]

\[
\approx m_{x,0,u,n,l} - v_{x,0,u,n,l}^{\rightarrow} \tag{33}
\]

With \( I_{x,0,u} \rightarrow f_{x,0,u}^{(2)}(x_{0,u,n}) \) \( \forall u \), the outgoing backward message at \( f_{z,0,n} \) can be expressed as

\[
I_{f_{z,0,n} \rightarrow f_{z,0,n}}(z_{0,n}) = \int f_{z,0,n}(z_{0,n}) \prod_{u=1}^{U} I_{x,0,u} \rightarrow f_{x,0,u}(x_{0,u,n}) dx_{0,u,n} \propto CN \left( \mu_{z,0,n}^{\rightarrow}, v_{z,0,n}^{\rightarrow} \right)
\]

where

\[
v_{z,0,n}^{\rightarrow} = \sum_{u=1}^{U} | P_{z,0,u} | \left( v_{z,0,n}^{\rightarrow} - v_{z,0,n}^{\rightarrow} \right) \approx \sum_{u=1}^{U} | P_{z,0,u} | ^2 \left( v_{z,0,n}^{\rightarrow} \right) \tag{35}
\]

\[
m_{z,0,n}^{\rightarrow} \approx \sum_{u=1}^{U} | P_{z,0,u} | m_{z,0,u,n}^{\rightarrow} - v_{z,0,n}^{\rightarrow} \left( \mu_{z,0,n}^{\rightarrow} - v_{z,0,n}^{\rightarrow} \right) \tag{36}
\]

and the derivation of (36) is provided in Appendix-B. Note that, to update \( m_{z,0,n}^{\rightarrow} \), we need \( v_{z,0,n}^{\rightarrow} \) and \( m_{z,0,n}^{\rightarrow} \) in the previous iteration, so the superscript \( i - 1 \) is introduced to differentiate them. With \( I_{f_{z,0,n} \rightarrow f_{z,0,n}}(z_{0,n}) \) and \( I_{f_{z,0,n} \rightarrow f_{z,0,n}}(z_{0,n}) \) computed in (13), the belief of \( z_{0,n} \) can be updated as

\[
b(z_{0,n}) = I_{f_{z,0,n} \rightarrow f_{z,0,n}}(z_{0,n}) I_{f_{z,0,n} \rightarrow f_{z,0,n}}(z_{0,n}) \propto CN \left( z_{0,n} ; m_{z,0,n}, v_{z,0,n}^{\rightarrow} \right)
\]

where

\[
v_{z,0,n}^{\rightarrow} = \left( \hat{\gamma}_n + \frac{1}{v_{z,0,n}^{\rightarrow}} \right)^{-1}
\]

\[
m_{z,0,n} = v_{z,0,n}^{\rightarrow} \left( y_{0,n} \hat{\gamma}_n + \frac{m_{z,0,n}}{v_{z,0,n}^{\rightarrow}} \right)
\]

Thus, the outgoing backward message at \( f_{z,0,n} \) is given by

\[
I_{f_{z,0,n} \rightarrow f_{z,0,n}}(\lambda_n) \propto \exp \left\{ \int \ln \left[ f_{z,0,n}(\lambda_n, z_{0,n}) \right] b(z_{0,n}) dz_{0,n} \right\} \propto \lambda_n \exp \left\{ -\lambda_n \left( m_{z,0,n} - y_{0,n}^{\rightarrow} \right) ^2 + v_{z,0,n}^{\rightarrow} \right\}
\]

With \( I_{f_{z,0,n} \rightarrow f_{z,0,n}}(\lambda_n) \) \( \forall \) and the a priori \( f_{s,u}(\lambda_n) \), the belief of \( \lambda_n \) can be updated by

\[
b(\lambda_n) = f_{s,u}(\lambda_n) \prod_{l=1}^{L} I_{f_{z,0,n} \rightarrow f_{z,0,n}}(\lambda_n) \propto \lambda_n ^{L-1} \exp \left\{ -\lambda_n \sum_{l=1}^{L} \left( m_{z,0,n} - y_{0,n}^{\rightarrow} \right) ^2 + v_{z,0,n}^{\rightarrow} \right\}
\]

Thus, the estimation of noise precision is given as

\[
\hat{\lambda}_n = \langle \lambda_n \rangle_{b_{s,u}(\lambda_n)} = \frac{L}{\lambda_n \sum_{l=1}^{L} \left( m_{z,0,n} - y_{0,n}^{\rightarrow} \right) ^2 + v_{z,0,n}^{\rightarrow}}.
\]

The BP-MF message passing algorithm (BP-MF-MPA) for active device detection is summarized in Algorithm 1. The estimated hyperparameter \( \hat{\gamma}_n \) is used to detect the activity of device \( u \) by comparing it with a threshold \( G_{th} \) (which can be calculated as [43]), so we have \( U_d = \text{find}(\hat{\gamma}_u < G_{th}) \).

**D. Message Passing Algorithm for Noncoherent Multidevice Detection**

It is worth mentioning that Fig. 3 is obtained based on Fig. 2, where the variable nodes associated with inactive devices are removed, and the differential modulation constraints are added. BP and MF message passing is used to realize the estimation of \[ \vert \psi_k \rangle \forall k \]. The message computations of the function nodes \( f_{x,0,n}(\lambda_n, \lambda_n) \) \( \forall n \) and \( f_{z,0,n}(\lambda_n, \lambda_n) \) are similar to those in Fig. 2, which are omitted in this section. The function nodes \( f_{x,0,n}(\lambda_n, \lambda_n, \psi_k, \psi_i) \) \( \forall k, n \) are handled by the BP rule, and some messages are approximated to be Gaussian based on moment matching to make the message passing tractable. As the message computation for the \( (r-1) \)th measurement is similar to that for the \( r \)th, we just detail the message computation for the \( r \)th measurement.
Algorithm 1 BP-MF-MPA for Active Device Detection and Noncoherent Multidevice Data Detection

**Input:** $Y^{(i)}, Y^{(i-1)}, \mathbf{P}, \{p_i\}, \{\rho_k\}

**Initialize:** $orall n, \hat{\lambda}_n = 10$; $\forall u, \hat{\gamma}_u = 1$; $\forall u, n, m_{u,n}^{(0)} = 0$; $\forall l, n, m_{l,n}^{(0)} = 0, \nu^{(0)}_{l,n} = 1, m_{l,n}^{(i-1)} = 0, \nu^{(i-1)}_{l,n} = 1$

**Active Device Detection:**
1: for $i = 1:N_{\text{dev}}$
2: $\forall u, n$: update $\tilde{m}_{u,n}^{(0)}, \tilde{\nu}_{u,n}^{(0)}$ by (21) and (20);
3: $\forall u, n$: update $m_{u,n}^{(0)}, \nu_{u,n}^{(0)}$ by (23) and (24);
4: $\forall l, n$: update $m_{l,n}^{(0)}, \nu_{l,n}^{(0)}$ by (26) and (25);
5: $\forall u$: update $\hat{\gamma}_u$ by (27);
6: update $\hat{\epsilon}$ by (28);
7: $\forall l, n$: update $m_{l,n}^{(0)}, \nu_{l,n}^{(0)}$ by (39) and (38);
8: $\forall n$: update $\hat{\lambda}_n$ by (42);
9: end for

**Output:** $U_a = \text{find}(\{\hat{\gamma}_u\} < G_{\text{th}})$.

**Non-Coherent Multi-Device Data Detection**
10: for $i = 1:N_{\text{dev}}$
11: $\forall k, n$: update $\tilde{m}_{k,n}^{(0)}, \tilde{\nu}_{k,n}^{(0)}$ by (45) and (44), and update $m_{k,n}^{(0)}, \nu_{k,n}^{(0)}$ similarly;
12: $\forall k, q$: update $\tilde{\rho}_{k,q}$ and $\alpha_{k,q}^{(0)}$ by (48) and (50) respectively;
13: $\forall k, q$: update $\tilde{\rho}_{k,q}$ by (53);
14: $\forall k, n$: update $m_{k,n}^{(i-1)}, \nu_{k,n}^{(i-1)}$ by (55) and (54), and update $m_{k,n}^{(i-1)}, \nu_{k,n}^{(i-1)}$ by (62) and (61) respectively;
15: $\forall k, n$: update $m_{k,n}^{(0)}, \nu_{k,n}^{(0)}$ by (57) and (58), and update $m_{k,n}^{(0)}, \nu_{k,n}^{(0)}$ similarly;
16: $\forall l, n$: update $\tilde{m}_{l,n}^{(0)}, \tilde{\nu}_{l,n}^{(0)}$ by (64) and (65), and update $m_{l,n}^{(0)}, \nu_{l,n}^{(0)}$ similarly;
17: $\forall l, n$: update $m_{l,n}^{(0)}, \nu_{l,n}^{(0)}$ by (39) and (38), and update $m_{l,n}^{(0)}, \nu_{l,n}^{(0)}$ similarly;
18: $\forall n$: update $\hat{\lambda}_n$ by (42);
19: end for

**Output:** $v_k(b_{k}^{(i)}) = \sum_{q \in X_d} \rho_{k,q}^{(i)} \delta(b_{k}^{(i)} - q)$, based on which hard decisions can be made.

1) **Forward Message Computations:** Similar to (13)–(21), we have

$$I_{k,n}^{(i)}(x_{k,n}^{(i)}) \propto \text{CN}\left(\bar{m}_{k,n}^{(i)}, \bar{\nu}_{k,n}^{(i)}\right)$$

where

$$\bar{\nu}_{k,n}^{(i)} \approx \left(\frac{L_i}{L_i + \frac{1}{\lambda_n} + \nu_{k,n}^{(i)}}\right)^{-1}$$

and

$$\bar{m}_{k,n}^{(i)} \approx \bar{\nu}_{k,n}^{(i)} \sum_{l=1}^{L} \frac{\bar{m}_{k,n}^{(i)}}{\bar{\nu}_{k,n}^{(i)}} + m_{k,n}^{(i)}.$$
\[ I^{(0)}_{j,n} \rightarrow I^{(0)}_{j,n} \]

where
\[
\mathcal{N}(\bar{x}_{k,n}, x_{k,n})
\]

and
\[
 m^{(t)}_{k,n} = V^{\top}_{k,n} \tilde{v}_{k,n} + |q|^2 V^{\top}_{k,n}
\]

Thus, \( I^{(0)}_{j,n} \) can be updated in the same way as (56)–(58).

Similar to (31)–(36), the outgoing backward message at \( I^{(t)}_{j,n} \) can be computed as
\[
 I^{(t)}_{j,n} \rightarrow I^{(t)}_{j,n} \propto \mathcal{N}(\bar{x}_{k,n}, m_{k,n}, \bar{v}_{k,n})
\]

where
\[
 m^{(t)}_{k,n} = V^{\top}_{k,n} \tilde{v}_{k,n} + |q|^2 V^{\top}_{k,n}
\]

As \( I^{(0)}_{j,n} \) is not Gaussian, the belief \( b(\bar{x}_{k,n}) \) is not Gaussian either. With moment matching, \( b(\bar{x}_{k,n}) \) is approximated to be Gaussian to make the message tractable. Then we have
\[
b^{G}(\bar{x}_{k,n}) = \text{Proj}_G \left( b(\bar{x}_{k,n}) \right)
\]

where \( \text{Proj}_G(*) \) denotes the operation of Gaussian approximation, and the mean and the variance of \( \bar{x}_{k,n} \) are given as
\[
m_{\bar{x}_{k,n}} = \sum_{q \in \mathcal{X}_d} \rho^q_{k,t} m_{\bar{x}_{k,n}}
\]

and
\[
v^{(t)}_{k,n} = \bar{v}_{k,n} + |q|^2 \bar{v}_{k,n}
\]

With \( I^{(0)}_{j,n} \rightarrow I^{(0)}_{j,n} \), the outgoing backward message from \( I^{(t)}_{j,n} \) to \( \bar{x}_{k,n} \) can be expressed as
\[
 I^{(t)}_{j,n} \rightarrow I^{(t)}_{j,n} (\bar{x}_{k,n}) = \int f^{(t)}_{j,n}(\bar{x}_{k,n}, x_{k,n}) \cdot \mathcal{N}(\bar{x}_{k,n}, m_{\bar{x}_{k,n}}, \bar{v}_{k,n})
\]

\[
 = \sum_{q \in \mathcal{X}_d} \alpha^q_{k,t} \mathcal{N}(\bar{x}_{k,n}, m_{\bar{x}_{k,n}} + V^{\top}_{k,n} \bar{v}_{k,n})
\]

With \( I^{(t)}_{j,n} \rightarrow I^{(t)}_{j,n} \), the belief of \( \bar{x}_{k,n} \) can be updated by
\[
b(\bar{x}_{k,n}) = I^{(0)}_{j,n} \rightarrow \bar{x}_{k,n} (\bar{x}_{k,n}) \cdot \mathcal{N}(\bar{x}_{k,n}, m_{\bar{x}_{k,n}}, \bar{v}_{k,n})
\]

where \( \rho^q_{k,t} = \rho^q_{k,t} \)
\[
v^{(t)}_{k,n} = \left( \bar{v}^{\top}_{k,n} + \frac{1}{V^{\top}_{k,n}} V^{\top}_{k,n} \right)^{-1}
\]

E. Computational Complexity

It can be seen from Algorithm 1 that the complexity of the proposed BP-MF-MPA algorithm is dominated by the multiplication operations to update the mean and variance of the relevant messages. The computational complexity is 6UNL + 2UN in line 2, 4UN in line 3, 3UNL + 3NL in line 4, UN + U in line 5, 2 in line 6, 5NL in line 7, NL + N in line 8, 12NLK + 6NK in line 11, 200NK – 96K in line 12, 164K in line 13, 19K in line 14, 24K in line 15, 8NLK + 6NL in line 16, 10NL in line 17, and NL + N in line 18. Thus, the computational complexity for noncoherent multidevice detection can be approximated as \( O(\text{UNL}) + O(\text{KLN}) \) per iteration.
TABLE IV
SIMULATION PARAMETERS

| Parameter                  | Symbol | Value          |
|----------------------------|--------|----------------|
| Number of devices          | $U$    | 100,300,500    |
| Number of antennas at AP   | $N$    | 50,100         |
| Number of active devices   | $K$    | [0, 1, $U$]   |
| Length of spreading sequences| $L$   | 11, 13         |

Fig. 4. Missed detection rate performance comparison.

Fig. 5. False detection rate performance comparison.

IV. SIMULATION RESULTS

We assume a MIMO-NOMA system with parameters shown in Table IV, and DQPSK modulation is employed. The number of active devices is about 10% of the total number of devices, which are randomly selected from the users and access the channel randomly.

The rate of incorrect detection (miss or false detection) is used to evaluate the performance of active device detection. The miss detection rate and false detection rate of the proposed algorithm are shown in Figs. 4 and 5, respectively. It can be seen that with a fixed number of antennas at AP $N = 100$, the detection performance becomes better with the increase of $L$, as longer spreading sequences lead to smaller correlations. In addition, with a fixed length of spreading sequences $L = 13$, we examine the miss detection rate and false detection rate by varying $N$. As expected, a larger number of antennas lead to a better detection performance as more observations can be obtained by the receiver.

In Fig. 6, we evaluate the support recovery rate of the algorithms. As a traditional compressed sensing support recovery algorithm, MMV-OMP is included. We assume the number of devices $U = 100$, the number of antennas at AP $N = 50$, and the number of active devices is 10% of the total devices. The support recovery rate is defined as the percentage of successful trials in the total trials. We defined $\sigma = 1$-support recovery rate, and evaluate the $\rho$ of the algorithms versus the length of the spreading sequences $L$, i.e., the column size of the spreading matrix $P$. It turns out that, due to the lack of the mechanism of exploiting common support, the support recovery performance of MMV-OMP is inferior to that of BP-MF-MPA.

We use the bit error rate (BER) to evaluate the performance of multidevice data detection. To demonstrate the superior performance of the proposed algorithm, which exploits the differential modulation constraint, we compare it with the conventional detection scheme. With the results of active device detection, the inactive devices are removed from the model. Then the estimation of $\hat{X}$ becomes a conventional problem, which can be solved by using the linear minimum mean squared error estimator. The estimates of $\hat{X}$ of two consecutive times can be obtained, which are denoted by $\hat{X}(t)$ and $\hat{X}(t-1)$. Then the demodulated symbol can be expressed as $\hat{\psi}_k = 1/N \sum_{n=1}^N \hat{x}_{k,n}(t)/\hat{x}_{k,n}(t-1)$, based on which hard decisions can be made. The proposed scheme is significantly different from the conventional scheme in that the estimation of $\{\psi_k \forall k\}$ is based on $Y(t-1)$ and $Y(t)$ directly and jointly. The BER performance of the proposed scheme and the conventional scheme with respect to signal-to-noise ratios (SNRs) is shown in Fig. 7, where the length of spreading sequence $L = 11$ and the number of antennas at AP $N = 100$. As a performance benchmark, the ID-aided MPA scheme, where the common support is perfectly known, is also included. It can be seen that the gap between the proposed scheme and the ID-aided MPA scheme is about 2 dB at the BER of $10^{-5}$. In addition, compared with the
conventional scheme, the proposed scheme can improve the BER performance significantly over the entire SNR range, because the proposed BP-MF-MPA algorithm make full use of the differential constrain information.

The convergence of the proposed scheme for noncoherent multidevice data detection is shown in Fig. 8. It can be seen that the BER of BP-MF-MPA falls rapidly within the first 5 iterations, and it converges with about $N_{Dir} = 10$. One of the advantage of the message passing algorithms is that they can be implemented in parallel if multiple processing units are available, so that the time required for convergence can be reduced.

With different $L$, the BER performance of the two schemes is shown in Fig. 9. It can be be observed that, the schemes with $L = 13$ delivers better BER performance than those with $L = 11$. This is because longer spreading sequence can reduce the cross-correlation of the spreading sequences, which brings down the multiuser interference. Finally, we examine the BER performance of the schemes by varying the number of antennas $N$ equipped at AP, and the results are shown in Fig. 10. It can be seen that, with the increase of $N$, the BER performance is improved as expected.

The BER performance with different number of (active) users is shown in Fig. 11. We assume that the number of antennas at AP $N = 100$, and the number of users $U = 100, 300$ and $500$, and the active users is 10% of the total users. It turns out that, as more users will lead to stronger multiuser
interference, the BER performance has decreased with the increase of the number of (active) users. But the proposed scheme is still able to handle the multiuser interference effectively.

V. Conclusion

In this article, we have investigated the design of grant-free MIMO-NOMA system for machine-type communications with the aim to achieve high efficiency and low latency. In particular, differential modulation is employed so that the costly channel estimation in MIMO-NOMA can be bypassed, and the use of long training signals are avoided. The receiver needs to perform active device detection and multidevice detection. We have designed message-passing-based SBL algorithm to solve the active device detection problem. We have also developed message-passing-based noncoherent multidevice data detector, where the differential modulation is exploited as a constraint in the detection, leading to significant performance improvement compared to conventional demodulation scheme. Both active device detection and multidevice data detection are performed symbol-by-symbol, which allow highly flexible transmission of the IoT devices. Simulation results verified the effectiveness of the proposed detectors.

Appendix

Derivations of (21) and (36)

A. Derivation of (21)

\[
\begin{align*}
\hat{m}_{z_i,n}^{(t)} &= \sum_{u=1}^{U} \hat{v}_{i,n,u}^{(t)} \left( \sum_{l=1}^{L} \frac{p_{i,l}^{(t)}}{\lambda_{i,n}^{(t)}} \hat{m}_{z_i,n}^{(t)} + P_{i,l}^{(t)} \hat{m}_{x_i,n}^{(t)} \right) \\
&\approx \sum_{u=1}^{U} \hat{v}_{i,n,u}^{(t)} \left( \sum_{l=1}^{L} \frac{p_{i,l}^{(t)}}{\lambda_{i,n}^{(t)}} \hat{m}_{z_i,n}^{(t)} + P_{i,l}^{(t)} \hat{m}_{x_i,n}^{(t)} \right) \quad (33)
\end{align*}
\]

B. Derivation of (36)

\[
\begin{align*}
m_{z_i,n}^{(t)} &= \sum_{u=1}^{U} p_{i,u}^{(t)} m_{x_i,n}^{(t)} \\
&\approx \sum_{u=1}^{U} p_{i,u}^{(t)} \left( m_{z_i,n}^{(t)} - \frac{\hat{m}_{z_i,n}^{(t)}}{\hat{v}_{i,n,u}^{(t)}} \right) \quad (34)
\end{align*}
\]

\[
\begin{align*}
\sum_{u=1}^{U} p_{i,u}^{(t)} m_{z_i,n}^{(t)} - \frac{\sum_{u=1}^{U} p_{i,u}^{(t)} m_{z_i,n}^{(t)}}{\sum_{u=1}^{U} \hat{v}_{i,n,u}^{(t)}} - \frac{\sum_{u=1}^{U} p_{i,u}^{(t)} m_{x_i,n}^{(t)}}{\sum_{u=1}^{U} \hat{v}_{i,n,u}^{(t)}}
\end{align*}
\]

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Zhongyong Wang received the B.S. and M.S. degrees in automatic control from Harbin Shipbuilding Engineering Institute, Harbin, China, in 1986 and 1988, respectively, and the Ph.D. degree in automatic control theory and application from Xi’an Jiaotong University, Xi’an, China, in 1998.

Since 1988, he has been a Lecturer with the Department of Electronics, Zhengzhou University, Zhengzhou, China, where he was an Associate Professor, from 1999 to 2002, and he was promoted to a Professor with the Department of Communication Engineering in 2002. His research interests include numerous aspects of embedded systems, signal processing, and communication theory.

Jiangtao Xi (Senior Member, IEEE) received the B.E. degree in electrical engineering from Beijing Institute of Technology, Beijing, China, in 1982, the M.E. degree in electrical engineering from Tsinghua University, Beijing, in 1985, and the Ph.D. degree in electrical engineering from the University of Wollongong, Wollongong, NSW, Australia, in 1996.

He was a Postdoctoral Fellow with the Communications Research Laboratory, McMaster University, Hamilton, ON, Canada, from 1995 to 1996, and a member of Technical Staff with Bell Laboratories, Lucent Technologies Inc., Murray Hill, NJ, USA, from 1996 to 1998. From 2000 to 2002, he was the Chief Technical Officer with TCL IT Group Company, Huizhou, China. In 2003, he was a Senior Lecturer with the University of Wollongong, where he is currently a Professor and also the Associate Dean (Global Engagement) of the Faculty of Engineering and Information Sciences. His research interests include signal processing and its applications in various areas, such as optoelectronics, instrumentation and measurement, and telecommunications.

Yanguang Yu (Senior Member, IEEE) received the B.E. degree from Huazhong University of Science and Technology, Wuhan, China, in 1986, and the Ph.D. degree from Harbin Institute of Technology, Harbin, China, in 2000.

She was with the University of Wollongong, Wollongong, NSW, Australia, in 2007, where she is currently an Associate Professor with the School of Electrical, Computer and Telecommunications Engineering. She was with the College of Information Engineering, Zhengzhou University, Zhengzhou, China, on various appointments, including a Lecturer from 1986 to 1999, an Associate Professor from 2000 to 2004, and a Professor from 2005 to 2007. From 2001 to 2002, she was a Postdoctoral Fellow with Opto-Electronics Information Science and Technology Laboratory, Tianjin University, Tianjin, China. She also had a number of visiting appointments, including a Visiting Fellow with the Optoelectronics Group, Department of Electronics, The University of Pavia, Pavia, Italy, from 2002 to 2003, a Principal Visiting Fellow with the University of Wollongong from 2004 to 2005, and a Visiting Associate Professor and a Professor with the Engineering School ENSEEIHT, Toulouse, France, in 2004 and 2006, respectively.

Her research interests include semiconductor lasers with optical feedback and their applications in sensing and instrumentations, and secure chaotic communications. She is also interested in signal processing and its applications to 3-D profile measurement and telecommunication systems.

Yonghui Li (Fellow, IEEE) received the Ph.D. degree from Beijing University of Aeronautics and Astronautics, Beijing, China, in November 2002.

Since 2003, he has been with the Centre of Excellence in Telecommunications, The University of Sydney, Sydney, NSW, Australia. He is currently a Professor and a Director of Wireless Engineering Laboratory, School of Electrical and Information Engineering, University of Sydney. His current research interests are in the area of wireless communications, with a particular focus on MIMO, millimeter wave communications, machine to machine communications, and coding techniques and cooperative communications. He holds a number of patents granted and pending in these fields.

Prof. Li is the recipient of the Australian Queen Elizabeth II Fellowship in 2008 and the Australian Future Fellowship in 2012. He received the Best Paper Awards from IEEE International Conference on Communications 2014, IEEE PIRMC 2017, and IEEE Wireless Days Conferences 2014. He was an Editor of IEEE TRANSACTIONS ON COMMUNICATIONS and IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY. He also served as the Guest Editor for several IEEE journals, such as IEEE JOURNAL ON SELECTED AREAS IN COMMUNICATIONS, IEEE Communications Magazine, IEEE INTERNET OF THINGS JOURNAL, and IEEE ACCESS.