Data-Aided Active User Detection With False Alarm Correction in Grant-Free Transmission
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Abstract—In most existing grant-free (GF) studies, the two key tasks, namely active user detection (AUD) and payload data decoding, are handled separately. In this letter, a two-step data-aided AUD scheme is proposed, namely the initial AUD step and the false alarm correction step respectively. To implement the initial AUD step, an embedded low-density-signature (LDS) based preamble pool is constructed. In addition, two message passing algorithm (MPA) based initial estimators are developed. In the false alarm correction step, a redundant factor graph is constructed based on the initial active user set, on which MPA is employed for data decoding. The remaining false detected inactive users will be further detected by the false alarm corrector with the aid of decoded data symbols. Simulation results reveal that both the data decoding performance and the AUD performance are significantly enhanced by more than 1.5 dB at the target accuracy of 10^{-3} compared with the traditional compressed sensing (CS) based counterparts.

Index Terms—Grant free, false alarm correction, MPA.

I. INTRODUCTION

MASSIVE machine-type communication (mMTC) is one of the most popular services in fifth-generation (5G) mobile communication systems. Since conventional orthogonal multiple access (OMA) cannot meet the explosive demand due to the limited orthogonal resources, non-orthogonal multiple access (NOMA) technologies are advocated to support the massive connectivity. Among the many available NOMA schemes, low-density-signature orthogonal frequency division multiplexing (LDS-OFDM) [1] is one of the most generic solutions in code domain. In an LDS-OFDM system, the message passing algorithm (MPA) with near-optimal performance is employed to cancel interference among multiple users. Benefiting from the LDS structure, the complexity of the MPA algorithm becomes affordable. However, the MPA algorithm is implemented based on the assumption that each user’s activity information is perfectly known at the base station (BS). However, in massive IoT networks, this assumption is impractical.

Now in 5G New Radio, the approval proposed to reduce latency is grant-free (GF) random access. This means channel resources can be accessed without being arranged through a handshaking process. To realize the GF requirement of LDS-OFDM system, there are two mainstream solutions widely studied. Firstly, a framework referred to as compressed sensing based MPA (CS-MPA) detector is proposed where active users will transmit their specific non-orthogonal preamble with length $L_p$ before their data transmission begins [2], [3]. By leveraging users’ activity sparsity, the active user detection (AUD) task is formulated as a standard CS problem and solved by the existing CS recovery algorithms efficiently, e.g., orthogonal matching pursuit (OMP) [2], dynamic compressed sensing (DCS) [3], and approximate message passing algorithm (AMP) [4] etc. Then, MPA is performed to reliably detect the transmitted symbols of the active users. On the other hand, some researchers propose to add an extended zero constellation point into the conventional LDS constellation alphabet [5]. The key idea is that one can recognize the activity states of users through their decoded symbols, i.e., if the detected zero symbols in a user’s packet is large enough, this user is considered as inactive.

However, in a CS-MPA detector, the AUD and data payload decoding are normally handled separately. The feasibility that error correction with the aid of decoded data symbols provides additional mechanism for performance improvement is ignored [6]. In [5], MPA is directly employed to decode data symbols of all potential users, at the absence of activity state information of potential users in the cell. But, the complexity of this approach would become prohibitive upon the increase of the potential user number.

Based on the above discussion, Our main contributions in this letter are summarized as follows.

- Firstly, a data-aided two-step AUD scheme is proposed. In step 1, an initial active user set which contains a small number of false alarms is estimated by the initial estimator from the received preamble signal. In step 2, these false alarms are further corrected by the designed false alarm corrector.

- Secondly, to estimate an initial active user set, an embedded LDS based preamble pool is firstly constructed. Then, an MPA based initial estimator is presented. To reduce the complexity of the MPA detector, a traffic load aided MPA (TL-MPA) based detector is further proposed.

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Finally, based on the fact that if a user is inactive, the number of detected zero symbols should be large, a false alarm corrector based on multiple zero symbol detection is implemented in the data decoding process to peel off the remaining false alarms in the initial active user set.

The rest of this letter is organised as follows. System model is introduced in Section II. The construction method of embedded LDS based user preamble and two MPA based initial estimators are depicted in Section III. In Section IV, the proposed false alarm corrector is described. Complexity analysis is provided in Section V. Simulation results are presented in Section VI. Finally, this letter is concluded in Section VII.

II. SYSTEM MODEL

An up-link scenario of a single IoT cell with $N$ IoT devices each of which is assigned a user-specific preamble, is considered. Only $N_u$ users are active at any given time point. The sparsity rate $\lambda$ is defined as $\lambda = \frac{N_u}{N}$. Meanwhile, only a single antenna is considered at both the user side and base station (BS) for low-cost IoT. Moreover, perfect symbol-wise synchronization is assumed.

Fig. 1. Graphic representation of the GF LDS-OFDM, where potential users are superposed and propagated simultaneously over $L_s$ sub-carriers. Fig. 1 shows that the LDS signature matrix $x_u$ of user $u$ is transmitted to the BS in a GF manner [4]. The number of detected zero symbols should be large, a false alarm corrector based on multiple zero symbol detection is implemented in the data decoding process to peel off the remaining false alarms in the initial active user set.

The whole transmission period contains two stages, namely the preamble transmission stage and the data transmission stage. In the preamble transmission stage, for user $u$, $1 \leq u \leq N$, once it becomes active, its activity state changes to $a_u = 1$ from $a_u = 0$. Then, its user-specific preamble $s_u$ with length $L_p$ is transmitted to the BS in a GF manner [4]. The construction of a user's preamble pool will be elaborated later in Section III. After that, its data transmission stage begins. Firstly, its data packet $x_u = \{x_u[1], x_u[2], \ldots, x_u[K]\} \in \mathbb{C}^{K \times 1}$ is prepared. The $k^{th}$ data symbol $x_u[k], 1 \leq k \leq K$ is selected from the alphabet $X_u = \chi \cup \{0\}$. The original alphabet $\chi$ is generated according to [7] where each standard $M$-ary phase shift keying (PSK) symbol is multiplied by a user-specific complex coefficient. The cardinality of the final alphabet is $M + 1$. Then, $x_u$ is modulated onto a user specific signature sequence $c_u$ with length $L_s$. All active users’ signals are superposed and propagated simultaneously over $L_s$ sub-carriers. In this letter, the signature sequence $c_u, 1 \leq u \leq N$ is selected from the columns of the parity check matrix of a regular low-density-parity-check (LDPC) code. For the example in Figure 1, the LDS signature matrix $C_{4,6} = [c_1, c_2, \ldots, c_6]$ is given by

$$C_{4,6} = \begin{bmatrix} 1 & 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 1 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 & 1 & 1 \end{bmatrix}. \quad (1)$$

At the receiver side, the received signal of users’ preamble can be modeled as

$$y_p = \sum_{u=1}^{N} a_u (h^p_u \otimes s_u) + n_p. \quad (2)$$

where ‘$\otimes$’ denotes Hadamard product. The received signal of $k^{th}$, $1 \leq k \leq K$ data symbol on the $l^{th}$ sub-carrier is modeled as

$$y[l_s, k] = \sum_{u=1}^{N} a_u h^p_u[l_s, k] c_u[l_s] x_u[k] + n_d[l_s, k], \quad (3)$$

where $c_u[l_s], 1 \leq l_s \leq L_s$ denotes the $l^{th}$ component of $c_u$. Here, $h^p_u$ and $h^d_u$ denote the complex channel coefficient between user $u$ and the BS in the preamble transmission period and data transmission period respectively, and are sampled independently from the distribution $CN(0,1)$ [2], [3]. Also, $n_p \in \mathbb{C}^{L_s \times 1}$ and $n_d \in \mathbb{C}^{L_s \times K}$ represent background noise which obeys i.i.d. Gaussian distribution $CN(0,\sigma^2 I)$. Additionally, as stated in [2], [3], the preamble length equals the sub-carrier number, i.e., $L_s = L_p$ in this letter.

III. INITIAL ACTIVE USER SET DETECTION

A. Embedded LDS Based User Preamble Construction

To obtain the initial active user set, which is also referred to as the super-set $\mathcal{U}_{ac}$ (i.e., $\mathcal{U}_{ac} \subset \mathcal{U}_{ac}^{[8]}$), only a test on each sub-carrier is required [9]. If there is no user transmitting data on the $l^{th}$ sub-carrier, the $l$ sub-carrier is idle and the outcome of the test is $Y[l_s] = 0$. Otherwise, the $l$ sub-carrier is busy and $Y[l_s] = 1$. Then, based on $Y[l_s], l \in \mathcal{U}_{ac}$ can be efficiently estimated with a cover decoder by directly removing the inactive users, i.e., $\{u \mid C[l_s, u] = 1, Y[l_s] = 0\}$ [9].

Informed by [9], in our case, the target of the user preamble $s_u, 1 \leq u \leq N$ is converted to convey the non-zero elements’ identities directly. To this end, we first generate a Zad-off Chu (ZC) sequence $z_r[n]$ and its $L_s − 1$ cyclic-shifting versions $z_r[n + 1], \ldots, z_r[n + L_s - 1]$ to form a ZC sequence set, 

$$\{z_r[n], z_r[n + 1], \ldots, z_r[n + L_s - 1]\}, z_r[n] = \exp \left[-j \pi r n \left(\frac{n + 1}{L_s}\right)ight], n = 0, 1, \ldots, L_s - 1$$

As a result, the elements of $h^p_u$ in (2) may reasonably be considered constant over the preamble duration, i.e., $h^p_u[l] \approx h^p_u[l], 1 \leq l \leq L_p$, which significantly simplifies the design of
the initial estimator. To be more concrete, the correlation value \( R[l_s], 1 \leq l_s \leq L_s \) between the preamble received signal \( y_p \) and the aforementioned \( L_s \) reference ZC sequences \( z_r[n + l_s] \), \( 0 \leq l_s \leq L_s - 1 \) in Section III-A is first calculated.

\[
R[l_s] = \frac{\sqrt{w_c}}{N_{zc}} \sum_{n=0}^{N_{zc}-1} y_p z_r^*[n + l_s],
\]

where \((\cdot)^*\) is the complex conjugate operator. As discussed in Section III-A, we can simply estimate \( R[E] \) iteration based on \( L_R \) the initial estimator. To be more concrete, the correlation value

However, a cover decoder will only make a hard decision according to the estimation of \( Y[l_s], 1 \leq l_s \leq L_s \), which is sensitive to the background noise. To improve the robustness of the initial estimator, an MPA based detector is proposed. Based on \( U_{ac}^l \), a redundant factor graph \( G(U_{ac}^l) \) can be constructed by regarding the sub-carriers as the check nodes and users in \( U_{ac}^l \) as the variable nodes. Define \( N(u) \) as the neighbor nodes connected to the \( u \)th variable node. \( N(u) \setminus l_s \) means excluding the \( l_s \)th check node from \( N(u) \). \( N(l_s) \) denotes the neighbor nodes connected to the \( l_s \)th check node. \( N(l_s) \setminus u \) denotes excluding \( u \)th variable node from \( N(l_s) \). According to [10], the values of \( R \) defined in (5) obey a Rice distribution, i.e., \( R[l_s] \sim \text{Rice}(\sum_{u' \in N(l_s)} a_{u'} h_{u'}^{2}, \frac{x}{\sigma^2}) \). We denote the probability density function of the Rice distribution as

\[
\text{Rice}(x|A,\sigma) = \frac{x}{\sigma^2} \exp(-\frac{x^2 + A^2}{2\sigma^2}) I_0(\frac{x A}{\sigma^2}),
\]

where \( I_0(\cdot) \) is the modified Bessel function of the first kind with the order zero. The rules of the proposed MPA detector in the \( i \)th iteration are given by

\[
E_{l_s \rightarrow u}^{(i)}(a_u) = R \sum_{a' \in N(l_s)} \text{Rice}(R[l_s] \mid a_u h_{u'}^{2} + \sum_{u' \in N(l_s) \setminus u} a_{u'} h_{u'}^{2}) - \sqrt{2N_{zc}} \prod_{u' \in N(l_s) \setminus u} E_{l_s \rightarrow u}^{(i-1)}(a_{u'}),
\]

\[
E_{u \rightarrow l_s}^{(i)}(a_u) = \prod_{l'_s \in N(u)} E_{l'_s \rightarrow u}^{(i-1)}(a_u),
\]

where \( E_{l_s \rightarrow u}^{(i)}(a_u) \) denotes the extrinsic information passed from the \( l_s \)th check node to the \( u \)th variable node in the \( i \)th iteration. \( E_{u \rightarrow l_s}^{(i)}(a_u) \) denotes the extrinsic information passed from the \( u \)th variable node to the \( l_s \)th check node in the \( i \)th iteration. Then constant \( R \) is chosen such that \( E_{l_s \rightarrow u}^{(i)}(a_u = 0) + E_{u \rightarrow l_s}^{(i)}(a_u = 1) = 1 \). The MPA based detector is initialized by \( E_{l_s \rightarrow u}^{(0)}(a_u = 0) = 1 - \lambda \) and \( E_{u \rightarrow l_s}^{(0)}(a_u = 0) = 1 - \lambda \). Then, the \( a \) posterior probability whether user \( u \) is active is computed as \( E(a_u) = \prod_{l'_s \in N(u)} E_{l'_s \rightarrow u}^{(0)}(a_u) \).

Note that in our scheme, the missing detection should be avoided as much as possible [9]. Hence, the decision rule of the proposed MPA based detector is

\[
\hat{a}_u = \begin{cases} 
0, & E(a_u = 0) > 0.99 \\
1, & \text{otherwise}
\end{cases}
\]

C. Traffic Load Aided MPA (TL-MPA) Based Initial Estimator

The search space of the proposed MPA based detector in (8) is in the order of \( O(2^{w_p}) \). \( w_p \) denotes the row weight of \( C \). The search space can be further reduced. Now, the traffic load of \( l_s \)th sub-carrier \( Y[l_s] \) can be estimated as

\[
a_{l_s} = \arg \min_{u} ||R[l_s] - a_{l_s}[u'] c_{u'}[l_s] h_{u'}^{2}||^2
\]

where \( a_{l_s} = \{ a_{u'} \mid u' \in N(l_s) \} \) is the user activity vector of \( l_s \)th sub-carrier. Meanwhile, \( Y[l_s] \) can be estimated as

\[
\hat{Y}[l_s] = \frac{1}{1, \text{otherwise}}
\]

In the detection process, we only search the possible combinations such that \( \sum_{u' \in N(l_s)} a_{u'} = Y[l_s] \) on the \( l_s \)th sub-carrier. The search space is reduced to the order of \( O(\hat{Y}[l_s]) \) where \( \binom{k}{n} \) denotes the number of combinations of \( n \) items taken \( k \) at a time. The decoding rules of TL-MPA are given by

\[
E_{l_s \rightarrow u}^{(i)}(a_u = 1),
\]

\[
E_{u \rightarrow l_s}^{(i)} = \sum_{l'_s \in N(u)} E_{l'_s \rightarrow u}^{(i-1)}(a_u),
\]

where

\[
p_{u, l_s} = \sum_{a' \in N(l_s) \setminus u} \prod_{u' \in N(l_s) \setminus u} \left(1 - p_{u'-l_s, u}(a_{u'})\right)^{(1-a_{u'})} \cdot (p_{u'-l_s, u}(a_{u'}))^{a_{u'}} \exp(\|R[l_s] - \sum_{u' \in N(l_s) \setminus u} a_{u'} h_{u'}^{2}\|^2),
\]

Particularly, \( E_{l_s \rightarrow u} = -\infty \) if \( \hat{Y}[l_s] = 0 \). The log-likelihood ratio (LLR) \( \log\frac{p(a_{u} = 1)}{p(a_{u} = 0)} \) is computed as \( r_u = \sum_{l'_s \in N(u)} E_{l'_s \rightarrow u}^{(0)}(0), E_{u \rightarrow l_s}^{(0)} \) is initialized as \( \log(\frac{1}{\lambda^2}) \). Similar to the MPA based detector, the decision rule of TL-MPA is

\[
\hat{a}_u = \begin{cases} 
0, & r_u < -15 \\
1, & \text{otherwise}
\end{cases}
\]

IV. DATA-AIDED FALSE ALARM CORRECTOR

Based on the redundant factor graph \( G(U_{ac}^l) \), the MPA algorithm [12] can be employed to perform data decoding [5]. The decoding process of the \( k \)th, \( 1 \leq k \leq K \) data symbol is formulated as

\[
\hat{x}_u[k] = \text{MAP}(y[k], G(U_{ac}^l)), u \in U_{ac}^l.
\]

However, the existence of the redundant variable nodes in \( G(U_{ac}^l) \) would degrade the decoding performance of MPA. Hence, removing these redundant variable nodes is of great importance, and this motivates our false alarm corrector.

In [8], a symbol energy based false alarm corrector is designed where the false detected users are recognized through detecting the energy of users’ decoded symbols. Nevertheless, such a false alarm corrector is susceptible to noise. In this
letter, a different false alarm corrector based on multiple zero symbol detection [5] is developed. The key idea is that if a user is active, the detected zero symbol number in its decoded packet $\hat{x}_u$ should be small, otherwise, the detected zero symbol number should be large. Let $\tau_{z_8} \geq 1 \in \mathbb{Z}_+$ denotes the threshold of the detected zero symbol number in any one data packet of users. For user $u$, $u \in \mathcal{U}_{ac}$, the proposed false alarm corrector can be summarized as

$$\hat{a}_u = \begin{cases} 0, & K - ||x_u||_0 > = \tau_{z_8} \\ 1, & \text{otherwise} \end{cases}$$

where $|| \cdot ||_0$ denotes the $l_0$-norm. When $\tau_{z_8} = 1$, our false alarm corrector is the same as that in [5]. In practical applications, a smaller $\tau_{z_8}$ would result in more missing detection, while a bigger $\tau_{z_8}$ would decrease the performance of the false alarm corrector. In this letter, to balance these two performances, the value of $\tau_{z_8}$ is chosen as $\lceil \frac{K}{4} \rceil$ empirically, where $\lceil \cdot \rceil$ denotes rounding up to the nearest integer. The pseudo-code of our proposal is given in Algorithm 1.

### V. Complexity Analysis

Instead of the perfect factor graph $\mathcal{G}(\mathcal{U}_{ac})$ [2], [3], executing MPA over the factor graph $\mathcal{G}(\mathcal{U}_{ac})$ will not increase the complexity order of MPA in the data decoding part, because the false alarms in $\mathcal{U}_{ac}$ are small. This fact is revealed later in Fig. 2. Hence, we mainly compare the complexity of the AUD part in this section.

The complexity order of OMP and AMP are analyzed in Table 1 in our previous work [4]. The complexity of DCS is approximately in the same order as OMP. Dominated by (8), the complexity of the MPA based detector $C_{MPA}$ is in the order of $O(L_s \lambda^{-w_2})$. The complexity of TL-MPA can be well approximated by

$$C_{TL-MPA} \approx O \left( L_s \left( p_{w_1} w_1 + p_{w_2} w_2 \right) \right),$$

where $w_1 = \lfloor \lambda w_r \rfloor$, $w_2 = 1 - p_{w_1}$, and $p_{w_2} = 1 - p_{w_1}$. Finally, the complexity orders of other algorithms are listed in Table I.

### VI. Simulation Results and Discussion

In this section, the AUD performance and data decoding performance are simulated. To evaluate the AUD performance, the probability of miss detection ($p_M$) and the probability of false detection ($p_F$) are adopted [4]. To measure the data decoding performance, the symbol error rate (SER) is adopted [13]. The system configuration is given in Table II.

Firstly, the $p_F$ and $p_M$ performance of super-set $\mathcal{U}_{ac}$ estimated by the proposed two initial estimators are evaluated. The $p_F$ performances of MPA based detector and TL-MPA outperform the cover decoder in [9] significantly when SNR > 4dB. This is because more specific traffic load information ($Y_I$) is exploited by the proposed two initial estimators. Moreover, the performance of TL-MPA is very closed to that of the MPA detector which verifies the efficiency of the proposed TL-MPA scheme.

The AUD performance of our proposed methods with $\lambda = 0.1$ is shown in Fig. 3. OMP-MPA indicates that the AUD is performed by OMP algorithm and data decoding is performed...
by MPA represented in (16). In the same spirit, we have AMP- 


decoding by MPA. DCS-MPA, which has the best AUD 


detection. In addition, a false alarm corrector is integrated into the data decoding stage to recognize the remaining false detected inactive users in the initial active user set. Simulation results verify the efficiency and superior performance of our proposed methods.

VII. CONCLUSION

In this letter, we transfer the AUD problem as a super-


set estimation problem based on the observation that the 

false detected users could be possibly corrected with the aid of decoded data symbols. Then, a two-step data-aided AUD scheme with false alarm correction is proposed. To estimate an initial active user set in step 1, the embedded LDS based user preamble pool is constructed and two MPA based initial estimators are developed to realize the detection. In addition, a false alarm corrector is integrated into the data decoding stage to recognize the remaining false detected inactive users in the initial active user set. Simulation results verify the efficiency and superior performance of our proposed methods.

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