Grant-Free Random Access in Massive MIMO for Static Low-Power IoT Nodes

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Abstract—Massive MIMO is a promising technology to enable a massive number of Internet of Things nodes to transmit short and sporadic data bursts at low power. In conventional cellular networks, devices use a grant-based random access scheme to initiate communications. This scheme relies on a limited set of orthogonal preambles, which simplify signal processing operations at network access points. However, it is not well suited for Internet of Things (IoT) devices due to: (i) the large protocol overhead, and (ii) the high probability of collision. In contrast to the grant-based scheme, a grant-free approach uses user-specific preambles and has a small overhead, at the expense of more complexity at access points. In this work, a grant-free method is proposed, applicable for both co-located and cell-free deployments. The method has a closed form solution, which results in a significantly lower complexity with respect to the state-of-the-art. The algorithm exploits the static nature of IoT devices through the use of prior channel state information. With a power budget of 1 mW, 64 antennas are sufficient to support 1000 nodes with 200 simultaneous access requests with a probability of false alarm and miss detection below $10^{-6}$ and $10^{-4}$, respectively.

Index Terms—cell-free, grant-free, initial access, Internet-of-things, massive mimo, random access

I. INTRODUCTION

In IoT networks, a high number of devices are connected. However, only a handful of these devices are active at the same time, resulting in sporadic uplink transmissions. In order to serve these nodes, the active devices need to be detected, prior to decoding the data. Due to this sporadic traffic and the high number of IoT devices, allocating orthogonal preambles to these devices would incur an unacceptable overhead. As the network is unable to predict when these devices are active, an adequate initial access scheme needs to be implemented. The specificities of massive IoT, i.e., energy-limited, uplink focused, and low-payload size transmissions, call for a tailored initial access scheme.

Several multiple access techniques have been proposed for massive IoT [1][5]. These techniques follow a grant-based or grant-free approach, as illustrated in Fig. 1a and 1b, respectively. In the former, the devices request access to the network, prior to the communication. This is commonly done by competing for a dedicated orthogonal pilot sequence. In the latter approach, the devices are not required to request access and other approaches to mitigate and resolve potential collisions are implemented. An overview of different techniques can be found in literature [6][7].

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Fig. 1: Grant-based and grant-free random access mechanisms.

Grant-based random access. Based on the random access protocol used in long term evolution (LTE), [Björnson et al.] propose the strongest-user collision resolution (SUCRe) protocol, illustrated in Fig. 1a. Each active device requests a dedicated and unique orthogonal pilot by transmitting a random access pilot, with the possibility of using the same pilot as another contending device. The base station estimates the channel to each user based on the received pilots, after which it responds with orthogonal precoded downlink pilot signals, corresponding to the used pilots in the uplink. In case multiple devices have used the same pilot, the downlink signal is multicasted in a maximum ratio transmission fashion towards these devices, causing the expected received signal strength to be lower than expected. The (average) expected signal strength can be determined at the device side thanks to the channel hardening effect experienced in massive MIMO. Each device can, hence, detect whether a collision occurred. In this protocol, the strongest user is considered the winner and is scheduled for communication using a dedicated and unique pilots sequence. Other work has extended this technique by introducing, a.o., a higher fairness among the contenders [9][10].

Grant-free random access. In contrast to the grant-based random access, in a grant-free scheme, the devices use preassigned pilot sequences [11]. As shown in Fig. 1b, by skipping the grant request and collision resolution, both the pilot and data are sent in a single step. As mentioned earlier, the disadvantage of this approach is that it is not possible to utilize orthogonal pilots because the number of devices is much larger than the preamble length, i.e., $K \gg \tau_p$. The challenge in grant-free random access...
is device activity detection. Taking advantage of the sparse nature of the activity of the devices, different algorithms have been proposed to tackle this challenge through compressed sensing techniques [12,15]. These algorithms perform well because of the high number of access point (AP) antennas in massive MIMO, facilitating device detection in massive IoT networks. Fengler et al. [16,17] study the performance of several estimators to detect the active devices for a co-located massive MIMO system. In [18,19], this work is extended to the cell-free case by considering different large-scale fading coefficients per AP. They, however, were unable to directly use the proposed algorithm of [17] and had to consider only the contribution of the most dominant AP.

In this work, we consider the generic case where devices are not scheduled, and they transmit whenever needed, i.e., they are uplink-centric. As in conventional systems, we consider that all devices are time synchronized and work in a time slotted fashion. This can be easily achieved through downlink synchronization reference signals. Because of the large number of devices, providing orthogonal preambles to each user would generate a too large pilot overhead, i.e., pilots of length $K$. In this algorithm, a unique but non-orthogonal preamble is randomly generated and assigned to each user. Similar to key distribution in conventional low-power wide-area network (LPWAN), this sequence is known by both the network and the device, and is easy to implement. Based on prior channel state information (CSI), the active devices are detected. In case both the IoT node and APs are static, i.e., immobile, the channel response will be static in time as long as the environment is static as well. Hence, we can expect that the previously estimated CSI can be used for a longer time period than assumed in literature [20], given the static nature of the devices.

The proposed approach has a lower complexity than the techniques reported in literature. Our algorithm is evaluated through numerical simulations. Next to conventional massive MIMO, i.e., co-located massive MIMO, a cell-free deployment is included in the investigation.

**Notations:** vectors are denoted by boldface lower case $\mathbf{x}$ and matrices by boldface capital letters $\mathbf{X}$. The superscript $(\cdot)^H$ is used to denote the conjugate transpose operation. The absolute value is denoted by $|\cdot|$. The Kronecker product is denoted by $\otimes$. The notation $\mathbb{E}\{\cdot\}$ denotes the expectation of a random variable. The set of complex numbers is denoted by the symbol $\mathbb{C}$. The uniform distribution bounded by the closed interval between $a$ and $b$ is denoted by $\mathcal{U}_{[a,b]}$. The complex normal and normal distribution with mean $\mu$, standard deviation $\sigma$ and covariance matrix $\Gamma$ is denoted by $\mathcal{CN}(\mu,\Gamma)$, respectively. The identity matrix $\mathbf{I}_n$ is a $n \times n$ square matrix with ones on the main diagonal and zeros elsewhere.

**II. MOTIVATION – RECURRENCE IN CSI**

IoT – and more specifically LPWAN – technologies are often put in the field with a deploy-and-forget strategy, where the devices remain immobile afterwards. As such, we can expect that the channel conditions are less time-variant than assumed in theoretical models often assumed in literature [20,21]. To investigate the long-term behavior of the channel, a uniform linear array (ULA), described in [22], is used to estimate the channel of two static IoT nodes, shown in Fig. 3 over a time period of more than 8 hours. This measurement campaign represents a typical IoT scenario where the base station or gateway is located at an elevated height and the IoT devices are fixed in place. As shown in Fig. 3b, during the experiment, movement of the nodes is present. Furthermore, the line-of-sight (LoS) was sometimes blocked due to cars passing by, as would be the case in real deployments.

![Figure 2](image2.png)  
(a) Co-located case $N = 1$.  
(b) Cell-free case $N = 32$.  

**Fig. 2:** Example of a simulation scenario with an area of $500 \times 500$ m$^2$ for the case of 32 total base station antennas for a co-located (a) and cell-free (b) deployment.

![Figure 3](image3.png)  
(a) ULA at the balcony with Node 1 positioned right and Node 2 left.  
(b) Movement in the proximity of Node 2 during the measurements.  

**Fig. 3:** Measurement setup to study long-term channel behavior.

The long-term behavior is measured by taking the channel correlation (Eq. 1) of the first channel estimate and the other channel $N$ measurements, i.e., $\delta_{1,j}$ for $j \in \{1,\ldots,N\}$.
The observed channel correlations are depicted in Fig. 4a. The empirical cumulative distribution function (eCDF) of these correlation coefficients is shown in Fig. 4b. Fig. 4a illustrates that most of the time the correlation coefficient is close to 1, indicating that the channel is highly correlated with the first estimate and thus can be considered static. It also shows that, while in some occasions the correlation drops, the channel quickly becomes again highly correlated with the first channel instance. More than 90% of the measured channels have a correlation coefficient higher than 0.9 over a window of more than 8 hours. This demonstrates the potential of re-using channel estimates in IoT contexts.

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where \( g_k \in \mathbb{C}^{M \times 1} \) is the known prior CSI of device \( k \), \( \gamma_k \) is an unknown complex scalar and \( w_t \in \mathbb{C}^{M \times 1} \) is additive white gaussian noise (AWGN), distributed as \( \sim \mathcal{CN}(0, \sigma^2 I) \). The unknown complex scalar, \( \gamma_k = \sqrt{\rho_k} a_k e^{j\phi_k} \), contains the transmit power \( \rho_k \), device activity \( a_k \in \{0,1\} \) and a potential phase offset \( \phi_k \). The device-specific phase offset can account for a carrier frequency offset (CFO), where the CFO is considered constant over the preamble duration. By assuming that all \( M \) antennas are perfectly synchronized, this offset is only dependent on the device. In case the device is inactive, \( \gamma_k \) will be zero. Defining the matrices of channel vectors and pilot symbols at time \( t \),

\[
G = [g_0, \ldots, g_{K-1}] \in \mathbb{C}^{M \times K},
\]

\[
D_t = \text{diag}(s_{0,t}, \ldots, s_{K-1,t}) \in \mathbb{C}^{K \times K},
\]

the received signal at the \( M \) base station antennas at time \( t \) can be rewritten as

\[
y_t = GD_t\gamma + w
\]

The matrix \( GD_t \in \mathbb{C}^{M \times K} \) is known at the APs as it consists of the known CSI, \( G \), and the transmitted preamble symbols from the \( K \) devices, \( D_t \). By stacking the \( \tau_p \) consecutive \( y_t \in \tilde{y} \), the received signal becomes,

\[
\tilde{y} = \begin{pmatrix} GD_0 & \cdots & GD_{\tau_p-1} \end{pmatrix} \gamma + \tilde{w}
\]

\[
= \begin{pmatrix} G \cdots G \end{pmatrix} \begin{pmatrix} D_0 & \cdots & D_{\tau_p-1} \end{pmatrix} \gamma + \tilde{w}
\]

\[
= (I_{\tau_p} \otimes G) D \gamma + \tilde{w},
\]

where \( D = \begin{pmatrix} D_0 & \cdots & D_{\tau_p-1} \end{pmatrix} \) and \( \Gamma = (I_{\tau_p} \otimes G) D \in \mathbb{C}^{M\tau_p \times K} \).

III. SYSTEM MODEL

Two deployment strategies, i.e., co-located and cell-free massive MIMO, are considered, as shown in Fig. 2. The former follows the conventional massive MIMO where all antennas are located in one array, often spaced by half a wavelength. In cell-free systems, APs are geographically distributed over the area equipped with one or more antennas. In our study, we assume single-antenna APs in the cell-free case. In the remainder of the manuscript, we will use the term AP to denote the base station (in the central case).

There are \( K \) devices, each trying to access the network with a certain activity probability \( \epsilon_k \). To do so, each active device \( k \in K_o \) sends a unique, non-orthogonal preamble of length \( \tau_p \), known to the network. The pilot symbol of the preamble sent by device \( k \) at pilot symbol \( t \) is denoted by \( s_{k,t} \). The vector of received symbols at the \( M \) antennas of the APs at time \( t \) is

\[
y_t = \sum_{k=0}^{K-1} g_k s_{k,t} \gamma_k + w_t,
\]

Fig. 4: Channel correlation over a full day (9h24-17h48) with over 10,000 channel instances.
IV. DEVICE ACTIVITY DETECTION

A novel algorithmic solution is proposed to find the active devices. After determining the active devices, conventional detection techniques, e.g., zero forcing (ZF), can be used to separate the devices in the uplink. As soon as $\tau_p \geq K/M$ and for well-conditioned channels and pilot sequences, the matrix $\Gamma$ will be of full rank $K$ and $\gamma$ can be estimated by using a left pseudo inverse,

$$\hat{\gamma} = \left( \Gamma^H \Gamma \right)^{-1} \Gamma^H \hat{y}$$

(6)

$$= \gamma + \left( \Gamma^H \Gamma \right)^{-1} \Gamma^H \hat{w}.$$  

This corresponds to the maximum likelihood estimate. Note that, when $M\tau_p \gg K$, $\Gamma^H \Gamma$ is expected to become a diagonal matrix because the device channels and unique preambles will become orthogonal $[20]$. This can lower the complexity of the inverse operation and allows for distributed processing.

A non-negative activity threshold $\gamma_{th,k}$ is applied for each device $k$. A device is considered active if $|\hat{\gamma}_k| > \gamma_{th,k}$. We define the real-valued threshold as,

$$\gamma_{th,k} = \nu \sqrt{\text{SNR}_k},$$

(7)

where $\nu$ is chosen to have a desired probability of false alarm and miss detection performance, as discussed in Section V. The signal-to-noise ratio (SNR) of device $k$, $\text{SNR}_k$, is $\rho_k ||\beta_k||^2 ||s_k||^2 / \sigma^2$, with $\sigma^2$ the noise power.

V. SIMULATION RESULTS

The performance of the proposed scheme is explored for a co-located and a cell-free system. An example of a simulation scenario, with a co-located or cell-free AP deployment, is shown in Fig. 2. The number of APs is denoted by $N$. The default simulation configurations are summarized in Table I.

### TABLE I: Simulation parameter set.

| Parameter            | Symbol | Default value |
|----------------------|--------|---------------|
| Number of devices    | $K$    | 1000          |
| Number of APs        | $N$    | -             |
| Number of total AP antennas | $M$ | -             |
| Area size            | $A$    | $500 \times 500 \text{ m}^2$ |
| Device activity probability | $\epsilon_a$ | 0.01         |
| Transmit power of the device | $\rho$ | 1 mW         |
| Bandwidth            | $B$    | 125 kHz       |
| Thermal noise        | $\sigma^2$ | $-122.88 \text{ dBm}$ |
| Path loss            | $\beta$ | urban model $[23]$ |
| Carrier Frequency    | $f_c$  | 808 MHz       |
| Pilot sequence       | $s_k$  | $CN(0,1)$     |
| Pilot length         | $\tau_p$ | 40 symbols   |
| IoT device height    | $h_k$  | 1 m to 4 m    |
| AP height            | $h_{BS}$ | 29 m         |
| Phase offset         | $\phi_k$ | $U[0,2\pi]$ |
| Number of simulations| $N_{\text{sim}}$ | 1000         |

We consider an area of $500 \times 500 \text{ m}^2$ with 1000 devices. The positions of the devices are randomly generated for each simulation. The locations are kept constant among the different scenarios in order to have a fair comparison. The locations of the access points are generated in order to have, on average, a uniform distribution of the AP positions, as shown in Fig. 2b.

For each simulation, a grid of size $\sqrt{N}$ by $\sqrt{N}$ is generated of which $N$ random positions are selected for the APs. In case there is only one AP, the AP is located in the center. The device activity profile is generated randomly and independently for each device with a probability $\epsilon_a = 0.01$, meaning that on average 10 devices are active simultaneously. Or equivalently, the devices have an average duty cycle of 1%, which can be considered high $[24]$ for the investigated applications and hence represents a worst-case scenario. A higher number of simultaneously active devices is simulated by increasing the activity probability $\epsilon_a$. All devices use the same transmit power of 1 mW. We assume the same bandwidth as used in long-range wide-area network (LoRaWAN), i.e., 125 kHz, and have adopted the thermal noise floor for a 125 kHz signal, i.e., $\sigma^2 = -122.88 \text{ dBm}$, at the receiver.

The channel between AP $n$ and device $k$ is modeled as $g_{k,n} = \sqrt{\beta_{k,n}}h$, with $\beta_{k,n}$ the path loss and $h$ the small-scale fading independently and identically distributed (i.i.d.) $\sim CN(0,1)$. The large-scale path loss follows the reported model in $[23]$ for an urban environment operating at 868 MHz, i.e., $\beta_{k,n} = 128.95 + 23.2 \log_{10}(d_{k,n}) + \chi \text{ dB}$ with $d_{k,n}$ the distance between device $k$ and AP $n$ and $\chi$ the shadow fading $\sim N(0,7.8)$. For the co-located case, $\beta_{k,n}$ becomes $\beta_k$.

In the proposed scheme, we consider that the channel $G$ is static in time. The pilot sequence is randomly generated from a complex Gaussian distribution $s_k \sim CN(0,1)$, and is assumed to be known by all APs. Each device uses a pilot sequence of 40 symbols, respecting the requirement of $\tau_p$ being greater than or equal to $K/M$. A random phase offset $\phi_k \sim U[0,2\pi]$ is generated to simulate a carrier frequency offset (considered time-invariant over the simulation period).

1) Trading-off the probability of false alarm and miss detection: The receiver operating characteristic (ROC) is studied based on the probability of miss detection and false alarm. False alarm happens when a device is considered active, while it was actually not transmitting. In contrast, a miss detection occurs if a device was active but is undetected. As in $[11]$, the probability of miss detection is defined as the average ratio of undetected devices to the number of active devices

$$P_{md} = 1 - \mathbb{E}\left\{ \frac{|\hat{K}_a \cap \tilde{K}_a|}{|\hat{K}_a|} \right\},$$

(8)

where $\hat{K}_a$ is the set of active devices and $\tilde{K}_a = \{k|\hat{a}_k = 1, \forall \in [1,K]\}$ denotes the estimated set of active devices. Note that on average $|\hat{K}_a| = K_{a}$. Similarly, the probability of false alarm is the ratio of inactive devices considered active to the number of inactive devices and is given by

$$P_{fa} = \mathbb{E}\left\{ \frac{|\hat{K}_a \setminus K_a|}{K - |\hat{K}_a|} \right\}. $$

(9)

The results presented in Fig. 5, 6, and 7 are scaled to the lowest non-zero probability measurable, which depends on the...
number of nodes, active nodes $|K_a|$ and number of simulations $N_{\text{sim}}$. The minimum obtained probability of miss detection is observed if only one device of all active devices is undetected, i.e., $1/\left(\sum_{l=1}^{N_{\text{sim}}} |K_{a,l}|\right) \approx 1/(K_a * N_{\text{sim}})$. Equivalently, the lower false alarm is perceived when only one inactive device is considered active, i.e., $1/\left( KN_{\text{sim}} - \sum_{l=1}^{N_{\text{sim}}} |K_{a,l}|\right) \approx 1/(N_{\text{sim}} - K_a)$. For the default case with 1000 simulations, this becomes on average $10^{-6}$ and $10^{-4}$ for the probability of false alarm ($P_{fa}$) and miss detection ($P_{md}$), respectively. A trade-off can be made between the two probabilities by varying $v$ in (7). A lower $v$ yields a lower activity threshold, resulting in more devices considered active. This in turn lowers the probability of miss detection, while increasing the probability of generating a false alarm. In the simulations, the parameter $v$ is swept across the range $[10^{-2}, 10^5]$. In the remainder of the manuscript, the optimal threshold $v_{\text{opt}}$ is used to denote the choice of $v$ yielding the lowest probability of false alarm and miss detection. Due to the limits imposed by the minimum probabilities observable, there exists a region where no errors of false alarm and miss detection, were observed.

In the following, the impact of varying the device transmit power, area size and activity level on the device detection performance is studied.

![ROC graphs for different transmit powers and BS antenna configurations](image1)

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**Effect of the transmit power:** The impact of the devices’ transmit power (1 mW, 10 mW, 25 mW) when using 32 and 64 antennas is shown in Fig. 5. In the case of 128 antennas, no false alarm or miss detection has been observed when using the optimal threshold $v_{\text{opt}}$ for all three transmit powers. For both 10 mW and 25 mW transmit power the cell-free and co-located case, even with only 32 antennas, perform optimal. In case of using 1 mW transmit power, 32 antennas show not to be sufficient. As of 64 antennas only in the co-located system, miss detection and false alarm are observed, but the probabilities are reduced by a factor of 100. This demonstrates that the transmit power of IoT devices could be greatly reduced by moving to a cell-free scenario, while still requiring only a limited number of AP antennas.

![ROC graphs for different transmit powers and BS antenna configurations](image2)

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**Effect of the area size:** Fig. 6 illustrates the impact of the area size on the performance of the initial access scheme for a $500 \times 500$ m$^2$ and a $1000 \times 1000$ m$^2$ area. The cell-free systems experience a lower performance degradation due to the higher path loss (PL) of the $1000 \times 1000$ m$^2$ area.

**Effect of the activity level:** Fig. 7 shows the impact of an increase in activity probability from 0.01 to 0.2. The latter implies that, on average, 200 devices simultaneously access the network. Similar to previous observations, the cell-free systems outperform the co-located networks. Despite this, even with 20% of the devices being active on average, the systems using 64 (cell-free) 128 (both cell-free and co-located) AP antennas, do not detect any errors.

![ROC graphs for different transmit powers and BS antenna configurations](image3)

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Fig. 6: ROC for a $500 \times 500$ m$^2$ and $1000 \times 1000$ m$^2$ area. The cell-free systems experience a lower performance degradation due to the higher path loss (PL) of the $1000 \times 1000$ m$^2$ area.

Fig. 7: The co-located system experiences more performance degradation than cell-free systems when increasing the activity probability. Even with 20% of the devices being active, the systems using 64 (cell-free) and 128 (both cell-free and co-located) AP antennas do not detect any errors. Notice that the x-axis is scaled differently as the minimal observable probability of miss detection is lower for the $\epsilon_a = 0.2$ case due to a higher number of active devices, which is on average 200 opposed to 10 for $\epsilon_a = 0.01$. 

![ROC graphs for different transmit powers and BS antenna configurations](image4)
VI. CONCLUSIONS

A grant-free algorithm is proposed using prior CSI for initial access in massive MIMO networks. It serves as a baseline for the potential of re-using channel state information to support massive and low-power IoT. The initial scheme has a closed form solution, without the need for iterations, to scale to a large number of devices, and is robust to CFO. The performance of the proposed algorithm is studied for a conventional co-located and cell-free system. A trade-off between the probability of false alarm and miss detection can be made. The simulation results demonstrate that with only 1 mW of transmit power, 64 base station antennas, deployed in a cell-free setup, will suffice to support a large area (1000 x 1000 m) and a high number of access requests (up to 200) and still having a probability of false alarm and miss detection below $10^{-6}$ and $10^{-4}$, respectively. Furthermore, the results also indicate that we could greatly reduce the transmit power of IoT devices by moving to a cell-free scenario, while requiring only a limited number of total AP antennas. In contrast to what is observed in [25], with our algorithm, the performance of a cell-free topology performs better than a co-located case. This is because we are able to exploit the full channel state information and thus also the increase in channel diversity due to the geographical distribution of the APs.

As an extension, the model and algorithm could be adapted to include partial CSI, as opposed to perfectly knowing the full channel state information. In addition, currently, single-antenna APs are considered for the cell-free case. The simulations can be extended by investigating the optimal number of APs for a fixed number of total receive antennas.

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