Non-Coherent Grant-Free Massive IoT Access for mMTC: An Index Modulation Perspective

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July 29, 2021

Outline

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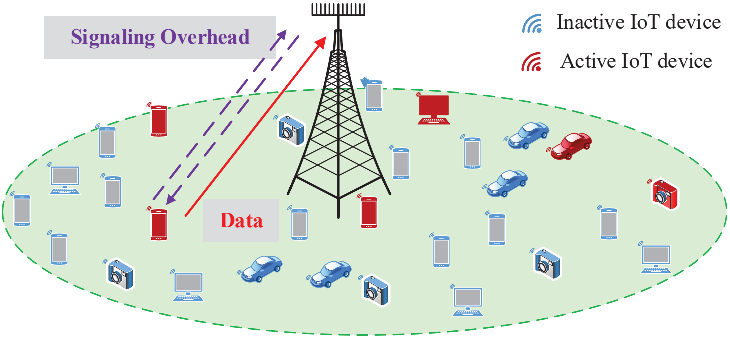
From Grant-Based to Grant-Free Random Access

- The mMTC are characterized by uplink transmissions with short packets from massively deployed IoT devices whose data traffic are sporadic
- **Grant-based random access**: Orthogonal, prohibitive signaling overhead and latency, even the access congestion
- **Grant-free random access (GFRA)**: Devices can transmit in the uplink without waiting for permission, reduces latency, non-orthogonal [1]



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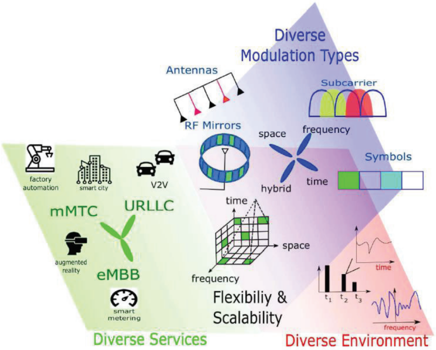
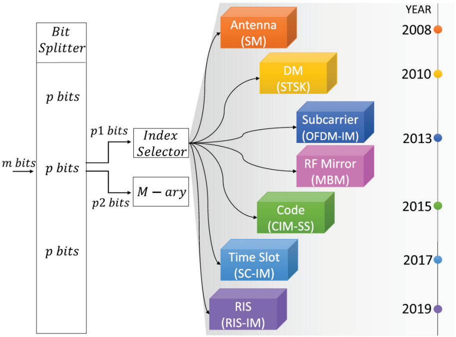
Index Modulation-Based GFMA

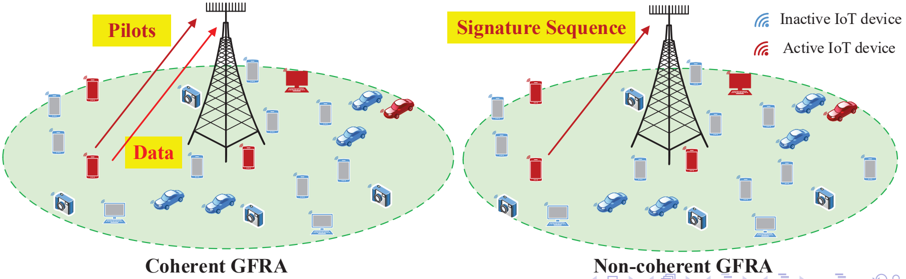
- Information bits are modulated onto a predefined codebook to enhance the data rate[1]
- Many realizations, i.e., spatial modulation, media modulation, and, more recently, reconfigurable intelligent surface (RIS)-based modulation [2]
- Due to its high spectrum- and energy-efficiency, IM-based GFMA for IoT access has been investigated recently [3]





[1] S. Doan Tusha, A. Tusha, E. Basar and H. Arslan, "Multidimensional index modulation for 5G and beyond wireless networks, " Proc. IEEE, vol. 109, no. 2, pp. 170-199, Feb. 2021..

- **Coherent GFRA Protocols**
- Data is detected based on the priorly detected channel state information (CSI)
- It is hard to obtain accurate CSI sometimes. Also, coherent approaches are not efficient for low-cost and small packets
- **Non-Coherent GFRA Protocol**
- Each device is assigned with a unique sequence codebook [4]
- Information bits are modulated into the transmitted signature sequence
- Suitable for low-cost and small packet IoT devices, also for scenarios that accurate CSI is hard to be acquired, i.e., fast time varying channel



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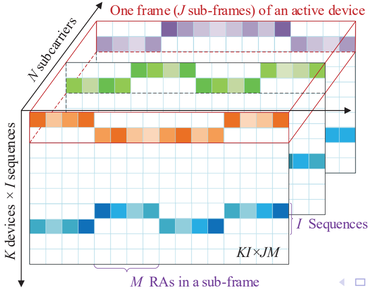
- Uniform linear array-based BS with M receive antennas, serving K single-antenna based IoT devices
- Only K_a out of K ($K \gg K_a$) devices are simultaneously active, which share the same time-frequency resources
- Orthogonal Frequency Division Multiplexing (OFDM) is considered for overcoming frequency-selective fading
- The CSI $\mathrm{h}_{k,n}$ of the n-th subcarrier and the k-th device in the UL, $\forall n, k$, can be denoted by

$$\mathrm{h}_{k,n} = \sqrt{\frac{M}{P}} \sum_{p=1}^{P} h_{k,p} \mathrm{a}(\theta_{k,p}) e^{-j2\pi\tau_{k,p}\left(-\frac{B_s}{2} + \frac{B_s(n-1)}{N}\right)}, \tag{1}$$

where $h_{k,p}$, $\theta_{k,p}$, and $\tau_{k,p}$ represent the channel gain, the angle of arrival (AoA), and the delay for the p-th path of the k-th device, respectively. B_s denotes the two-sided bandwidth and the antenna array spatial steering vector is $\mathrm{a}(\theta_{k,p}) = \frac{1}{\sqrt{M}} \left[1, e^{j2\pi\frac{d\sin(\theta_{k,p})}{\lambda}}, \ldots, e^{j2\pi(M-1)\frac{d\sin(\theta_{k,p})}{\lambda}}\right]^T$, where λ is the carrier wavelength and the antenna spacing at the BS $d = \lambda/2$

- $I = 2^r$ unique signature sequences with length L ($L \ll K$) are allocated to each device, r-bit embedded information
- The codebook of the k-th device, $\forall k \in [K]$, is denoted by $\Phi_k = [\phi_{k,1}, ..., \phi_{k,I}] \in \mathbb{C}^{L \times I}$, whose elements are generated by sampling an independent and identically distributed (i.i.d.) symmetric Bernoulli distribution.
- The selected sequence is transmitted in L successive OFDM symbols of the same subcarrier, which is called a sub-frame
- The device activity and the CSI are commonly assumed to be unaltered within a frame (J sub-frames) in slowly time-varying IoT scenarios



The received signal $\mathbf{Y}_n^j \in \mathbb{C}^{L\times M}$ of the n-th subcarrier in the j-th sub-frame, $\forall j \in [J]$, can be expressed as

$$\begin{aligned} \mathbf{Y}_n^j &= \sum\nolimits_{k=1}^{K} a_k \boldsymbol{\Phi}_k \mathbf{e}_{k,n}^j (\mathbf{h}_{k,n})^T + \mathbf{N}_n^j \\ &= \sum\nolimits_{k=1}^{K} \boldsymbol{\Phi}_k \mathbf{X}_{k,n}^j + \mathbf{N}_n^j = \boldsymbol{\Phi}\mathbf{X}_n^j + \mathbf{N}_n^j \end{aligned} \tag{2}$$

- The activity indicator $a_k^j \in \{0,1\}$ is equal to one (zero) if the k-th device is active (inactive)
- $\mathbf{e}_{k,n}^j \in \{0,1\}^{I\times 1}$, $\mathbf{h}_{k,n} \in \mathbb{C}^{M\times 1}$, $\mathbf{X}_{k,n}^j = a_k \mathbf{e}_{k,n}^j (\mathbf{h}_{k,n})^T \in \mathbb{C}^{I\times M}$ denote the sequence selection vector, the CSI, and the equivalent channel matrix
- $\mathbf{N}_n^j$ is Gaussian noise with its elements following the i.i.d. complex Gaussian distribution $\mathcal{CN}(0, \sigma_n^2)$
- $\boldsymbol{\Phi} = [\boldsymbol{\Phi}_1, ..., \boldsymbol{\Phi}_K] \in \mathbb{C}^{L\times KI}$, and $\mathbf{X}_n^j = [(\mathbf{X}_{1,n}^j)^T, ..., (\mathbf{X}_{K,n}^j)^T]^T \in \mathbb{C}^{KI\times M}$
- The device activity detection and embedded information detection problem focuses on the estimation of the none-zero indices of $\mathbf{X}_n^j$, $\forall n, j$
- **The exact value of $\mathbf{X}_n^j$ is unnecessary**

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Problem Formulation

- Supposing that Q $(1 < Q \leq N)$ subcarriers are utilized for joint signal processing. Due to the intermittent traffic of IoT devices, only a fraction of devices is active within a frame, i.e., $K_a \ll K$, we have

$$\left|\mathrm{supp}\left\{\mathbf{X}_q^j\right\}\right|_c = K_a \ll K, \quad \forall q \in [Q], \ \forall j \in [J], \tag{3}$$

  where $\mathrm{supp}\left\{\cdot\right\}$ denotes the support, i.e., the indices of non-zero rows
- Owing to the structured sparsity of the sequence selection vector within a sub-frame, i.e., $\|\mathbf{e}_{k,q}^j\|_0 = 1$, $\forall k, q, j$, we have

$$\mathrm{supp}\left\{\mathbf{e}_{k,q}^j\right\} = \mathrm{supp}\left\{\left[\mathbf{X}_{k,q}^j\right]_{:,m}\right\}, \quad \forall m \in [M] \tag{4}$$

- The common device activity in multiple subcarriers within a frame can be expressed by

$$\left\lceil \mathrm{supp}\left\{\mathbf{X}_1^1\right\}/I \right\rceil = \left\lceil \mathrm{supp}\left\{\mathbf{X}_q^j\right\}/I \right\rceil, \quad \forall q, j \tag{5}$$

- We refer to Eqs. (3)-(5) collectively as the space-frequency structured sparsity

To exploit the **space-frequency structured sparsity** in Q contiguous subcarriers within a frame (J sub-frames), we can rewrite (2) as a compact matrix form, i.e.,

$$\mathrm{Y} = \Phi \mathrm{X} + \mathrm{N} \tag{6}$$

- $\mathrm{Y} = \left[\mathrm{Y}_1^1, ..., \mathrm{Y}_1^J, ..., \mathrm{Y}_Q^J\right] \in \mathbb{C}^{L \times JMQ}$
- $\mathrm{N} = \left[\mathrm{N}_1^1, ..., \mathrm{N}_1^J, ..., \mathrm{N}_Q^J\right] \in \mathbb{C}^{KI \times JMQ}$
- Denote $M'=JMQ$ and the m'-th column of X, $\forall m' \in [M']$, is denoted as $\mathrm{x}_{m'}$, where $\mathrm{x}_{m'} = [(\mathrm{x}_1^{m'})^T, (\mathrm{x}_2^{m'})^T, ..., (\mathrm{x}_K^{m'})^T]^T \in \mathbb{C}^{KI \times 1}$ and $\mathrm{x}_k^{m'} = [x_{k,1}^{m'}, ..., x_{k,I}^{m'}]^T \in \mathbb{C}^{I \times 1}$, $\forall m', k$
- Similarly, we denote the m'-th column of Y and N as $\mathrm{y}_{m'}$ and $\mathrm{n}_{m'}$, respectively

Prior Information Modeling and MMSE Estimation

- Minimizing the mean square error between Y and ΦX of (6) equals to estimating the *a* posteriori mean of X
- he posterior mean of $x_{k,i}^{m'}$, $\forall k \in [K]$, $\forall i \in [I]$, $\forall m' \in [M]$, can be expressed as

$$x_{k,i}^{m'} = \int x_{k,i}^{m'} p\left(x_{k,i}^{m'} | \mathrm{y}_{m'}\right) dx_{k,i}^{m'}, \tag{7}$$

where $p(x_{k,i}^{m'}|\mathrm{y}_{m'})$ is the marginal distribution of $p(\mathrm{x}_{m'}|\mathrm{y}_{m'})$ and it can be described as

$$p\left(x_{k,i}^{m'} | \mathrm{y}_{m'}\right) = \int_{\backslash x_{k,i}^{m'}} p\left(\mathrm{x}_{m'} | \mathrm{y}_{m'}\right) \tag{8}$$

- Based on Bayesian theorem, the posterior distribution $p(\mathrm{x}_{m'}|\mathrm{y}_{m'})$ can be expressed as

$$\begin{aligned} p\left(\mathrm{x}_{m'} | \mathrm{y}_{m'}, \mathrm{a}; \boldsymbol{\theta}\right) &= \frac{1}{p\left(\mathrm{y}_{m'}\right)} p\left(\mathrm{y}_{m'} | \mathrm{x}_{m'}; \boldsymbol{\theta}\right) f\left(\mathrm{x}_{m'} | \mathrm{a}; \boldsymbol{\theta}\right) h(\mathrm{a}; \boldsymbol{\theta}) \\ &= \frac{1}{p\left(\mathrm{y}_{m'}\right)} \prod_{l=1}^{L} p\left([\mathrm{y}_{m'}]_l | \mathrm{x}_{m'}; \boldsymbol{\theta}\right) \prod_{k=1}^{K} f\left(\mathrm{x}_k^{m'} | a_k; \boldsymbol{\theta}\right) h(a_k; \boldsymbol{\theta}), \end{aligned} \tag{9}$$

where the likelihood function is denoted as

$$p\left([\mathrm{y}_{m'}]_l | \mathrm{x}_{m'}; \boldsymbol{\theta}\right) = \frac{1}{\pi \sigma_n^2} \exp\left(-\frac{1}{\sigma_n^2} \left| [\mathrm{y}_{m'}]_l - \sum_{k=1}^{K} \left[\Phi_k \mathrm{x}_k^{m'}\right]_l \right|^2\right) \tag{10}$$

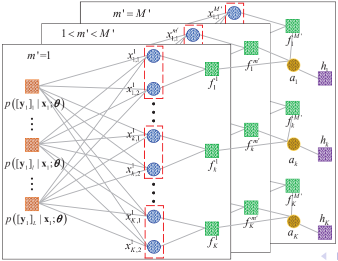
- By leveraging the structured sparsity in (4), the prior distribution is assumed to be

$$f\left(\mathrm{x}_k^{m'} \,|\, a_k; \boldsymbol{\theta}\right) = (1-a_k)\sum\nolimits_{i=1}^{I} \delta\left(x_{k,i}^{m'}\right) + a_k \sum\nolimits_{i=1}^{I} \mathcal{CN}\left(x_{k,i}^{m'}; \mu_0, \tau_0\right) \prod\nolimits_{g\neq i} \delta\left(x_{k,g}^{m'}\right), \tag{11}$$

where the distribution of the activity indicator is denoted as

$$h\left(a_k; \boldsymbol{\theta}\right) = (1-\lambda_k)\delta\left(a_k\right) + \lambda_k \delta\left(a_k - 1\right), \tag{12}$$

the parameter set is denoted as $\boldsymbol{\theta}=\{\mu_0, \tau_0, \sigma_n^2, \lambda_1, ..., \lambda_K\}$, a=$[a_1, a_2, ..., a_K]^T$, and $\delta(\cdot)$ is the Dirac delta function



Why AMP?

- Calculating the marginal distribution $p(x_{k,i}^{m'}|\mathrm{y}_{m'})$ in (8) from $p\left(\mathrm{x}_{m'}|\mathrm{y}_{m'}\right)$ is extremely complicated in massive access, due to the large value of K
- AMP algorithm achieves near MMSE performance with relatively low complexity in large system regime

How to use AMP?

- **AMP decoupling step:** [5]
- we can approximately decouple (6) into $KIJMQ$ scalar problems as

$$\mathrm{Y} = \Phi\mathrm{X} + \mathrm{N} \ \rightarrow \ r_{k,i}^{m'} = x_{k,i}^{m'} + \widetilde{n}_{k,i}^{m'}, \tag{13}$$

where $k \in [K]$, $i \in [I]$, $m' \in [JMQ]$, $r_{k,i}^{m'}$ is the mean of $x_{k,i}^{m'}$ estimated by AMP algorithm, and $\widetilde{n}_{k,i}^{m'} \sim \mathcal{CN}(\widetilde{n}_{k,i}^{m'}; 0, \varphi_{k,i}^{m'})$ is the associated noise with zero mean and variance $\varphi_{k,i}^{m'}$

In the t-th AMP iteration, $r_{k,i}^{m'}$ and $\varphi_{k,i}^{m'}$ are updated on the variable nodes $\{x_{k,i}^{m'}\}$, $\forall k, i, m'$, which can be denoted as

$$\varphi_{k,i}^{m'} = \left(\sum\nolimits_{l=1}^{L} \frac{\left|[\Phi_k]_{l,i}\right|^2}{\sigma_n^2 + V_l^{m'}}\right)^{-1}, \tag{14}$$

$$r_{k,i}^{m'} = \widehat{x}_{k,i}^{m'} + \varphi_{k,i}^{m'} \sum\nolimits_{l=1}^{L} \frac{[\Phi_k^*]_{l,i}\left([\mathrm{y}_{m'}]_l - Z_l^{m'}\right)}{\sigma_n^2 + V_l^{m'}}, \tag{15}$$

where $V_l^{m'}$ and $Z_l^{m'}$, $\forall l, m'$, are updated at the factor nodes $\{p\left([\mathrm{y}_{m'}]_l|\mathrm{x}_{m'};\boldsymbol{\theta}\right)\}$ of the factor graph as

$$V_l^{m'} = \sum\nolimits_{k=1}^{K} \left|[\Phi_k]_{l,:}\right|^2 \widehat{\mathrm{v}}_k^{m'}, \tag{16}$$

$$Z_l^{m'} = \sum\nolimits_{k=1}^{K} [\Phi_k]_{l,:}\widehat{\mathrm{x}}_k^{m'} - V_l^{m'} \frac{[\mathrm{y}_{m'}]_l - \left(Z_l^{m'}\right)^{t-1}}{\sigma_n^2 + \left(V_l^{m'}\right)^{t-1}}, \tag{17}$$

$\widehat{\mathrm{x}}_k^{m'} = [\widehat{x}_{k,1}^{m'}, \ldots, \widehat{x}_{k,l}^{m'}]^T$ and $\widehat{\mathrm{v}}_k^{m'} = [\widehat{v}_{k,1}^{m'}, \ldots, \widehat{v}_{k,l}^{m'}]^T$ are the posterior mean and posterior variance, respectively, $(Z_l^{m'})^{t-1}$ and $(V_l^{m'})^{t-1}$ correspond to the $(t-1)$-th iteration, and index t is omitted for simplicity

- Sum-product algorithm [6] is used to exploit the prior distribution of $x_{k,i}^{m'}$
- we start with the message through the path $\{x_{k,i}^{m'}\} \rightarrow \{f_k^{m'}\} \rightarrow \{a_k\}$
- Furthermore, we calculate the backward message through the path $\{h_k\} \rightarrow \{a_k\} \rightarrow \{f_k^{m'}\} \rightarrow \{x_{k,i}^{m'}\}$
- Then, the approximate posterior distribution of $x_{k,i}^{m'}$ is given by

$$q(x_{k,i}^{m'}|\mathrm{y}_{m'}) = (1-\pi_{k,i}^{m'})\delta(x_{k,i}^{m'}) + \pi_{k,i}^{m'}\mathcal{CN}\left(x_{k,i}^{m'}; \overline{\mu}_{k,i}^{m'}, \overline{\tau}_{k,i}^{m'}\right), \tag{18}$$

where we have

$$\overline{\mu}_{k,i}^{m'} = \left(\mu_0\varphi_{k,i}^{m'} + \tau_0 r_{k,i}^{m'}\right) / \left(\varphi_{k,i}^{m'} + r_{k,i}^{m'}\right), \tag{19}$$

$$\overline{\tau}_{k,i}^{m'} = \left(\tau_0\varphi_{k,i}^{m'}\right) / \left(\varphi_{k,i}^{m'} + r_{k,i}^{m'}\right), \tag{20}$$

$$\mathcal{L}_{k,i}^{m'} = \ln\frac{\varphi_{k,i}^{m'}}{\tau_0 + \varphi_{k,i}^{m'}} - \frac{\left(r_{k,i}^{m'} - \mu_0\right)^2}{\tau_0 + \varphi_{k,i}^{m'}} + \frac{\left|r_{k,i}^{m'}\right|^2}{\varphi_{k,i}^{m'}}, \tag{21}$$

$$\pi_{k,i}^{m'} = \frac{\lambda_k \exp(\mathcal{L}_{k,i}^{m'})}{\sum_{i=1}^{I}\exp(\mathcal{L}_{k,i}^{m'})\left[\lambda_k + I^{M'}(1-\lambda_k)\prod_{m'=1}^{M'}\frac{1}{\sum_{i=1}^{I}\exp(\mathcal{L}_{k,i}^{m'})}\right]}. \tag{22}$$

Posterior Mean and Variance Estimation

- The posterior mean and variance of $x_{k,i}^{m'}$, $\forall k, i, m'$, are, respectively, denoted as

$$\widehat{x}_{k,i}^{m'} = \int x_{k,i}^{m'} q(x_{k,i}^{m'} | \mathrm{y}_{m'}) dx_{k,i}^{m'} = \pi_{k,i}^{m'} \overline{\mu}_{k,i}^{m'}, \tag{23}$$

$$\widehat{v}_{k,i}^{m'} = \int \left(x_{k,i}^{m'} - \widehat{x}_{k,i}^{m'} \right)^2 q(x_{k,i}^{m'} | \mathrm{y}_{m'}) dx_{k,i}^{m'} = \pi_{k,i}^{m'} \left(\left| \overline{\mu}_{k,i}^{m'} \right|^2 + \overline{\tau}_{k,i}^{m'} \right) - \left(\widehat{x}_{k,i}^{m'} \right)^2 . \tag{24}$$

- (23) and (24) constitute the AMP denoising step

Outline

- The EM algorithm is an iterative approach to find the maximum likelihood solutions for probabilistic models with the unknown parameters
- The EM algorithm updates the parameter set $\boldsymbol{\theta}$ ($\boldsymbol{\theta} = \{\mu_0, \tau_0, \sigma_n^2, \lambda_1, ..., \lambda_K\}$) as follows [7]

$$Q\left(\boldsymbol{\theta}, \boldsymbol{\theta}^t\right) = \mathbb{E}\left\{\ln\ p\left(\mathsf{X}, \mathsf{Y}; \boldsymbol{\theta}\right) | \mathsf{Y}; \boldsymbol{\theta}^t\right\}, \tag{25}$$

$$\boldsymbol{\theta}^{t+1} = \arg\max_{\boldsymbol{\theta}} Q\left(\boldsymbol{\theta}, \boldsymbol{\theta}^t\right), \tag{26}$$

where $\boldsymbol{\theta}^t$ denotes the estimated parameters in the t-th iteration, $\mathbb{E}\{\cdot|\mathsf{Y}; \boldsymbol{\theta}^t\}$ represents the expectation conditioned on the received signal Y under $\boldsymbol{\theta}^t$.

- The update rules of the parameters indicating the devices' activity λ_k, $\forall k$, is denoted as

$$\lambda_k = \frac{1}{M'} \sum\nolimits_{m'=1}^{M'} 1 \Big/ \left(1 + 1 \Big/ \sum\nolimits_{i=1}^{I} \frac{\pi_{k,i}^{m'}}{1 - \pi_{k,i}^{m'}}\right) \tag{27}$$

Arithmetic Flow

Summary of the proposed space-frequency joint activity and blind information detection (SF-JABID) algorithm

Algorithm 1: Proposed SF-JABID Algorithm

Require: The received signals $\mathbf{Y} = [\mathbf{y}_1, \mathbf{y}_2, ..., \mathbf{y}_{M'}] \in \mathbb{C}^{L\times M'}$, the pre-allocated sequences $\mathbf{\Phi} = [\mathbf{\Phi}_1, ..., \mathbf{\Phi}_K] \in \mathbb{C}^{L\times KI}$, the noise variance σ_n^2, the maximum iteration number T_0, and the termination threshold ϵ.

Ensure: The estimated equivalent channel matrix $\widehat{\mathbf{X}} = [\widehat{\mathbf{x}}_1, \widehat{\mathbf{x}}_2, ..., \widehat{\mathbf{x}}_{M'}] \in \mathbb{C}^{KI\times M'}$, the set of active devices Ω, and the support of $\mathbf{e}_{k,q}^j$, where $\mathbf{e}_{k,q}^j$ is denoted in (1).

$\forall k, i, l, m'$: We initialize the iterative index t=1, the activity indicator $\lambda_k^1 = \lambda_0 = \frac{L}{KI}\left\{\max\limits_{c>0} \frac{1-2KI\left[(1+c^2)\Psi(-c)-c\psi(c)\right]/L}{1+c^2-2[(1+c^2)\Psi(-c)-c\psi(c)]}\right\}$, the prior mean $\mu_0^1 = 0$, the prior variance $\tau_0^1 = \frac{\|\mathbf{Y}\|_F - L\sigma_n^2}{\|\mathbf{\Phi}\|_F \lambda_0}$, $(Z_l^{m'})^1 = [\mathbf{y}_{m'}]_l$, $(V_l^{m'})^1 = 1$, $(\widehat{x}_{k,i}^{m'})^1 = 0$, and $(\widehat{v}_{k,i}^{m'})^1 = 1$;

for $t = 2$ to T_0 **do**

    %AMP operation:

    $\forall k, i, l, m'$: Compute $(V_l^{m'})^t, (Z_l^{m'})^t, (\varphi_{k,i}^{m'})^t$, and $(r_{k,i}^{m'})^t$ by using (16), (17), (14), and (15), respectively;{Decoupling step}

    $\forall k, i, m'$: Compute $(\widehat{x}_{k,i}^{m'})^t$ and $(\widehat{v}_{k,i}^{m'})^t$ by using (23) and (24), respectively; {Denoising step}

    %EM operation:

    $\forall k$: Update μ_0^t, τ_0^t, and λ_k^t by using (27), (28), and (29), respectively;

    if $\left\|\widehat{\mathbf{X}}^t - \widehat{\mathbf{X}}^{t-1}\right\|_F / \left\|\widehat{\mathbf{X}}^{t-1}\right\|_F < \epsilon$ **then**

        break; {End the iteration}

    end if

end for

The estimated equivalent channel matrix $\widehat{\mathbf{X}} = \widehat{\mathbf{X}}^t$;

%Extract the active devices:

$\forall k \in [K]$: The set of active devices $\Omega = \{k|\lambda_k^t > 0.5\}$;

%Extract the embedded information of active devices:

$\forall k \in \Omega, j, q$: $\mathrm{supp}\{\mathbf{e}_{k,q}^j\} = \operatorname*{argmax}\limits_{i\in[I]}\left\{\sum\limits_{m=1}^{M}\left|\left[\widehat{\mathbf{X}}_{k,q}^j\right]_{i,m}\right|^2\right\}$, where $\mathbf{X}_{k,q}^j = a_k \mathbf{e}_{k,q}^j (\mathbf{h}_{k,q}^j)^T$ is denoted in (1).

Outline

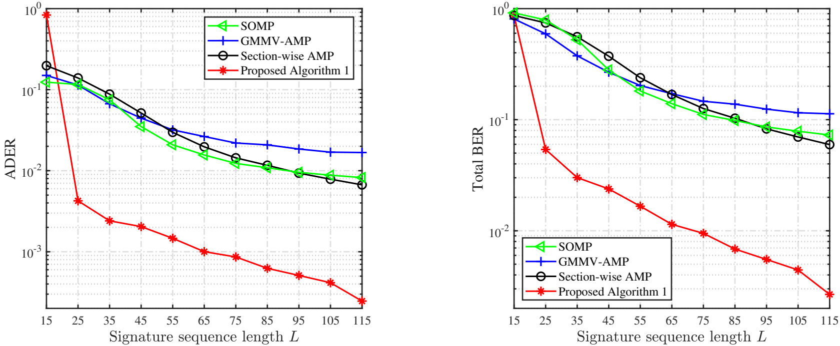
- The activity detection error rate (ADER) and the total bit error rate (BER) are investigated:

$$\mathrm{ADER} = \frac{E_m + E_f}{K}, \quad \mathrm{Total\ BER} = \frac{(E_m + E_f)r + B_d}{(K_a + E_f)r}, \tag{28}$$

  where E_m is the number of active devices missed to be detected, E_f is the number of inactive devices falsely detected to be active, B_d denotes the error numbers of bits for detected active devices, and r is the number of bits embedded in each sequence selection

- The number of devices is $K = 100$ with $K_a = 10$ active devices, the maximum iteration number is set to $T_0 = 200$, and the termination threshold $\epsilon = 10^{-6}$. Furthermore, the carrier frequency is $f_c = 6$ GHz, the bandwidth is $B_s = 10$ MHz, and the system employs OFDM with $N = 512$ subcarriers and a cyclic prefix of length $N_{\mathrm{CP}} = 64$. We consider the maximum number of paths P varies from 8 to 14 and the related AoA of each path is generated within an angular spread 10° for any active device

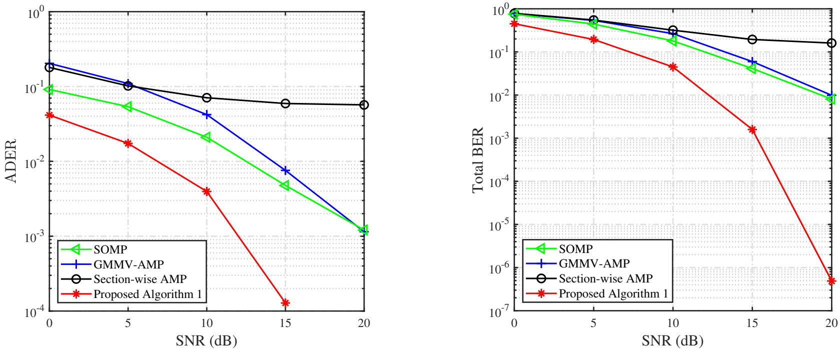
- **SOMP**: The simultaneous orthogonal matching pursuit algorithm, where the iteration stops if the average power of the residual is smaller than the noise power. Note that the noise power is known in advance
- **GMMV-AMP**: The algorithm 1 proposed in [8], where the noise variance is known and the common support in multiple antennas, as shown in (4), is exploited
- **Section-wise AMP**: The **state-of-the-art** AMP-based algorithm with inseparable denoiser proposed in [9] for NC-IM in frequency-flat channel fading, where noise variance and channel power are known in advance



(a) (b)

Fig.. Performance comparison of different algorithms versus signature sequence length L: (a) ADER performance comparison; (b) Total BER performance comparison.

Performance versus SNR



(a) (b)

Fig.. Performance comparison of different algorithms versus SNR: (a) ADER performance comparison; (b) Total BER performance comparison.

Outline

Conclusions

Contributions: Proposed SF-JABID algorithm for improving the ADER and BER performance of IM-based non-coherent massive IoT access

Limitations: The proposed algorithm might has little performance improvement, if the number of receive antennas is very large, i.e., 32, 64,...

Future Directions

- How to **reduce the access latency** of such non-coherent massive IoT access scheme, i.e., how to reduce the signature sequence length
- Applying non-coherent massive IoT access in **UAV/Satellite**-based IoT networks

Outline

[1] X. Chen, D. W. K. Ng, W. Yu, E. G. Larsson, N. Al-Dhahir, and R. Schober, "Massive access for 5G and beyond," *IEEE J. Select. Areas Commun.*, vol. 39, no. 3, pp. 615-637, Mar. 2021.

[2] S. Doğan Tusha, A. Tusha, E. Basar and H. Arslan, "Multidimensional index modulation for 5G and beyond wireless networks," *Proc. IEEE*, vol. 109, no. 2, pp. 170-199, Feb. 2021.

[3] L. Qiao, J. Zhang, Z. Gao, D. W. K. Ng, M. Di Renzo, and M.-S. Alouini, "Massive access in media modulation based massive machine-type communications," *IEEE Trans. Wireless Commun.*, vol. PP, no. PP, Jul. 2021.

[4] K. Senel and E. G. Larsson, "Grant-free massive MTC-enabled massive MIMO: A compressive sensing approach," *IEEE Trans. Commun.*, vol. 66, no. 12, pp. 6164-6175, Dec. 2018.

[5] X. Meng, S. Wu, L. Kuang, D. Huang, and J. Lu, "Multi-user detection for spatial modulation via structured approximate message passing," *IEEE Commun. Lett.*, vol. 20, no. 8, pp. 1527-1530, Aug. 2016.

[6] F. R. Kschischang, B. J. Frey, and H.-A. Loeliger, "Factor graphs and the sum-product algorithm," *IEEE Trans. Inform. Theory*, vol. 47, no. 2, pp. 498-519, Feb. 2001.

[7] A. P. Dempster, N. M. Laird, and D. B. Rubin, "Maximum likelihood from incomplete data via the EM algorithm," *J. Roy. Statist. Soc. B (Methodol.)*, vol. 39, no. 1, pp. 1-38, 1977.

[8] M. Ke, Z. Gao, Y. Wu, X. Gao, and R. Schober, "Compressive sensing based adaptive active user detection and channel estimation: Massive access meets massive MIMO," *IEEE Trans. Signal Process.*, vol. 68, pp. 764-779, Jan. 2020.

[9] Z. Tang, J. Wang, J. Wang, and J. Song, "Device activity detection and non-coherent information transmission for massive machine-type communications," *IEEE Access*, vol. 8, pp. 41452-41465, Feb. 2020.

Thanks for your attention!

Q & A