Massive MIMO-Enabled Semi-Blind Detection for Grant-Free Massive Connectivity

Malong Ke, Zhen Gao*, Shufeng Tan, Liang Fan,
Mengnan Jian, Hanqing Xu, Yajun Zhao

Beijing Institute of Technology, Beijing, China;
Beijing TASSON Technology Co., Ltd, Beijing, China;
State Key Laboratory of Mobile Network and Mobile Multimedia Technology, Shenzhen, China;
ZTE Corporation, Beijing, China

Email: gaozhen16@bit.edu.cn

Outline

- Research Background
- System Model
- Proposed Semi-Blind Detection Scheme
- Simulation Results

Background

- **Massive Connectivity**

  The BS is expected to support wireless connectivity with billions of devices

- **Grant-Based Random Access**
  - Require multiple signaling interactions for access scheduling
  - Orthogonal multiple access to avoid inter-device interference
  - High access latency, limited number of devices

- **Grant-Free Random Access**
  - No access scheduling for reduced access latency
  - Non-orthogonal multiple access for a larger number of devices
  - Data detection under severe inter-device interference

- **Training-Based Coherent Detection**
  - "Pilot + data" two phase transmission
  - CS-based joint active device detection and channel estimation
  - Pilot overhead scales with the number of potential devices
  - Rely heavily on accurate CSI

Outline

- Research Background
- System Model
- Proposed Semi-Blind Detection Scheme
- Simulation Results

System Model

- **Grant-Free Massive Connectivity**
  - BS is equipped with *N*-antenna uniform linear array
  - Serve *K* single-antenna devices, *K* is large
  - K_a out of *K* devices are active, K_a is far small than *K*
  - Communicate with the BS in a grant-free fashion
  - Channel and activity remain unchanged during the frame

- **Received Signal over *T* Time Slots**

$$\mathbf{R} = \sum_{k=1}^{K} \alpha_k \widetilde{\mathbf{h}}_k \mathbf{x}_k^{\mathrm{T}} + \mathbf{W} = \widetilde{\mathbf{H}}\mathbf{X} + \mathbf{W} \qquad (1)$$

  - α_k is the device activity indicator
  - $\widetilde{\mathbf{H}} = \left[\alpha_1 \widetilde{\mathbf{h}}_1, \alpha_2 \widetilde{\mathbf{h}}_2, \cdots, \alpha_K \widetilde{\mathbf{h}}_K\right] \in \mathbb{C}^{N \times K}$ is the massive access channel matrix
  - $\mathbf{X} = [\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_K]^{\mathrm{T}} \in \mathbb{C}^{K \times T}$ is the access signal matrix

System Model

- **Angular-Domain Received Signal**
  - To leverage the clustered sparsity of angular-domain channel matrix

$$\mathbf{Y} = \mathbf{A}_R\mathbf{R} = \mathbf{HX} + \mathbf{N} \quad (2)$$

  - Our goal: Jointly infer channel matrix **H** and signal matrix **X** from the overlapped received signal **Y**

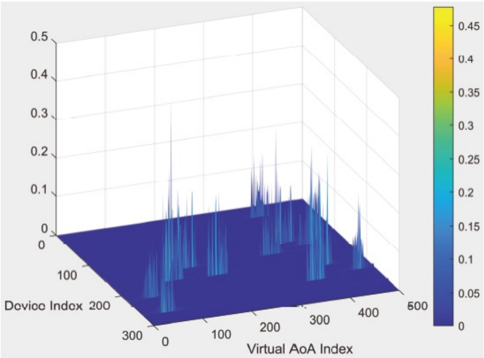


Fig. 1 Clustered sparsity of **H**

- **Phase and Permutation Ambiguities**
  - $\boldsymbol{\Sigma}$ is a phase shift matrix, $\boldsymbol{\Pi}$ is a permutation matrix
  - if $(\widehat{\mathbf{H}}, \widehat{\mathbf{X}})$ is a solution to the matrix factorization based on (2)
  - $(\widehat{\mathbf{H}}\boldsymbol{\Sigma}^{-1}\boldsymbol{\Pi}^{-1}, \boldsymbol{\Pi}\boldsymbol{\Sigma}\widehat{\mathbf{X}})$ is also a valid solution
  - Estimation error $\|\mathbf{Y} - \widehat{\mathbf{H}}\widehat{\mathbf{X}}\|_{\mathrm{F}}^2$ is invariant to any phase shifts and permutations

Outline

- Research Background
- System Model
- Proposed Semi-Blind Detection Scheme
- Simulation Results

Transmitter Design

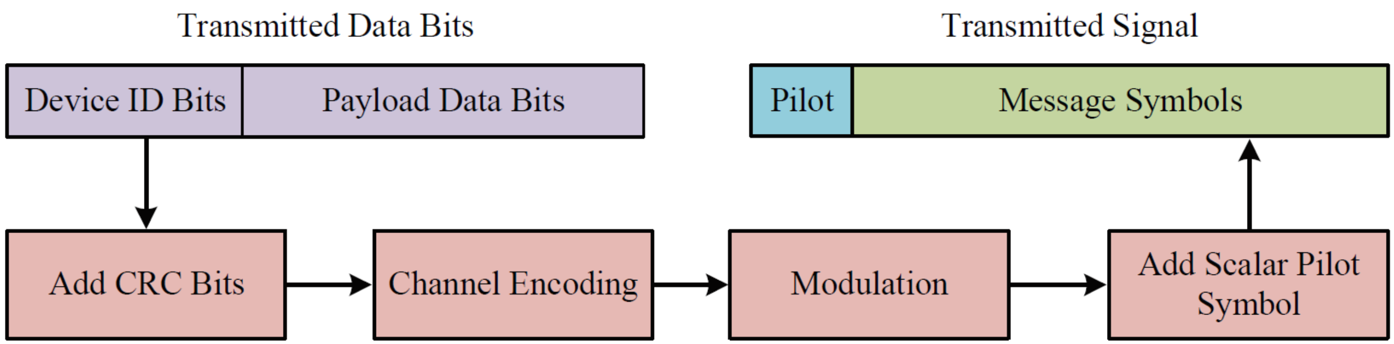


Fig. 1 Transmitter design for semi-blind detection

- A device ID sequence with $L_i = \lceil \log_2(K) \rceil$ is inserted to identify *K* devices
- Device ID is the binary representation of the decimal device index
- A L_c-bit CRC code is added to verify the correctness of the detected data bits
- Channel coding for error detection and correction
- A scalar pilot symbol is inserted to eliminate phase ambiguity

SIC-Based Semi-Blind Detection

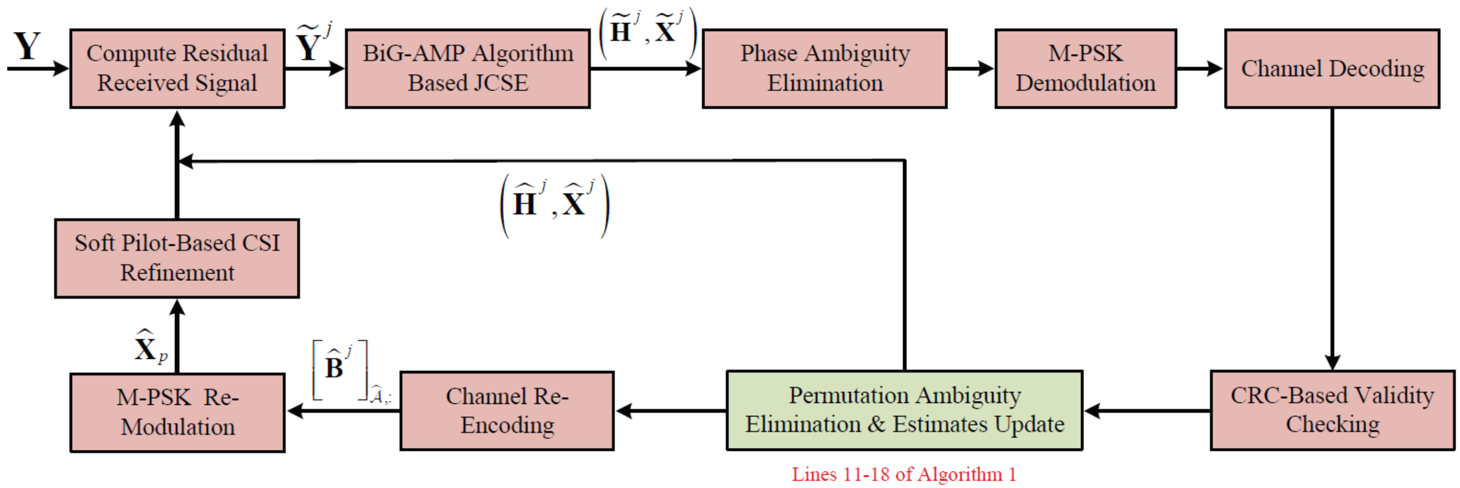


Fig. 3 Block diagram of SIC-based semi-blind detection

- **Compute Residual**
  - Remove the signal components of the detected devices
  - Reduce inter-device interference
- **BiG-AMP-Based JCSE**
  - Jointly estimate channel and signal matrices
  - Leverage the clustered sparsity for improved performance

SIC-Based Semi-Blind Detection

- **Eliminate Phase Ambiguity**
  - Each device's phase shift would be the same for all transmitted data symbols

$$\widehat{\Sigma} = \mathrm{diag}\left(x_p / \left[\widetilde{\mathbf{X}}^j \right]_{:,1} \right), \ \widetilde{\mathbf{H}}^j = \widetilde{\mathbf{H}}^j \widehat{\Sigma}^{-1}, \ \widetilde{\mathbf{X}}^j = \widehat{\Sigma} \widetilde{\mathbf{X}}^j \quad (3)$$

- **Demodulation and Decoding**
  - Obtain the estimated binary data matrix $\widetilde{\mathbf{B}}^j$

- **Eliminate Permutation Ambiguity**

$$
\begin{array}{l}
\textbf{for } k = 1, \cdots, K_a^j \textbf{ do} \\
\quad \widehat{k} = \mathrm{bin2dec}\left(\left[\widetilde{\mathbf{B}}^j \right]_{k, \mathcal{I}_{id}} \right), \ \mathcal{I}_{id} = \{1, \cdots, L_i\} \\
\quad \textbf{if } 0 \le \widehat{k} \le K \ \&\& \ \mathbf{c}^j(k) == 0 \textbf{ then} \\
\quad\quad \widehat{\mathcal{A}}^j = \widehat{\mathcal{A}}^{j-1} \cup \widehat{k}, \ \left[\widehat{\mathbf{B}}^j \right]_{\widehat{k},:} = \left[\widetilde{\mathbf{B}}^j \right]_{k,:} \\
\quad\quad \left[\widehat{\mathbf{H}}^j \right]_{:,\widehat{k}} = \left[\widetilde{\mathbf{H}}^j \right]_{:,k}, \ \left[\widehat{\mathbf{X}}^j \right]_{\widehat{k},:} = \left[\widetilde{\mathbf{X}}^j \right]_{k,:} \\
\quad \textbf{end if} \\
\textbf{end for}
\end{array}
$$

BiG-AMP-Based JCSE Algorithm

- **Bayesian inference for exploiting the statistical information**
  - MMSE estimates of residual channel and signal matrices

$$\left(\widetilde{\mathbf{H}},\widetilde{\mathbf{X}}\right)=\iint\frac{1}{Z}p\left(\widetilde{\mathbf{Y}}|\mathbf{H},\mathbf{X}\right)p\left(\mathbf{H}\right)p\left(\mathbf{X}\right)d\mathbf{H}d\mathbf{X} \qquad (4)$$

  - Likelihood function

$$p\left(\widetilde{\mathbf{Y}}|\mathbf{H},\mathbf{X}\right)=\prod_{n=1}^{N}\prod_{t=1}^{T}\frac{1}{\pi\sigma^2}\exp\left(-\frac{1}{\sigma^2}\left|\tilde{y}_{n,t}-z_{n,t}\right|^2\right) \qquad (5)$$

  - Bernoulli-Gaussian a priori for channel matrix

$$p\left(\mathbf{H}\right)=\prod_{n=1}^{N}\prod_{k=1}^{K}\left[\left(1-\gamma_{n,k}\right)\delta\left(h_{n,k}\right)+\gamma_{n,k}f\left(h_{n,k}\right)\right] \qquad (6)$$

  - Discrete a priori for signal matrix

$$p\left(\mathbf{X}\right)=\prod_{k=1}^{K}\prod_{t=1}^{T}\frac{1}{M}\sum_{m=1}^{M}\delta\left(x_{k,t}-s_m\right) \qquad (7)$$

  - Challenges: high-dimensional integrals, unacceptable complexity

BiG-AMP-Based JCSE Algorithm

- **BiG-AMP Algorithm for Low-Complexity Approximation**
  - Central-limit theorem and Taylor-series approximation
  - The matrix estimation problem is decoupled into multiple independent scalar estimation problems
  - The marginal posterior distribution of channel elements

$$\widehat{q}_{n,k} = h_{n,k} + w^q_{n,k}, \forall n,k, \text{ with } w^q_{n,k} \sim \mathcal{CN}\left(w^q_{n,k}; 0, v^q_{n,k}\right) \quad (8)$$

$$\begin{aligned} \forall n,k\colon v^h_{n,k}(u+1) &= \mathbb{V}\left[h_{n,k} | \widehat{q}_{n,k}(u), v^q_{n,k}(u)\right] \\ \forall n,k\colon \widehat{h}_{n,k}(u+1) &= \mathbb{E}\left[h_{n,k} | \widehat{q}_{n,k}(u), v^q_{n,k}(u)\right] \end{aligned} \quad (9)$$

  - The marginal posterior distribution of signal elements

$$\widehat{r}_{k,t} = x_{k,t} + w^x_{k,t}, \forall k,t, \text{ with } w^x_{k,t} \sim \mathcal{CN}\left(w^x_{k,t}; 0, v^r_{k,t}\right)$$

$$\begin{aligned} \forall k,t\colon v^x_{k,t}(u+1) &= \mathbb{V}\left[x_{k,t} | \widehat{r}_{k,t}(u); v^r_{k,t}(u)\right] \\ \forall k,t\colon \widehat{x}_{k,t}(u+1) &= \mathbb{E}\left[x_{k,t} | \widehat{r}_{k,t}(u); v^r_{k,t}(u)\right] \end{aligned}$$

BiG-AMP-Based JCSE Algorithm

- **Clustered Sparsity-Based A Priori Refining Strategy**
  - Employ EM algorithm to learn the unknown hyper-parameters

$$\boldsymbol{\xi} = \left\{\sigma^2, \mu, \tau, \gamma_{n,k}, \forall n, k\right\}$$

  - Introduce a constraint term to leverage the clustered sparsity

Traditional E-step of EM algorithm

$$\widehat{\boldsymbol{\xi}}(u+1) = \arg\max_{\boldsymbol{\xi}} \left\{ \mathbb{E}\left[\log p\left(\mathbf{H}, \mathbf{X}, \mathbf{Z}, \mathbf{Y}; \boldsymbol{\xi}\right) | \mathbf{Y}; \widehat{\boldsymbol{\xi}}(u)\right] - \omega \sum_{n=1}^{N_{BS}} \sum_{k=1}^{K} \sum_{(n',k') \in \mathcal{N}_{n,k}} \left(\gamma_{n,k} - \gamma_{n',k'}\right)^2 \right\},$$

constrain term

- one element will be nonzero (zero) with a high probability if most of its neighboring elements are non-zero (zero)

Outline

- Research Background
- System Model
- Proposed Semi-Blind Detection Scheme
- Numerical Results

Numerical Results

Simulation Setup

- The BS is equipped with N = 320 antennas
- Serve K = 500 single-antenna devices
- The number of active devices K_a varies from 30 to 80

Parameter	Value
Radius of BS coverage	2 km
Length of CRC bits L_c	8
Length of data bits L_d	100
Generator polynomial of CRC $\mathbf{p}_c$	$[1,1,1,0,1,0,1,0,1]$
Carrier frequency	2 GHz
System bandwidth	10 MHz
Number of MPCs L_k	$\mathcal{U}(L_k;30,60)$
Angular spread in degree	10°
Complex gain of MPCs $\beta_{k,l}$	$\mathcal{CN}(\beta_{k,l};0,1)$
Modulation Type	BPSK
Channel coding	(2,1,7) convolutional code
Number of SIC iterations J	1 or 5
Termination threshold ϵ_{sic}	10^{-5}

Baseline Scheme

- Training-based coherent detection
- GMMV-AMP-based JADCE[Ke'20]
- Pilot overhead

$$T_p = (L_i + L_c) / \left[\log_2(M) R\right] + 1$$

device ID (L_i) CRC (L_c) scalar pilot (1)

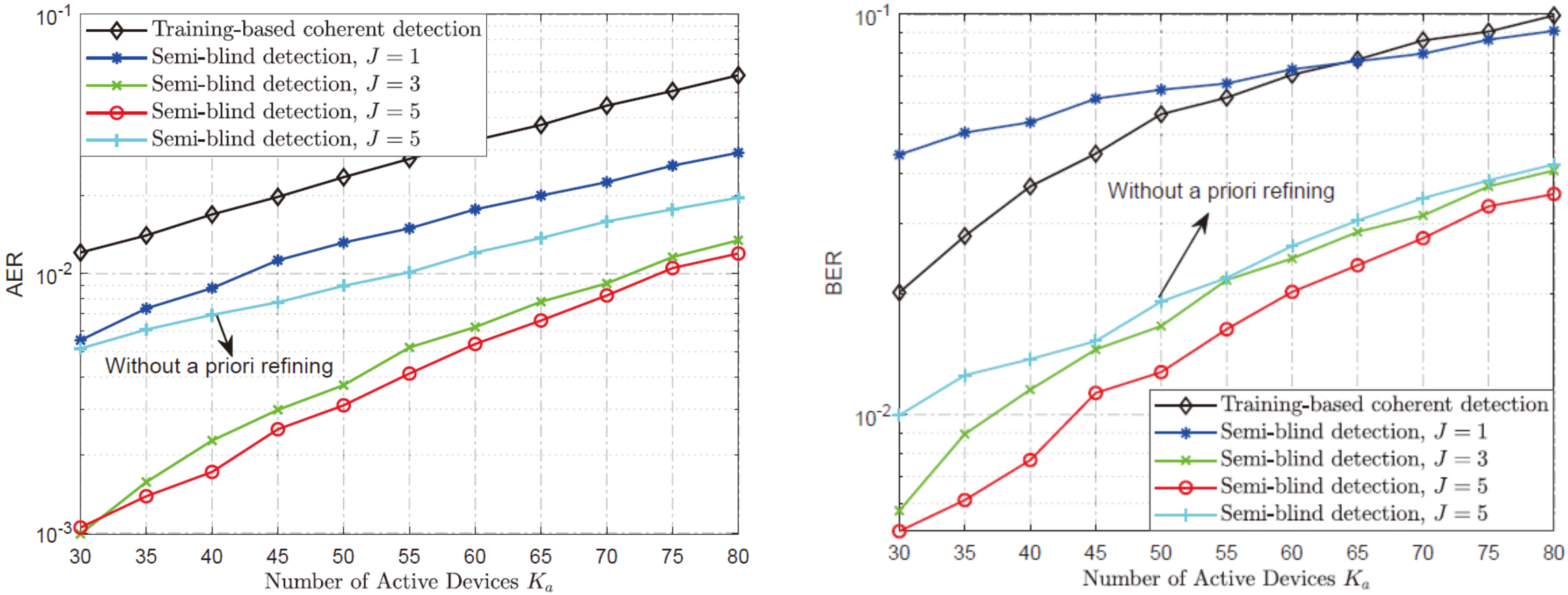
Performance Metrics

$$\text{AER} = \left| \left(\hat{\mathcal{A}} - \mathcal{A}\right) \cup \left(\mathcal{A} - \hat{\mathcal{A}}\right) \right|_c / K$$ and $$\text{BER} = \sum_{k\in\mathcal{A}} \sum_{l\in\mathcal{L}_d} \left|\hat{b}_{k,l} - b_{k,l}\right| / (K_a L_d)$$

[Ke'20] M. Ke et al., "Compressive sensing-based adaptive active user detection and channel estimation: Massive access meets massive MIMO," IEEE Trans. Signal Process., vol. 68, pp. 764-779, 2020.

Numerical Results

Simulation Results



- The proposed scheme outperforms the training-based coherent detection scheme
- The performance becomes better as the number of SIC iterations *J* increases
- The clustered sparsity-based a priori refining further enhances the performance

THANKS!

Q&A