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Joint Active Device and Data Detection for Massive MTC Relying on Spatial Modulation

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System Model

- Massive machine-type communications (mMTC) meet **spatial modulation**
- The BS employs massive MIMO with N_r antennas for reliable detection.
- K machine-type devices adopt spatial modulation for enhanced throughput in massive access, and only K_a devices are active simultaneously, where $K_a \ll K$ [1]-[4].
- For spatial modulation, each device adopt an RF chain and N_t transmit antennas. For each device, if M-QAM is adopted, the throughput is $\eta = \log_2 M + \lfloor \log_2 N_t \rfloor$ bit per channel use (bpcu) [4]-[7].

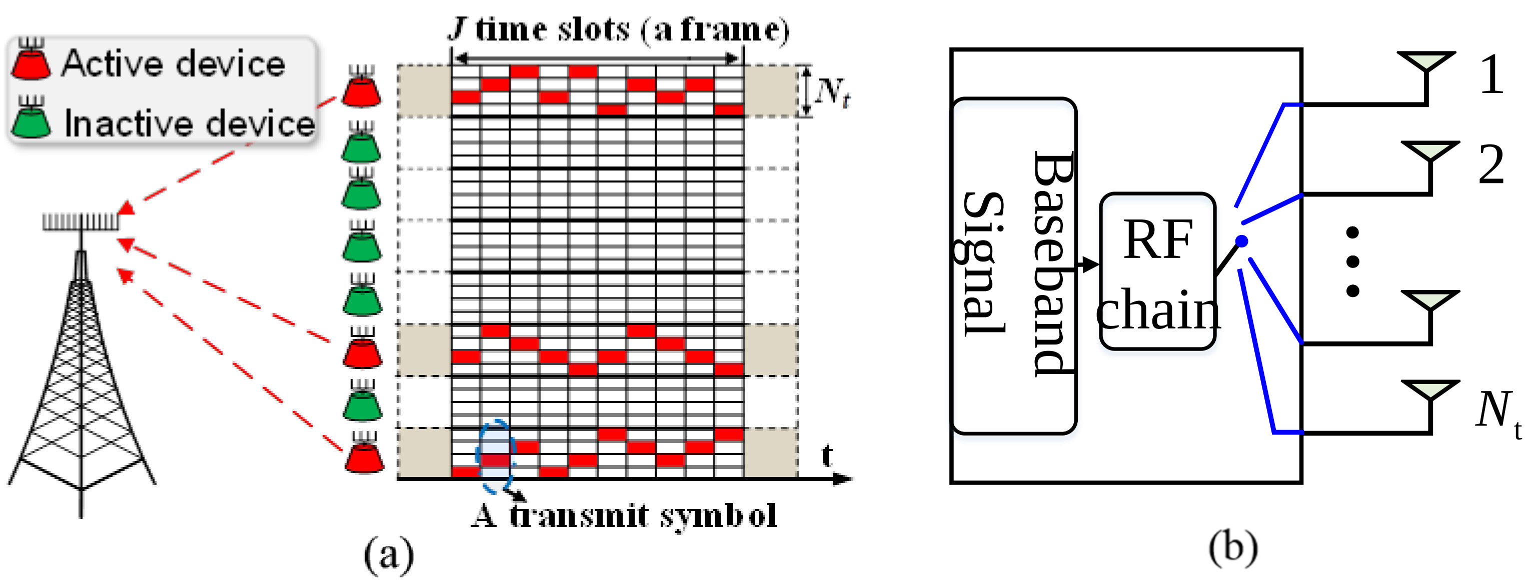

Fig. 1. (a) Proposed spatial modulation based mMTC scheme; (b) A diagram of spatial modulation [4]-[7].

Uplink transmission

- we assume the active and inactive states of K devices remain unchanged in a frame (J successive time slots)
- The received signal $\mathbf{y}_j \in \mathbb{C}^{N_r \times 1}$ at the BS in the j-th ($\forall j \in [J]$) time slot can be expressed as

$[N] = \{1, 2, \ldots, N\}$

$$\mathbf{y}_{\mathrm{j}} = \sum_{k=1}^{K} a_k s_{k,j} \mathbf{H}_k \mathbf{d}_{k,j} + \mathbf{w}_j = \sum_{k=1}^{K} \mathbf{H}_k \mathbf{x}_{k,j} + \mathbf{w}_j = \mathbf{H}\ \mathbf{x}_j + \mathbf{w}_j, \qquad \boxed{(1)}$$

a_k — activity indicator of the k-th device

$s_{k,j} \in \mathbb{S}$, and $\mathbb{S}$ is the conventional modulated constellation symbol set

$\mathbf{d}_{k,j}$ is the spatial modulated symbol, and " $\mathrm{supp}\{\mathbf{d}_{k,j}\} \in [N_t]$, $\|\mathbf{d}_{k,j}\|_0 = 1$, $\|\mathbf{d}_{k,j}\|_2 = 1$, " $\boxed{(2)}$

$\mathbf{x}_{k,j} = a_k s_{k,j} \mathbf{d}_{k,j} \in \mathbb{C}^{N_t \times 1}$ is the effective transmit symbol

$\mathbf{H}_k \in \mathbb{C}^{N_r \times N_t}$ is the MIMO channel matrix associated with the k-th device

$\mathbf{w}^j \in \mathbb{C}^{N_r \times 1}$ is the noise, whose elements obey i.i.d. complex Gaussian distribution $\mathcal{CN}(0, \sigma_w^2)$

$\mathbf{H} = [\mathbf{H}_1, \mathbf{H}_2, \ldots, \mathbf{H}_K] \in \mathbb{C}^{N_r \times (KN_t)}$ can be obtained at the BS

$\tilde{\mathbf{x}}_j = [(\mathbf{x}_{1,j})^T, (\mathbf{x}_{2,j})^T, \ldots, (\mathbf{x}_{K,j})^T]^T \in \mathbb{C}^{(KN_t) \times 1}$

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Proposed AMP-based massive access solution

- ***A. Motivations and problem formulation***
- Sporadic traffic [1]-[4]

  $\mathbf{a}=[a_1, a_2, \ldots, a_K]^T \in \mathbb{C}^{K\times 1}$ is a sparse vector, and $K_a=\|\mathbf{a}\|_0 \ll K$.
- Block sparsity [3],[4]

  The device activity is invariant in a frame.
- Structured sparsity [5],[7]

  As illustrated in $\boxed{(2)}$, spatial modulated signal has structured sparsity.

motivated us to use → **CS-based framework**

Considering the structured sparsity, we formulate the prior distribution of $\mathbf{x}_{k,j}$ as

$$p(\mathbf{x}_{k,j} \mid a_k) = (1-a_k)\underbrace{\prod_{i=1}^{N_t}\delta([\mathbf{x}_{k,j}]_i)}_{\textbf{Inactive}} + \underbrace{a_k}_{\text{Activity indicator}}\underbrace{\left\{\frac{1}{N_t}\sum_{i=1}^{N_t}\left[\frac{1}{M}\sum_{s\in\mathbb{S}}\delta([\mathbf{x}_{k,j}]_i - s)\prod_{n\in[N_t],n\neq i}\delta([\mathbf{x}_{k,j}]_n)\right]\right\}}_{\textbf{Active}}, \qquad \boxed{(3)}$$

$M=|\mathbb{S}|_c$, i.e., M is the size of the constellation symbol set $\mathbb{S}$,

$\delta(\cdot)$ is the Dirac delta function.

A. Motivations and problem formulation

- We rewrite the received signals within a frame as

$$\mathbf{Y} = \mathbf{H}\mathbf{X} + \mathbf{W}, \qquad \boxed{(4)}$$

where $\mathbf{Y} = [\mathbf{y}^1, \mathbf{y}^2, \ldots, \mathbf{y}^J] \in \mathbb{C}^{N_r \times J}$, $\mathbf{X} = [\mathbf{x}^1, \mathbf{x}^2, \ldots, \mathbf{x}^J] \in \mathbb{C}^{(KN_t) \times J}$, and $\mathbf{W} = [\mathbf{w}^1, \mathbf{w}^2, \ldots, \mathbf{w}^J] \in \mathbb{C}^{N_r \times J}$.

- Then, the massive access problem can be formulated as the following optimization problem

$$\begin{aligned} \min_{\mathbf{X}} \| \mathbf{Y} - \mathbf{H}\mathbf{X} \|_F^2 &= \min_{\{\mathbf{x}^j\}_{j=1}^J} \sum_{j=1}^J \| \mathbf{y}^j - \mathbf{H}\mathbf{x}^j \|_2^2 \\ &= \min_{\{a_k, \mathbf{d}_k^j, g_k^j\}_{j=1,k=1}^{J,K}} \sum_{j=1}^J \| \mathbf{y}^j - \sum_{k=1}^K a_k g_k^j \mathbf{H}_k \mathbf{d}_k^j \|_2^2 \\ \text{s.t.} \ (2) \ \text{and} \ \| \mathbf{a} \|_0 \ll K \end{aligned} \qquad \boxed{(5)}$$

- Our proposed joint structured approximate message passing (JS-AMP) algorithm estimates the posterior mean of the uplink signals and learns the activity indicators iteratively.

- ***B. Proposed JS-AMP algorithm for joint active device and data detection***

- Approximate message passing (AMP) decouples Eq. (4) into KJN_t scalar problems as[3],[7],[8]

$$\mathbf{Y} = \mathbf{H}\mathbf{X} + \mathbf{W} \rightarrow r_{l,j} = [\mathbf{x}_{k,j}]_i + \hat{w}_{l,j}, \quad \boxed{(6)} \quad \begin{cases} r_{l,j} \text{ is the posterior mean estimation of } [\mathbf{x}_{k,j}]_i \\ \hat{w}_{l,j} \in \mathcal{CN}\left(0,\ \phi_{l,j}\right) \text{ is the equivalent noise} \\ l = i + (k-1)N_t,\ k \in [K],\ j \in [J],\ i \in [N_t] \end{cases}$$

- Based on the Bayes' theorem, given any $k \in [K]$, $j \in [J]$ and $i \in [N_t]$, the posterior probability of $[\mathbf{x}_{k,j}]_i$ is expressed as

$$f([\mathbf{x}_{k,j}] \mid r_{l,j}, a_k) = \frac{f(r_{l,j} \mid [\mathbf{x}_{k,j}])\, p([\mathbf{x}_{k,j}] \mid a_k)}{f(r_{l,j} \mid a_k)}, \qquad \boxed{(7)}$$

- How to calculate the distributions in (7) ?

- **B. Proposed JS-AMP algorithm for joint active device and data detection**

- The likelihood function

$$f(r_{l,j} \| [\mathbf{x}_{k,j}]_i) = \frac{1}{\pi \phi_{l,j}} \exp\left(-\frac{|r_{l,j} - [\mathbf{x}_{k,j}]_i|^2}{\phi_{l,j}}\right), \quad \boxed{(8)}$$

- The prior distributions of scalar signals

$$p(\mathbf{x}_{k,j} \mid a_k) = (1-a_k)\prod_{i=1}^{N_t} \delta([\mathbf{x}_{k,j}]_i) + a_k \left\{\frac{1}{N_t}\sum_{i=1}^{N_t}\left[\frac{1}{M}\sum_{s\in\mathbb{S}} \delta([\mathbf{x}_{k,j}]_i - s)\prod_{n\in[N_t],n\neq i} \delta([\mathbf{x}_{k,j}]_n)\right]\right\}, \quad \boxed{(3)}$$

Calculate the marginal distribution of (3)

$$p([\mathbf{x}_{k,j}]_i \mid a_k) = \left(1-\frac{a_k}{N_t}\right)\delta([\mathbf{x}_{k,j}]_i) + \frac{a_k}{N_t M}\sum_{s\in\mathbb{S}} \delta([\mathbf{x}_{k,j}]_i - s), \quad \boxed{(9)}$$

- And

$$f(r_{l,j} \mid a_k) = \sum_{[\mathbf{x}_{k,j}]_i \in \bar{\mathbb{S}}} (r_{l,j} \mid [\mathbf{x}_{k,j}]_i)\, p([\mathbf{x}_{k,j}]_i \mid a_k) \quad \boxed{(10)}$$

$$\bar{\mathbb{S}} = \{\mathbb{S}, 0\}$$

- Then, we calculate the posterior mean of $\left[\mathbf{x}_{k,j}\right]_i$ as

$$[\mathbf{x}_{k,j}]_i = \sum_{[\mathbf{x}_{k,j}]_i \in \bar{\mathbb{S}}} [\mathbf{x}_{k,j}]_i\, f([\mathbf{x}_{k,j}]_i \mid r_{l,j}, a_k) \quad \boxed{(11)}$$

- And the associated posterior variance as

$$[\mathbf{v}_{k,j}]_i = \sum_{[\mathbf{x}_{k,j}]_i \in \bar{\mathbb{S}}} \left|[\mathbf{x}_{k,j}]_i\right|^2 f([\mathbf{x}_{k,j}]_i \mid r_{l,j}, a_k) - \left|[\mathbf{x}_{k,j}]_i\right|^2, \quad \boxed{(12)}$$

- ***B. Proposed JS-AMP algorithm for joint active device and data detection***

- Expectation maximization (EM) is used to learn the activity indicators [9] ,

$$a_k^{t+1} = \arg\max_{\hat{a}_k \in [0,1]} \sum_{j=1}^{J} E\left\{\ln p(\mathbf{x}_{k,j} \mid \hat{a}_k) \mid \mathbf{Y},\ a_k^t\right\} \qquad \boxed{(13)}$$

$E(\cdot \mid \mathbf{Y}, a_k^t)$ denotes the expectation conditioned on the received signal $\mathbf{Y}$ and a_k^t .

- Due to the decoupling of AMP,

$$f([\mathbf{x}_{k,j}]_i \mid \mathbf{Y}, a_k^t) = f([\mathbf{x}_{k,j}]_i \mid r_{l,j}, a_k^t), \qquad \boxed{(16)}$$

- The updated a_k^{t+1} is obtained as

$$a_k^{t+1} = \frac{1}{J} \sum_{j=1}^{J} \sum_{\mathbf{x}_{k,j} \in \Omega_0} \prod_{i=1}^{N_t} f([\mathbf{x}_{k,j}]_i \mid r_{l,j}, a_k^t), \qquad \boxed{(18)}$$

- $\Omega = \{\Omega_0, \mathbf{0}_{N_t}\}$, Ω_0 is the set of all possible $\mathbf{x}_{k,j}$ for active devices

2.B Proposed AMP-based massive access solution

- ***B. Proposed JS-AMP algorithm for joint active device and data detection***

Algorithm 1: Proposed JS-AMP Algorithm

Input: The observation $\mathbf{Y}=[\mathbf{y}_1,...,\mathbf{y}_J]\in\mathbb{C}^{N_r\times J}$, and the channel matrix $\mathbf{H}=[\mathbf{H}_1,...,\mathbf{H}_K]\in\mathbb{C}^{N_r\times(KN_t)}$, and noise variance σ_w^2.

Output: The activity indicator vector $\mathbf{a}=[a_1,...,a_K]^T$ and the reconstructed signal $\mathbf{X}=[\widetilde{\mathbf{x}}_1,\widetilde{\mathbf{x}}_2,...,\widetilde{\mathbf{x}}_J]$.

1. Initialization:

The iterative index t=1, and $a_k^1=0.5$, $[\widehat{\mathbf{x}}_{k,j}^1]_i=a_k^1\sum_{s\in\mathbb{S}}s/MN_t$, $v_{k,j}^1=a_k^1\sum_{s\in\mathbb{S}}|s|^2/MN_t-|[\widehat{\mathbf{x}}_{k,j}^1]_i|^2$, and $Z_{n,j}^0=[\mathbf{y}_j]_n$, $V_{n,j}^0=1$, for $k\in[K],i\in[N_t],j\in[J]$, and $n\in[N_r]$.

2. AMP operation:

Decoupling step: for $k\in[K]$, $i\in[N_t]$, $j\in[J]$, and $n\in[N_r]$,

$$V_{n,j}^t=\sum_{k=1}^K|\mathbf{H}_{\mathbf{k}[n,:]}|^2\widehat{\mathbf{v}}_{k,j}^t,$$

$$Z_{n,j}^t=\sum_{k=1}^K\mathbf{H}_{\mathbf{k}[n,:]}\widehat{\mathbf{x}}_{k,j}^t-V_{n,j}^t\frac{[\mathbf{y}_j]_n-Z_{n,j}^{t-1}}{\sigma_w^2+V_{n,j}^{t-1}},$$

$$\phi_{l,j}^t=\Big(\sum_{n=1}^{N_r}\frac{\mathbf{H}_{[n,l]}}{\sigma_w^2+V_{n,j}^t}\Big)^{-1},$$

$$r_{l,j}^t=[\widehat{\mathbf{x}}_{k,j}^t]_i+\phi_{l,j}^t\sum_{n=1}^{N_r}\frac{\mathbf{H}_{[n,l]}^*([\mathbf{y}_j]_n-Z_{n,j}^t)}{\sigma_w^2+V_{n,j}^t}.$$

Denoising step: compute $[\widehat{\mathbf{x}}_{k,j}^{t+1}]_i$ and $v_{k,j}^{t+1}$, for $k\in[K]$, $i\in[N_t]$, and $j\in[J]$, using Eqs. (11) and (12).

3. EM operation:

Compute a_k^{t+1}, for $k\in[K]$, using Eq. (18).

4. Termination criteria:

If $t\geq T_0$ is reached, the algorithm stops; otherwise set $t=t+1$ and start again step **2** and step **3**.

Result:

Given $\forall k\in[K]$, if $a_k^{T_0}>0.5$, then a_k is set to 1; otherwise a_k is set to 0. The reconstructed signal $\mathbf{X}=[\widetilde{\mathbf{x}}_1^{T_0},\widetilde{\mathbf{x}}_2^{T_0},...,\widetilde{\mathbf{x}}_J^{T_0}]$, where $\widetilde{\mathbf{x}}_j^{T_0}=[(\widehat{\mathbf{x}}_{1,j}^{T_0})^T,(\widehat{\mathbf{x}}_{2,j}^{T_0})^T,...,(\widehat{\mathbf{x}}_{K,j}^{T_0})^T]^T$.

Computational complexity

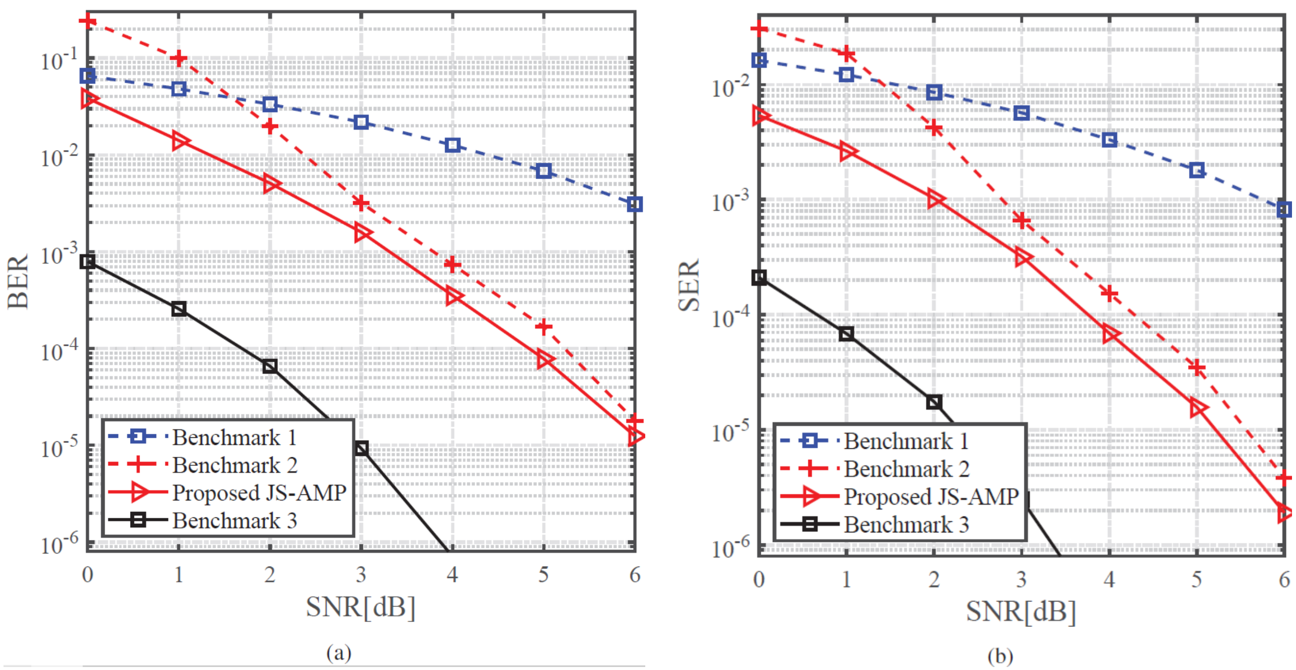
For each iteration, the number of matrix multiplications is on the order of $\mathcal{O}(JN_rKN_t)$, which scales linearly with the number of devices, transmit antennas and receive antennas.

CONTENTS

Simulation Parameters

- K= 150, K_a =10, J= 7
- N_r = 100, N_t = 4
- T_0 = 15 for the proposed JS-AMP algorithm
- 4-QAM for devices with spatial modulation
- 16-QAM in **Benchmark 1**

Benchmark 1:Zero forcing multi-user detector with K_a single antenna devices
Benchmark 2:The state-of-the-art TLSSCS detector from [4]
Benchmark 3:Oracle LS detector



◆ The proposed JS-AMP has better BER and SER performance.

Fig. 2. (a) BER performance comparison of different solutions versus SNRs; (b) SER performance comparison of different solutions versus SNRs.

3 Simulation Results

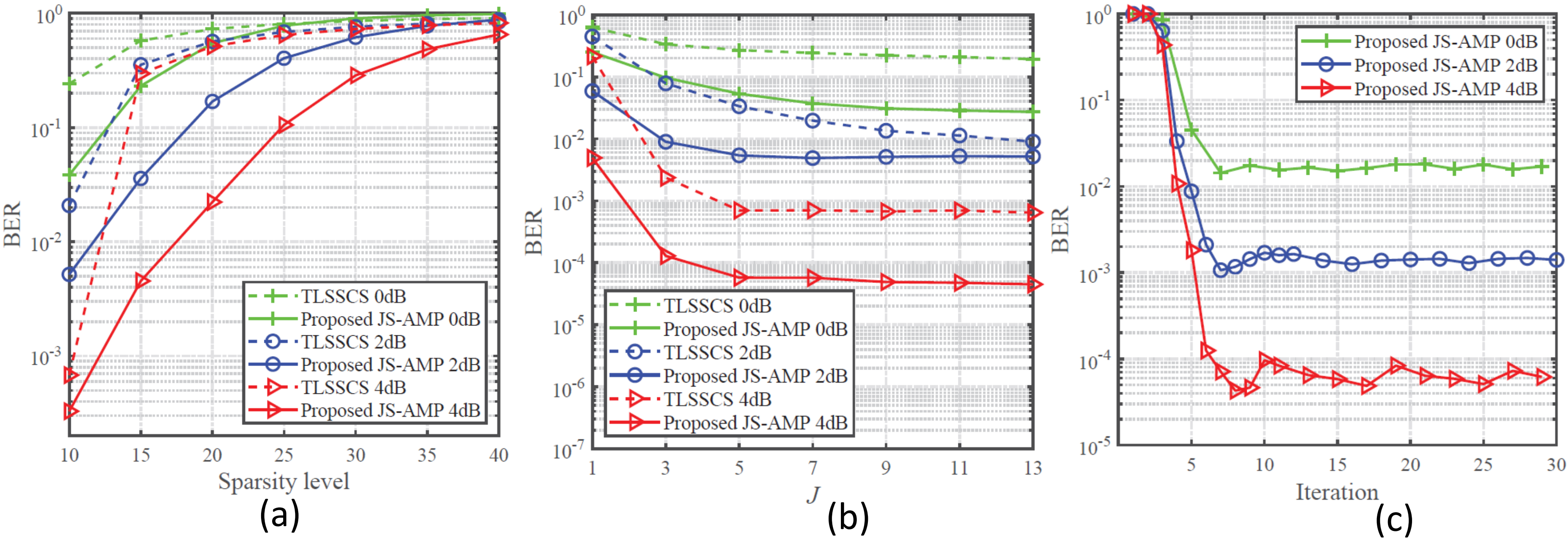


Fig. 3. (a) BER performance comparison versus sparsity level K_a; (b) BER performance comparison versus different frame lengths J; (c) BER performance of the proposed JS-AMP algorithm versus iteration numbers.

- Fig.3.(a): The proposed JS-AMP is robust to the sparsity level
- Fig.3.(b): The exploitation of the block sparsity improves BER performance
- Fig.3.(c): The convergence of the proposed JS-AMP is guaranteed.

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Thanks for your listening!

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