Grant-free Rateless Multiple Access: A Novel Massive Access Scheme for Internet of Things

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Abstract—Rateless Multiple Access (RMA) is a novel non-orthogonal multiple access framework that is promising for massive access in Internet of Things (IoT) due to its high efficiency and low complexity. In the framework, after certain registration, each active user respectively transmits to the access point (AP) randomly based on an assigned random access control function (RACf) until receiving an acknowledgement (ACK). In this work, by exploiting the intrinsic access pattern of each user, we propose a grant-free RMA scheme, which no longer needs the registration process as in the original RMA, thus greatly reduces the signalling overhead and system latency. Furthermore, we propose a low-complexity joint iterative detection and decoding algorithm in which the channel estimation, active user detection, and information decoding are done simultaneously. Finally, we propose a method based on density evolution (DE) to evaluate the system performance.

Index Terms—Internet of Things (IoT), massive access, non-orthogonal multiple access.

I. INTRODUCTION

Recently, massive access technology in Internet of Things (IoT) has been attracting more and more attention due to the great demand and big challenges confronted in system design and deployment [1], [2]. In such a system, numerous always-on-line devices, probably 100 times more than those served by an up-to-date access point (AP) [1], require the system to support the massive connections. Furthermore, short packets (e.g., hundreds of bits or less) will constitute the majority of the traffic [2], which necessitates the minimization of signalling overhead. Last but not least, in some applications such as Internet of Vehicles (IoV), the devices should be served with extremely low latency (e.g., 1ms). However, in the current Long Term Evolution (LTE) system, the uplink transmission is scheduled by the AP with a request-grant procedure, i.e., the user should send a scheduling request (SR) to the AP during the registration procedure at first and then the AP performs scheduling to grant resources to users in a centralized manner [3]. If adopting this framework in IoT, the resultant signalling overhead and system latency will be totally unacceptable. These bring the necessity for novel grant-free access mechanism in the physical (PHY) layer, based on which, the aforementioned request-grant procedure can be omitted and user identities and user data can be transmitted to the AP simultaneously. Such a protocol design is challenging since it needs to meet the above requirements at the same time.

Recently, a novel random massive access framework called rateless multiple access (RMA) was proposed (see [4] and references therein). In this framework, after the registration, instead of granting each active user with fixed resources elements (RE, e.g., certain subcarrier-time slot pair), the AP assigns to each user a random access control function (RACf) which enables them to share a block of REs in a random manner. In particular, for every RE, each user independently chooses a random number of coded symbols according to the assigned RACf, and then sends out their sum over it. At the AP, a low-complexity belief propagation (BP) algorithm is used to recover the original information. The capacity-approaching, highly flexible and low-complexity characteristics make the framework attractive for future large-scale networking. However, RMA still has its limitation when applied to IoT which in general consists of a large number of machine-type nodes, in which the registration procedure will greatly reduce the efficiency and increase the system latency.

In this work, we propose a grant-free RMA scheme to overcome the above challenges. We exploit an intrinsic feature of RMA, i.e., each user has its own unique pseudo-random pattern for the access of REs, as a hidden clue to identify the user’s activity within the current RE block. Since the number of active users is typically orders of magnitude smaller than the access pattern space, it results in certain sparsity that can be exploited to do the active user detection. A low-complexity joint iterative detection and decoding algorithm based on BP is then proposed in which the channel estimation, the active user detection, and the information decoding are done simultaneously. Finally, we propose a method based on density evolution (DE) to evaluate the system performance.

Note that the active user detection in sparse system has also been investigated in [5]–[7]. Compared with these works, the advantages of our scheme are two-fold: (i) Previous works require that the channel state information (CSI) are available to the AP while our scheme does not, which makes sense for short packet transmission in IoT since the acquisition of CSI often incurs large amount of signalling; (ii) Unlike the previous works that apply the relatively complicated maximum a posteriori probability (MAP) detection, the proposed BP-based joint detection and decoding is of affordably low complexity, which makes it viable for massive access.

This work was supported in part by National Key Basic Research Program of China (No. 2012CB316104), National Hi-Tech R&D Program of China (No. 2014AA01A702), National Natural Science Foundation of China (No. 61371094, No. 61401391), the open project of Zhejiang Provincial Key Laboratory of Info. Proc., Commun. & Netw., China, and Huawei Technologies Co., Ltd (YB2013120029).

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II. PROTOCOL AND ALGORITHM

Consider a cellular network in which massive potential users independently access the AP sporadically. All the users are perfectly synchronized according to the downlink beacon from the AP. When one user is active, it transmits to the AP a short data packet. Since the packet is relatively short, the links between users and the AP are assumed to keep static during each transmission cycle.

A. The Proposed Grant-free access protocol

When the system is set up, user $k$, denoted by $U_k$, $k \in \{1, 2, ..., K\}$, is assigned by the AP an RACf (please be referred to [4] for the detailed design and optimization) as follows:

$$\rho(x) = \sum_{d=0}^{d_{\text{max}}} p_d x^d$$

where $\sum_{d=0}^{d_{\text{max}}} p_d = 1$.

At a given time, each user is active with probability $p_a$. If $U_k$ is inactive, it just keeps silent. Otherwise, as illustrated in Fig.1, it first encodes its message ($m$ bits) with a low-density parity-check (LDPC) encoder and maps the resultant coded bits to a symbol vector $\{x_{k,1}, x_{k,2}, ..., x_{k,N}\}$ with $\pm 1$-valued indices. Then as the AP broadcasts a beacon to start the access period, for each RE $t$ ($t \in \{1, 2, ..., T\}$), $U_k$ first pseudo-randomly generates a degree $d_{k,t}$ from 0 to $d_{\text{max}}$ with probability $p_{d_{k,t}}$ according to its RACf. If $d_{k,t} = 0$, it transmits nothing over that RE. Otherwise, it then uniformly selects $d_{k,t}$ symbols from its coded symbol vector, linearly combines them and then sends out the resultant over RE $t$. Denote the set of indices of the selected symbols as $\mathcal{V}(k, t) \subseteq \{1, 2, ..., N\}$. Thus the signal sent by $U_k$ over RE $t$ is

$$x'_{k,t} = \begin{cases} \sum_{j \in \mathcal{V}(k,t)} x_{k,j} & d_{k,t} \neq 0 \\ 0 & d_{k,t} = 0 \end{cases}$$

(2)

The signals transmitted over the same RE $t$ from all the users are linearly added together in the air, thus the signal received by the AP over RE $t$ can be written as

$$y_t = \sum_{k \in \{1, 2, ..., K\}} h_k x'_{k,t} + z_t$$

(3)

where $h_k$ denotes the channel gain from $U_k$ to the AP, which is 0 for inactive users, and $z_t$ denotes the Gaussian noise at RE $t$ with mean 0 and variance $\xi_w$.

The AP consistently and coherently collects signals from the available REs and keeps attempting to detect the activity of the potential users and decode all the active users’ messages until they are successfully retrieved or there are no active users, by viewing the transmission process as a special kind of linear superposition rateless encoder. Once a user message is successfully decoded, the AP feeds back to that user an acknowledgement (ACK) to end its current transmission cycle.

B. Joint active user detection and decoding algorithm

Fig. 2. Graph representation of the grant-free RMA. Each subgraph within a rectangle represents the LDPC code applied at a user. The edge between a VN and an REN means that the corresponding symbol is transmitted over that RE. Each USN connects to the set of RENs that the corresponding user pseudo-randomly selects during the access process. The soft messages transmitted on solid and dashed edges are about information bits and the user status, respectively.

Following [4], the aforementioned process can be elegantly represented by a factor graph as depicted in Fig 2. However, unlike [4], in which only three types of nodes, including check nodes (CNs), variable nodes (VNs) and resource element nodes (REns), are involved, the user status of activity, indicated by its channel gain, is expressed as a special type of variable nodes called user status nodes (USNs).

The AP performs iterative detection and decoding on the graph. More specifically, by exchanging soft messages on the graph iteratively, the AP recovers VNs and USNs, which correspond to the information decoding, the channel estimation and active user detection respectively. Here we introduce some notations that will be used later. The superscript $n$ denotes the iteration $n$. $L^n_{(k,j)\rightarrow t}$ denotes the log likelihood ratio passed from $j$th VN of $U_k$, namely VN $(k,j)$, to $t$th REN $(\mu^n_{h_k}, \xi^n_{h_k})$ denotes the estimated mean and variance of the channel gain from $U_k$ to the AP, and $q^n_k$ denotes the estimated active probability of $U_k$ in the current transmission cycle. In the initial stage, we have

$$L^0_{(k,j)\rightarrow t} = 0; \quad (\mu^0_{h_k}, \xi^0_{h_k}) = (\bar{\mu}_{h_k}, \bar{\xi}_{h_k}); \quad q^0_k = p_a$$

(4)

where $(\bar{\mu}_{h_k}, \bar{\xi}_{h_k})$ is the initial mean and variance of User $k$’s channel gain, and $p_a$ is the average user active probability.

1We assume that the AP knows some rough information about the mean and variance of channel gains so as to start the iterative detection process. In case they are unavailable, we can simply set them to be some proper non-zero values (e.g. 1 and 10, respectively) and use the asymptotic LDPC codes to eliminate the phase ambiguity [8]. The joint iterative algorithm can then re-estimate their exact values.
In the following, the iterative joint detection and decoding algorithm is described. First, we consider the messages passed from RENs to VNs. Let $\mathcal{M}(t)$ denote $\bigcup_{k=1}^{K} \mathcal{V}(k, t)$. Thereby, (4) can be equivalently reformulated as

$$y_t = h_k x_{k,j} + \varsigma_t,$$

where $\varsigma_t(k,j) = \sum_{(k',j') \in \mathcal{E}(k,j)} h_{k'} x_{k',j'}$. To reduce complexity, we resort to Gaussian Approximation (GA) as in [9], and approximate $\varsigma_t(k,j)$ to be Gaussian-distributed with mean $\mu_{\varsigma_t(k,j)}$ and variance $\xi_{\varsigma_t(k,j)}$ (please refer to [9] for details about them). As such, (5) can be further formulated as

$$y_t = \mu_{h_k}^{n+1} x_{k,j} + z_{h_k} + \varsigma_t(k,j) + \zeta_t,$$

where $z_{h_k} \sim \mathcal{N}(0, \xi_{h_k})$. Based on this, the message from REN $(k,j)$ to VN $(k,j)$ can be calculated by

$$L_{n+1}^{(k,j)} = \log \left( \frac{p(y_t|x_{k,j} = 1)}{p(y_t|x_{k,j} = -1)} \right) = \frac{2\mu_{h_k}^{n+1}(y_t - \mu_{\varsigma_t(k,j)}^{n+1})}{\xi_{h_k}^{n+1} + \xi_{\varsigma_t(k,j)}^{n+1} + \xi_w}.$$

Second, the soft message that VN $(k,j)$ gets from all the connected RENs can be expressed as

$$L_{n+1}^{(k,j)} = \sum_{v \in \mathcal{R}(k,j)} L_{n+1}^{(v,k,j)},$$

where $\mathcal{R}(k,j)$ denotes the set of indices of RENs that connect to VN $(k,j)$. Based on this, the LDPC coding part can be updated iteratively as in [10] and feeds back $L_{n+1}^{(k,j)} \rightarrow t$ to aid the active user detection as described below.

Third, we approximate $h_k$ with soft messages received from RENs. From (5), employing similar approximation method as in [11], we can get the symbol-wise channel estimate from messages passed from REN $t$ to USN $k$ as follows:

$$\mu_{h_k}^{n+1} = \frac{y_t - \mu_{\varsigma_t(k,j)}^{n+1}}{\tanh(h_k^{n+1}/2)},$$

and the estimation variance is

$$\xi_{h_k}^{n+1} = \frac{\xi_{\varsigma_t(k,j)}^{n+1} + \xi_w}{\tanh(L_{n+1}^{(k,j)}/2)}.$$

Denote the set of indices of RENs that connect to USN $k$ as $Q(k)$. Using the result for the product of Gaussian distributions [12], USN $k$ optimally combines all the messages from $Q(k)$ as well as the initial channel information, and re-estimates the mean and variance of the channel gain as

$$\left(\mu_{h_k}^{n+1}, \xi_{h_k}^{n+1}\right) = \left(\sum_{v \in Q(k)} \frac{\mu_{h_k}^{n+1}}{\xi_{h_k}^{n+1}}, \sum_{v \in Q(k)} \frac{1}{\xi_{h_k}^{n+1}} + \frac{1}{\xi_{h_k}^{n+1}}\right).$$

Finally, based on the re-estimated mean and variance of the channel gain, USN $k$ calculates the active probability of $U_k$ using the MAP criterion:

$$q_k = \frac{p_{\varsigma_t}^{n+1} \exp\left(-\frac{(\mu_{\varsigma_t(k,j)}^{n+1} - \mu_{\varsigma_t(k,j)}^{n+1})^2}{2\xi_{\varsigma_t(k,j)}^{n+1}}\right)}{p_{\varsigma_t}^{n+1} \exp\left(-\frac{(\mu_{h_k}^{n+1} - \mu_{h_k}^{n+1})^2}{2\xi_{h_k}^{n+1}}\right) + 1},$$

Note that (11) and (12) are used in the iterative decoding part such as in (7) and the calculation of $\mu_{\varsigma_t(k,j)}^{n+1}$ and $\xi_{\varsigma_t(k,j)}^{n+1}$.

### III. Performance Analysis

The average system throughput $T = \frac{K p_m}{E_{\text{er}}}$, and the average signal-to-noise ratio (SNR) over all the REs, denoted by $\gamma$, can be calculated by $\gamma = \frac{\sum_{k=1}^{K} \mathcal{E}(k,j) E_{\text{er}}}{L_{n+1}^{(k,j)}}$. The main object of this section is to derive the relationship between the system throughput and the corresponding threshold SNR, above which the error rate is able to converge to zero as the algorithm iterates. The DE analysis is an effective approach to analyze the performance of iterative decoding algorithms in the asymptotic sense, i.e., the quantities of each type of nodes in the decoding graph tend to infinity [10]. However, in our model, as depicted in Fig 2, each user only has one USN, which does not satisfy the asymptotic condition, and the channel estimate distribution cannot be used as in the conventional DE.

More specifically, to estimate the decoding performance based on the DE analysis [10], we need to analyze the evolution process of the mutual information (MI)

$$I(L_{n+1}^{(k,j)}; x_{k,j}).$$

According to (7)-(8), the relationship between $L_{n+1}^{(k,j)}$ and $x_{k,j}$ can be expressed as:

$$L_{n+1}^{(k,j)} = \sum_{v \in \mathcal{R}(k,j)} \left(2\mu_{h_k}^{n+1} x_{k,j} + 2\mu_{\varsigma_t(k,j)}^{n+1} - \mu_{\varsigma_t(k,j)}^{n+1} + z_t\right) / \xi_{h_k}^{n+1} + \xi_{\varsigma_t(k,j)}^{n+1} + \xi_w,$$

where $n_{h_k}^{n+1}$ is Gaussian distributed with mean 0 and variance $\xi_{h_k}^{n+1}$. Note that $L_{n+1}^{(k,j)}$ is also influenced by the soft message of the channel gain, i.e., $\mu_{h_k}^{n+1}$. Since $\xi_{h_k}^{n+1} \neq 0$ due to the relatively short block length, the distribution of $L_{n+1}^{(k,j)}$ is not symmetric [13], i.e., $\mu_{L_{n+1}^{(k,j)}} = 0$. Furthermore, the estimated mean of the channel gain, $\mu_{h_k}^{n+1}$, is a random variable, and the MI defined by (13) in each iteration is also a random variable, which makes the direct application of the conventional DE impossible. For rescue, we propose to use $E_{\mu_{h_k}^{n+1}}(I(L_{n+1}^{(k,j)}; x_{k,j}))$ instead.

To this end, we first need to obtain the distribution of $\mu_{h_k}^{n+1}$. Since it is generally hard to get the exact distribution of $\mu_{h_k}^{n+1}$ based on the above iterative process, by using the fact that its distribution well approximates the Gaussian distribution and tends to $\mathcal{N}(h_k, \xi_{h_k}^{n+1})$ when the MI of VNs approaches 1, we assume that $\mu_{h_k}^{n+1} \sim \mathcal{N}(h_k, \xi_{h_k}^{n+1})$. Then, we derive $I(L_{n+1}^{(k,j)}; x_{k,j})|\mu_{h_k}^{n+1}$.

More specifically, we consider it under two cases. First, in the case in which $\mu_{h_k}^{n+1} \leq h_k$, based on (13), we have $\mu_{L_{n+1}^{(k,j)}} > \frac{\xi_{h_k}^{n+1}}{2}$, and thus $L_{n+1}^{(k,j)}$ supplies more information to VNs than the message with distribution $\mathcal{N}(\mu_{h_k}^{n+1}, 2\mu_{L_{n+1}^{(k,j)}})$ on the other hand, in the case $\mu_{h_k}^{n+1} > h_k$, since the BP decoding of LDPC codes is less sensitive to the overestimation than it is to the underestimation of channel gains [13], the decoding performance is better than that in the contrary case.

At last, since $\xi_{h_k}^{n+1}$ defined in (14) is expected to be independent of $t$ and $(k,j)$, due to the law of large numbers,
we simply define $\xi^n_{(k,i)} \triangleq \xi^n_{c(k,i)}$. Thus, we have
\[
\mu^{n+1}_{L_k} = \frac{2h_k E(d_k,t) T}{(\xi^n_w + \xi^n_{h_k} + \xi^n_w) N} \mu^n_{h_k} \triangleq L_1(\mu^n_{h_k}).
\] (15)
Since the decoding performance of LDPC codes in the case $\mu^n_{h_k} \leq h_k$ is worse than that of the contrary case [13], we only consider the case $\mu^n_{h_k} \leq h_k$ approximately. Thus, we have
\[
E^n_{\mu^n_{h_k}}(I(L^{n+1}_k; x_{k,j})) \geq \int_{-\infty}^{h_k} I(L^{n+1}_k; x_{k,j}|\mu^n_{h_k}) \cdot 2p(\mu^n_{h_k}) d\mu^n_{h_k}.
\] (16)
Since $I(L^{n+1}_{k,j}; x_{k,j}|\mu^n_{h_k})$ in this case can be lower bounded by the MI of a symmetric Gaussian distribution, we approximately model $I^{n+1}_k$ by a random variable that is distributed as $N(\mu^n_{L_k}, x_{k,j}, 2\mu^n_{L_k})$, and by doing so the analysis of LDPC coding part can be done with reduced complexity. Thereby,
\[
E^n_{\mu^n_{h_k}}(I(L^{n+1}_k; x_{k,j})) \geq \int_{-\infty}^{h_k} \sqrt{2L_1(\mu^n_{h_k})} \cdot 2p(\mu^n_{h_k}) d\mu^n_{h_k},
\] (17)
where $J(x)$ is defined as
\[
J(x) = 1 - \int_{-\infty}^{x} \frac{1}{\sqrt{2\pi}} \exp \left\{ -\frac{(t - x)^2}{2} \right\} \cdot \log_2(1 + e^{-t}) \, dt.
\] (18)
Furthermore, let $d_x$ denote the average degree of VNs of the adopted LDPC codes and $\mu^{n+1}_{c(k,v)}$ denote the mean of the log likelihood ratio passed from the CNs to VNs of $U_k$, which can be calculated based on the aforementioned $\mu^{n+1}_{L_k}$ and $\mu^n_{h_k}$ (please be referred to [10] for details). For clarity, we define the calculation of $\mu^{n+1}_{c(k,v)}$ as $L_2(\mu^n_{h_k})$. As a result, the MI of VNs of $U_k$ in iteration $n + 1$ can be expressed as follows:
\[
\mu^{n+1}_{L_k} = \int_{-\infty}^{h_k} J \left( \sqrt{2L_1(\mu^n_{h_k}) + d_x L_2(\mu^n_{h_k})} \right) \cdot 2p(\mu^n_{h_k}) d\mu^n_{h_k}.
\] (19)
As such, the threshold SNR $\gamma_{th}$ can be expressed as
\[
\gamma_{th} = \min\{\gamma : I^n_{k} = 1, k \in K_n\},
\] (20)
where $K_n$ is the set of indices of active users.

IV. SIMULATION RESULTS

In the simulation, we set that there are 100 potential users. Among them, 10 randomly chosen ones are active (i.e., $p_n = 0.1$) and each transmits a packet of 240 bits to the AP. We set the total number of REs as 6400 and consider the scenario where the channels from the active users to the AP are the same. The initial mean and variance of the channel gains, $(\mu_{h_k}, \xi_{h_k})$, are all set as (1, 10). Following the optimization in [4], we choose RACf $\rho(x) = 0.062 + 0.04$ and that each active user encodes its packet with an LDPC code of rate 0.6. As illustrated in Fig 3 analytical and simulation results are consistent in demonstrating that the grant-free RMA only has a very little sacrifice in the block error rate (BLER) performance.

V. CONCLUSION

In this work, a grant-free RMA scheme is proposed to address the challenge brought by short-packet and low-latency transmissions in IoT networks. Our scheme omits the requirement of registration with a very little performance degradation, thus is a viable candidate for massive access in the IoT system. Furthermore, we propose a method based on DE to theoretically analyze the system performance, which gives instructions to the practical system design. At last, extending the proposed framework to the case with fast fading channels is left as a future work [14].

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