Compressive Sensing Based Grant-Free Random Access for Massive MTC

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1 Introduction

- Massive machine-type communications (mMTC) are poised to provide ubiquitous and unprecedent connectivity for billions of Internet of Things (IoT) devices[1-2] .

- The mMTC have the following features [1-3] :
  - uplink-dominated
  - sporadic traffic
  - low rates and short package

- Challenges :
  - the current grant-based random access schemes suffer from the low access efficiency and high latency caused by the complicated handshake procedure [3].
  - due to the limited available spectrum, it is impossible to allocate orthogonal radio resources to all potential devices.

A promising alternative:,
grant-free random access scheme using non-orthogonal radio resources

1 Introduction

- In grant-free random access scheme, the devices can directly transmit data to the base station (BS) without complicated handshaking process [4-5].
- Since non-orthogonal radio resources are adopted, the joint activity and data detection (JADD) needs to be efficiently solved at the BS.
- Due to the inherent sparsity of sporadic traffic, the JADD can be formulated as a compressive sensing (CS) problem [4-5].
- Our works:
  - We design a beacon-aided grant-free massive access scheme based on the orthogonal frequency division multiplexing (OFDM) systems for mMTC.
  - An orthogonal approximate message passing-multiple measurement vectors (OAMP-MMV) algorithm is developed for JADD, where the prior knowledge of discrete constellation symbol and the structured sparsity of MMV model are fully exploited for improved performance.

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System Model

- A single-antenna BS serves K single-antenna IoT devices, where K can be very large but only K_a ($K_a \ll K$) devices are active in each OFDM symbol interval.
- At the BS, the received signal $\mathbf{y}_t \in \mathbb{C}^{M\times 1}$ during the t-th OFDM symbol can be written as

$$\mathbf{y}_t = \sum_{k=1}^{K} \mathbf{H}_k \mathbf{s}_k \alpha_{k,t} x_{k,t} + \mathbf{w}_t = \mathbf{S}\mathbf{x}_t + \mathbf{w}_t, \qquad (1)$$

where

- $\mathbf{H}_k = \mathrm{diag}\left(\left[h_{1,k}, h_{2,k}, \cdots, h_{M,k}\right]^{\mathrm{T}}\right) \in \mathbb{C}^{M\times M}$, $h_{m,k}$ is the m-th subchannel between the k-th device and BS, $\mathbf{s}_k \in \mathbb{C}^{M\times 1}$ is the unique spreading sequence for the k-th device,
- $\alpha_{k,t}$ is the binary activity indicator that equals one when the k-th device is active and zero otherwise,
- for active devices, $x_{k,t}$ comes from a modulation constellation set $\Omega = \{a_1, a_2, \cdots, a_L\}$,
- $\mathbf{w}_t \sim \mathcal{CN}\left(\mathbf{0}, \sigma^2\mathbf{I}\right)$ is the additive white Gaussian noise,
- $\mathbf{S} = [\mathbf{H}_1\mathbf{s}_1, \mathbf{H}_2\mathbf{s}_2, \cdots, \mathbf{H}_K\mathbf{s}_K] \in \mathbb{C}^{M\times K}$, and $\mathbf{x}_t = \left[\alpha_{1,t}x_{1,t}, \alpha_{2,t}x_{2,t}, \cdots, \alpha_{K,t}x_{K,t}\right]^{\mathrm{T}} \in \mathbb{C}^{K\times 1}$.

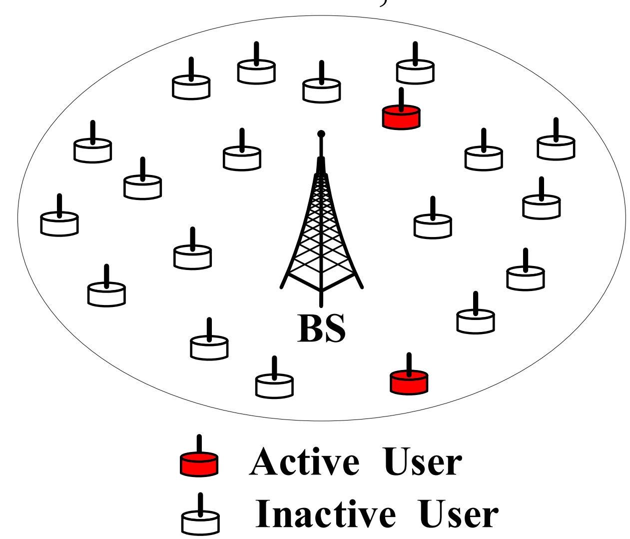

Fig. 1. Active devices in mMTC are sparse.

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A. Overall Framework

- First, the BS periodically broadcasts a beacon for facilitating the synchronization and channel estimation at the devices.
- Define the estimated channel $\hat{\mathbf{H}}_k$, we assume that $\mathbf{H}_k\hat{\mathbf{H}}_k^{-1}=\mathbf{I}$ for simplicity.
- By taking the pre-equalization at the devices, we have the equivalent sensing matrix

$$\tilde{\mathbf{S}}=\left[\mathbf{H}_1\hat{\mathbf{H}}_1^{-1}\mathbf{s}_1,\mathbf{H}_2\hat{\mathbf{H}}_2^{-1}\mathbf{s}_2,\cdots,\mathbf{H}_K\hat{\mathbf{H}}_K^{-1}\mathbf{s}_K\right]$$
$$=\left[\mathbf{s}_1,\mathbf{s}_2,\cdots,\mathbf{s}_K\right]. \quad (2)$$

- In our scheme, we adopt that partial DFT matrix as the equivalent sensing matrix $\tilde{\mathbf{S}}$.

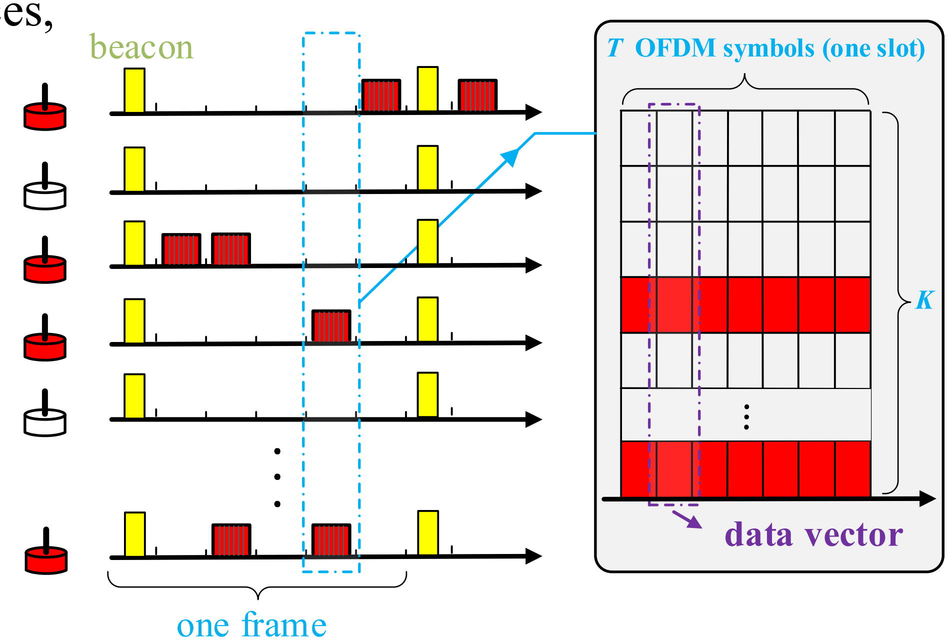

Fig. 2. For the proposed frame structure, the beacon is periodically broadcast by the BS, and the activity of devices remains unchanged in T OFDM symbols.

A. Overall Framework

- Then, by stacking the received data signals in T continuous OFDM symbols, we have

$$\mathbf{Y} = \tilde{\mathbf{S}}\mathbf{X} + \mathbf{W}, \tag{3}$$

where

$$\mathbf{Y} = [\mathbf{y}_1, \mathbf{y}_2, \cdots, \mathbf{y}_T] \in \mathbb{C}^{M \times T},$$
$$\mathbf{X} = [\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_T] \in \mathbb{C}^{K \times T}, \text{ and}$$
$$\mathbf{W} = [\mathbf{w}_1, \mathbf{w}_2, \cdots, \mathbf{w}_T].$$

- We further assume that the activity of devices remains unchanged in T continuous OFDM symbols, i.e.,

$$\mathrm{supp}\{\mathbf{x}_1\} = \mathrm{supp}\{\mathbf{x}_2\} = \cdots = \mathrm{supp}\{\mathbf{x}_T\}, \tag{4}$$

where $\mathrm{supp}\{\bullet\}$ denotes the set of non-zero elements in a vector.

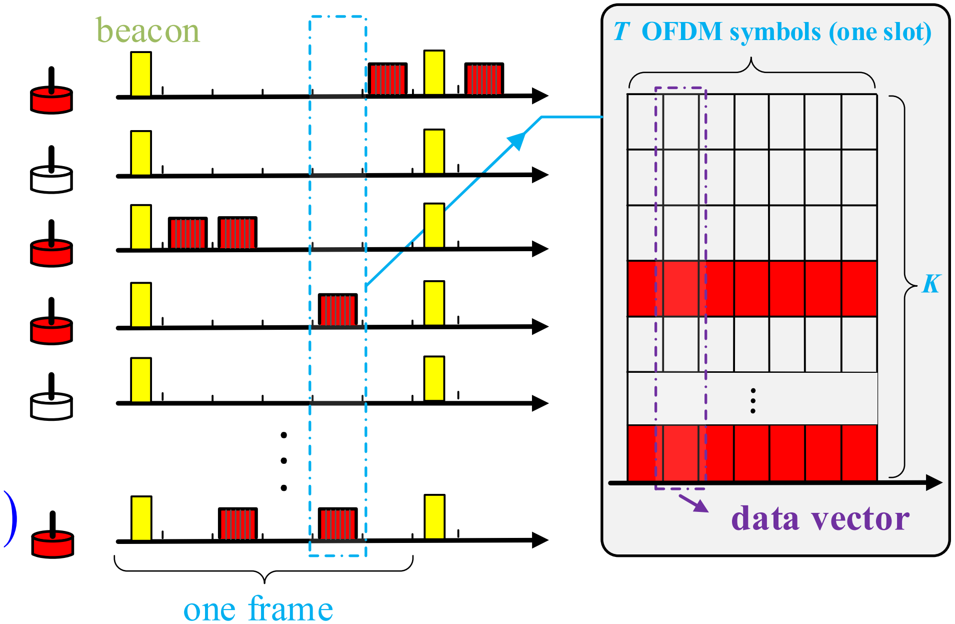

Fig. 2. For the proposed frame structure, the beacon is periodically broadcast by the BS, and the activity of devices remains unchanged in T OFDM symbols.

B. OAMP-MMV Algorithm for JADD

- We extend the conventional OAMP [6] algorithm to the OAMP-MMV algorithm to leverage the structured sparsity in (4).
- Assume the distribution of $x_{k,t}$ as

$$p\left(x_{k,t}\right)=\left(1-\lambda_{k,t}\right)\delta\left(x_{k,t}\right)+\frac{\lambda_{k,t}}{L}\sum_{l=1}^{L}\delta\left(x_{k,t}-a_l\right), \quad (5)$$

where $\lambda_{k,t}\in[0,1]$ denotes the non-zero probability of $x_{k,t}$ and can be termed as the sparsity ratio.

- By combining the a priori distribution in (5) with additive Gaussian noise model in [6], we can derive the approximate posterior distribution of $x_{k,t}$ as

$$p\left(x_{k,t}\,|\,r_{k,t}\right)=\left(1-\pi_{k,t}\right)\delta\left(x_{k,t}\right)+\pi_{k,t}\frac{\sum_{l=1}^{L}g_{k,t,l}\delta\left(x_{k,t}-a_l\right)}{\sum_{l=1}^{L}g_{k,t,l}}, \quad (6)$$

where $\pi_{k,t}$ can be termed as the posterior sparsity ratio.

B. OAMP-MMV Algorithm for JADD

- Similar to the conventional OAMP algorithm [6], the proposed OAMP-MMV algorithm has two basic modules, linear estimation (LE) module and non-linear estimation (NLE) module. They are iteratively executed until convergence.

- The final output is the MMSE estimation obtained in the NLE module, which relies on the posterior distribution in (6).

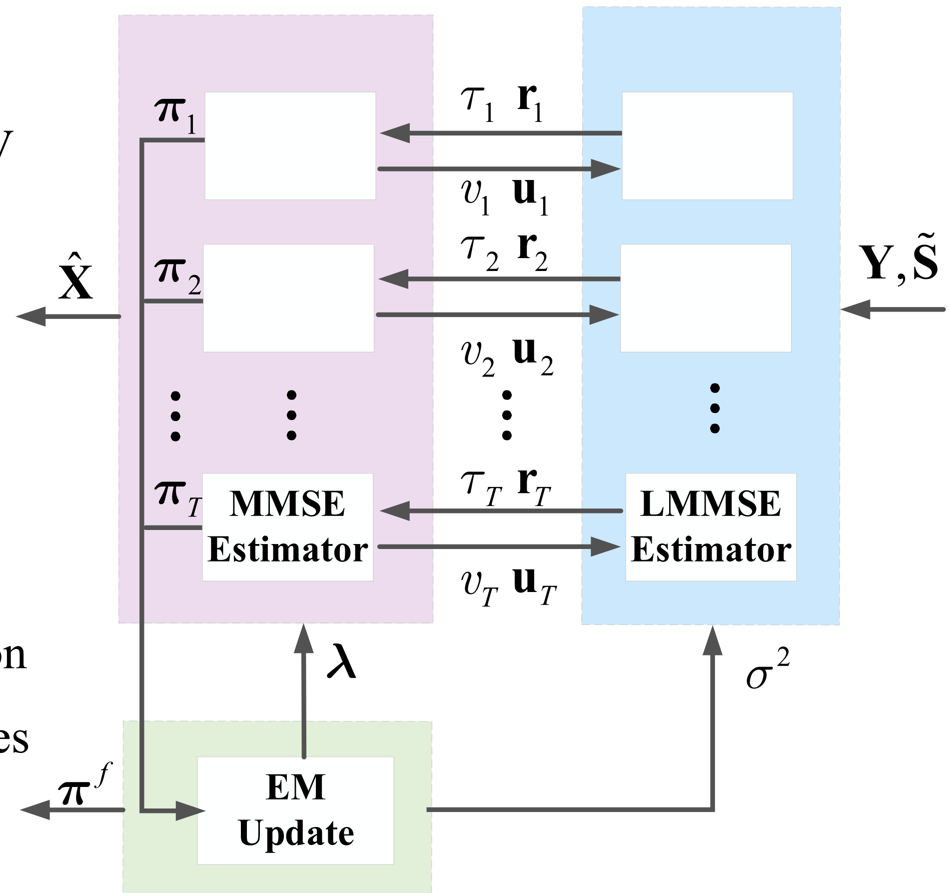

Fig. 3. Block diagram of the proposed OAMP-MMV algorithm.

B. OAMP-MMV Algorithm for JADD

- The expectation maximization (EM) algorithm [7] is employed to learn the unknown parameters $\boldsymbol{\theta} = \left\{ \sigma_t^2, \lambda_{k,t}, \forall k,t \right\}$.

$$\lambda_{k,t}^{i+1} = \pi_{k,t}^{i}, \forall k,t, \tag{9}$$

$$\left(\sigma^2\right)_t^{i+1} = \frac{1}{M}\left[\left\| \mathbf{y}_t - \tilde{\mathbf{S}}\boldsymbol{\mu}_t^i \right\|_2^2 + \frac{M}{K}\sum_{k=1}^{K}\gamma_{k,t}^i \right], \forall t. \tag{10}$$

Exploit sparsity structure

The update rule of $\lambda_{k,t}$ in (9) is refined as

$$\lambda_{k,1}^{i+1} = \lambda_{k,2}^{i+1} = \cdots = \lambda_{k,T}^{i+1} = \frac{1}{T}\sum_{t=1}^{T}\pi_{k,t}^{i}, \forall k. \tag{11}$$

Algorithm 1: OAMP-MMV algorithm

Input: $\mathbf{Y}$, $\tilde{\mathbf{S}}$, I_{iter}.
Output: $\{\hat{\boldsymbol{x}}_t\}_{t=1}^{T}$, $\boldsymbol{\pi}^f$.

$\forall k,t$: Set iteration index i to 1. Initialize $\mathbf{u}_t^0 = \mathbf{0}_K$ and $v_t^0 = 1$. $\lambda_{k,t}^0$ and $(\sigma^2)_t^0$ are initialized as [12].
for $i = 1$ to I_{iter} **do**
  %LE Module:
  $\forall t$: $\mathbf{r}_t^i = \mathbf{u}_t^{i-1} + \frac{K}{M}\tilde{\mathbf{S}}^{\mathrm{H}}\left(\mathbf{y}_t - \tilde{\mathbf{S}}\mathbf{u}_t^{i-1}\right)$.
  $\forall t$: $\tau_t^i = \frac{K-M}{M}v_t^{i-1} + \frac{K}{M}(\sigma^2)_t^{i-1}$.
  %NLE Module:
  $\forall k,t,l$: $g_{k,t,l}^i = \exp\left(-\frac{|a_l|^2 - 2\Re\mathrm{e}\{a_l^* r_{k,t}^i\}}{\tau_t^i}\right)$.
  $\forall k,t$: $\pi_{k,t}^i = \left[1 + (1-\lambda_{k,t}^{i-1})/(\frac{\lambda_{k,t}^{i-1}}{L}\sum_{l=1}^{L} g_{k,t,l}^i)\right]^{-1}$.
  $\forall k,t$: $\mu_{k,t}^i = (\pi_{k,t}^i \sum_{l=1}^{L} a_l g_{k,t,l}^i)/(\sum_{l=1}^{L} g_{k,t,l}^i)$.
  $\forall k,t$: $\gamma_{k,t}^i = (\pi_{k,t}^i \sum_{l=1}^{L} |a_l|^2 g_{k,t,l}^i)/(\sum_{l=1}^{L} g_{k,t,l}^i) - |\mu_{k,t}^i|^2$.
  $\forall t$: $\bar{\gamma}_t^i = \frac{1}{K}\sum_{k=1}^{K}\gamma_{k,t}^i$, $v_t^i = \left(\frac{1}{\bar{\gamma}_t^i} - \frac{1}{\tau_t^i}\right)^{-1}$.
  $\forall k,t$: $C_t^i = \frac{\tau_t^i}{\tau_t^i - \bar{\gamma}_t^i}$, $u_{k,t}^i = C_t^i\left(\mu_{k,t}^i - \frac{\bar{\gamma}_t^i}{\tau_t^i} r_{k,t}^i\right)$.
  %EM Update:
  $\forall t$: Update $(\sigma^2)_t^i$ using (10).
  $\forall k,t$: Update $\lambda_{k,t}^i$ using (11).
end for
$\forall t$: $\hat{\boldsymbol{x}}_t = \boldsymbol{\mu}_t^i$, $\boldsymbol{\pi}^f = \boldsymbol{\lambda}^i$.

B. OAMP-MMV Algorithm for JADD

- To identify active devices, a hard threshold based activity detector is developed as follows

$$\hat{\alpha}_k = \begin{cases} 1, & \pi_k^f \geq T_h \\ 0, & \text{otherwise} \end{cases}, \forall k, \tag{12}$$

where $\hat{\alpha}_k = 1$ indicates that the k-th device is active, and T_h is a threshold which is determined empirically.

Algorithm 1: OAMP-MMV algorithm

Input: $\mathbf{Y}$, $\tilde{\mathbf{S}}$, I_{iter}.
Output: $\{\hat{\boldsymbol{x}}_t\}_{t=1}^T$, $\boldsymbol{\pi}^f$.
$\forall k, t$: Set iteration index i to 1. Initialize $\mathbf{u}_t^0 = \mathbf{0}_K$ and $v_t^0 = 1$. $\lambda_{k,t}^0$ and $(\sigma^2)_t^0$ are initialized as [12].
for $i = 1$ to I_{iter} **do**
  %LE Module:
  $\forall t$: $\mathbf{r}_t^i = \mathbf{u}_t^{i-1} + \frac{K}{M}\tilde{\mathbf{S}}^{\text{H}}\left(\mathbf{y}_t - \tilde{\mathbf{S}}\mathbf{u}_t^{i-1}\right)$.
  $\forall t$: $\tau_t^i = \frac{K-M}{M}v_t^{i-1} + \frac{K}{M}(\sigma^2)_t^{i-1}$.
  %NLE Module:
  $\forall k, t, l$: $g_{k,t,l}^i = \exp\left(-\frac{|a_l|^2 - 2\Re\{a_l^* r_{k,t}^i\}}{\tau_t^i}\right)$.
  $\forall k, t$: $\pi_{k,t}^i = \left[1 + (1-\lambda_{k,t}^{i-1})/(\frac{\lambda_{k,t}^{i-1}}{L}\sum_{l=1}^{L} g_{k,t,l}^i)\right]^{-1}$.
  $\forall k, t$: $\mu_{k,t}^i = (\pi_{k,t}^i \sum_{l=1}^{L} a_l g_{k,t,l}^i)/(\sum_{l=1}^{L} g_{k,t,l}^i)$.
  $\forall k, t$: $\gamma_{k,t}^i = (\pi_{k,t}^i \sum_{l=1}^{L} |a_l|^2 g_{k,t,l}^i)/(\sum_{l=1}^{L} g_{k,t,l}^i) - |\mu_{k,t}^i|^2$.
  $\forall t$: $\bar{\gamma}_t^i = \frac{1}{K}\sum_{k=1}^{K} \gamma_{k,t}^i$, $v_t^i = \left(\frac{1}{\bar{\gamma}_t^i} - \frac{1}{\tau_t^i}\right)^{-1}$.
  $\forall k, t$: $C_t^i = \frac{\tau_t^i}{\tau_t^i - \bar{\gamma}_t^i}$, $u_{k,t}^i = C_t^i\left(\mu_{k,t}^i - \frac{\bar{\gamma}_t^i}{\tau_t^i} r_{k,t}^i\right)$.
  %EM Update:
  $\forall t$: Update $(\sigma^2)_t^i$ using (10).
  $\forall k, t$: Update $\lambda_{k,t}^i$ using (11).
end for
$\forall t$: $\hat{\boldsymbol{x}}_t = \boldsymbol{\mu}_t^i$, $\boldsymbol{\pi}^f = \boldsymbol{\lambda}^i$.

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4 Simulation Results

- Simulation Parameters

The number of potential IoT devices K	500
The number of active devices K_a	50
The number of measurements M	70
Modulation	QPSK
The threshold of activity detector T_h	1/3
The number of iterations	30

- We define the error detection probability of activity detection (P_e) and BER as follows

$$P_e = \frac{1}{K}\sum_{k=1}^{K}\left|\hat{\alpha}_k - \alpha_k\right|, \qquad \text{BER} = 1 - \frac{N_s}{K_a T \log_2 L}, \tag{13}$$

where N_s denotes the number of correctly decoded bits of successfully detected devices.

4 Simulation Results

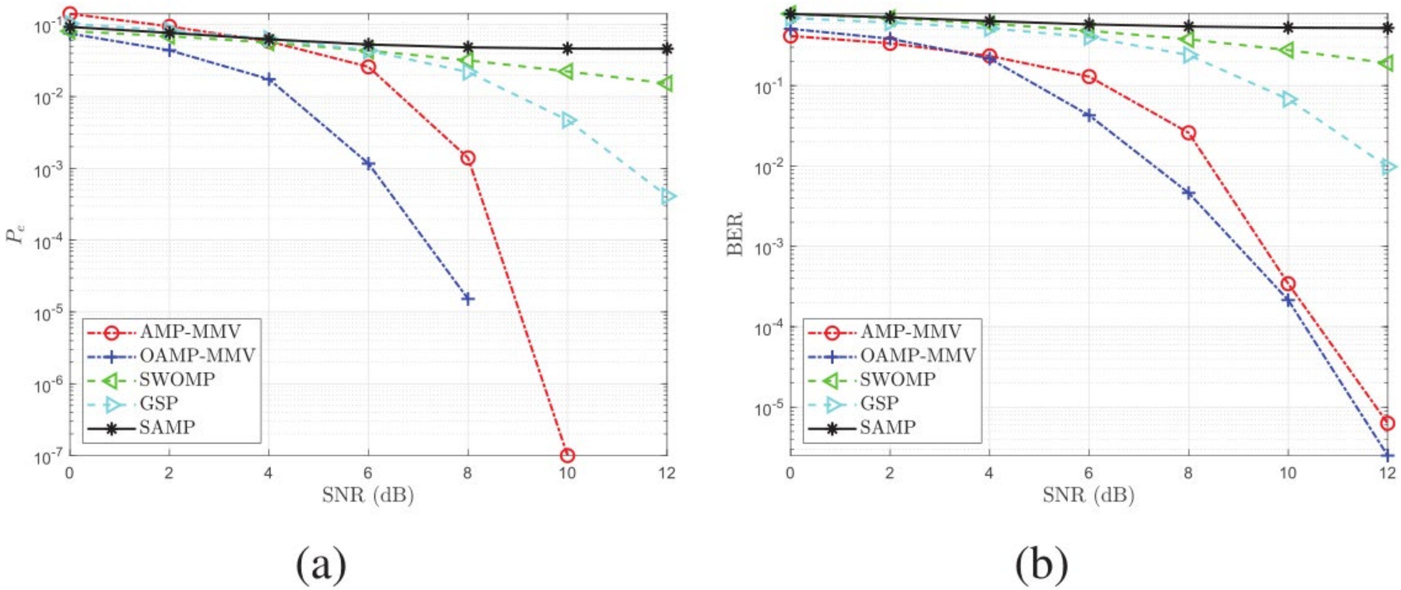

Fig. 4. Comparison of the different detection algorithms versus SNR with $T = 10$: (a) P_e; (b) BER.

Our proposed OAMP-MMV algorithm achieves superior performance over the baseline algorithms!

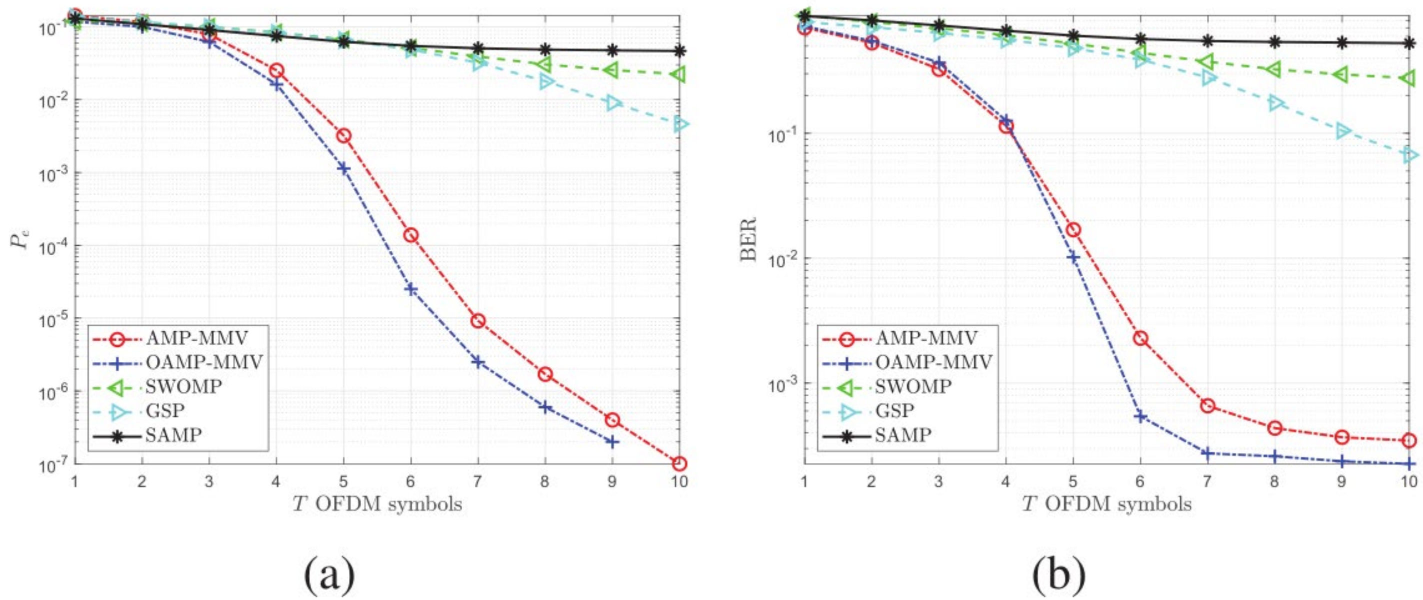

Fig. 5. Comparison of the different detection algorithms versus T continuous OFDM symbols with SNR = 10 dB: (a) P_e; (b) BER.

Our proposed OAMP-MMV algorithm outperforms the baseline algorithms!

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Thanks for your listening!