# A Coupled Compressive Sensing Scheme for Unsourced Multiple Access

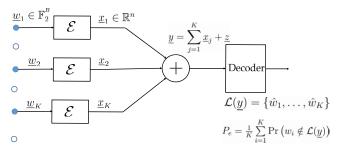
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## Uncoordinated and Unsourced Multiple Access

- ▶ K active users out of  $K_{\text{tot}}$  total users  $K \in [25:300]$ ,  $K_{\text{tot}}$  is very large
- lacktriangle Each user has a B-bit message. B is small pprox 100
- ▶ *N* channel uses available  $N \approx 30,000$



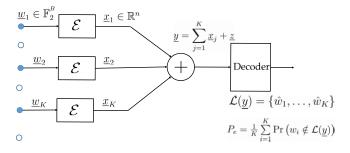
#### Objective

Design a coding scheme minimizing the required SNR P such that

- ► Low complexity encoding and decoding complexities
- ▶ Prob. of decoding error per user  $P_e \le \epsilon \in [0.05, 0.1]$

### Differences From Traditional Information Theoretic MAC

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- ► Uncoordinated: Resource allocation not allowed
- Unsourced: Decoding done upto permutation of messages
- ► Finite block length regime

#### Prior Work

#### [Polyanskiy' 17] Gaussian coding for unsourced MAC

- ► Derived achievability limits via random Gaussian coding
  - ML decoder: exponential complexity in B, K.  $\mathcal{O}(N \cdot \binom{2^B}{K}) \approx \mathcal{O}(N2^{BK})$
- ▶ In comparison, ALOHA, TIN was shown to be very energy-inefficient

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### [Ordentlich and Polyanksiy'17] Compute-and-Forward based coding scheme

- ► Decoding modulo-2 sums
- ► Low complexity but still large gap to Polyanksiy's bound

## Compressed Sensing View

$$\begin{bmatrix} y_1 \\ y_2 \\ \dots \\ y_N \end{bmatrix} = \begin{bmatrix} \begin{vmatrix} & & & & & \\ \vec{a}_1 & \vec{a}_2 & \cdots & \vec{a}_{2^B} \\ & & & & & \end{vmatrix} \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ 1 \\ \vdots \\ 1 \\ 0 \end{bmatrix} + \begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_N \end{bmatrix}$$

### Unsourced nature $\leftrightarrow$ compressed sensing

- ▶  $\vec{\mathbf{b}} \in \{0,1\}^{2^B}, ||\vec{\mathbf{b}}||_1 = K$
- $ightharpoonup \vec{\mathbf{a}}_i \in \mathbb{R}^N$

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#### Challenges

- ▶ Huge sensing matrix: impractical even for  $B \approx 100$
- ightharpoonup is binary: optimal sensing matrix & decoder design are open problems
- ► Finding fundamental limits appears to be an open problem

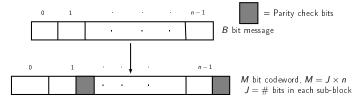
## Compressive Sensing and MAC

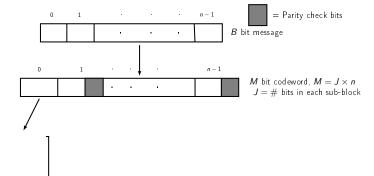
#### Neighbor Discovery for Wireless Networks [Zhang, Guo'12]

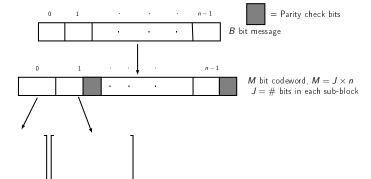
- ► Each node wishes to identify the network interface addresses (NIAs) of those nodes within a single hop
- lacktriangle Nodes assigned NIAs from address space  $\{0,1,\cdots,N\}$  (e.g.  $N=2^{48}-1)$
- ► Strong connection with support recovery problem in compressive sensing
- Deterministic signatures based on second order Reed-Muller codes
- ► Chirp decoding algorithm complexity sub-linear in N
- ▶ We don't know the gap of this from information theoretic bounds

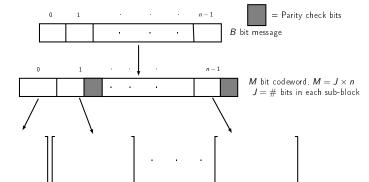
B bit message

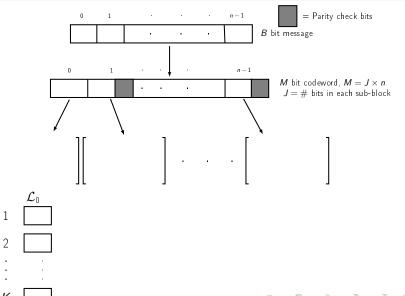


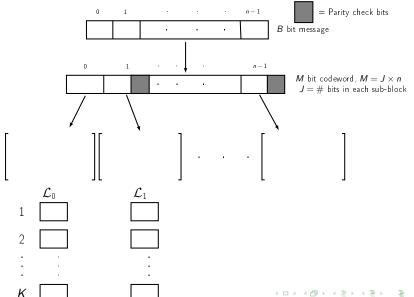


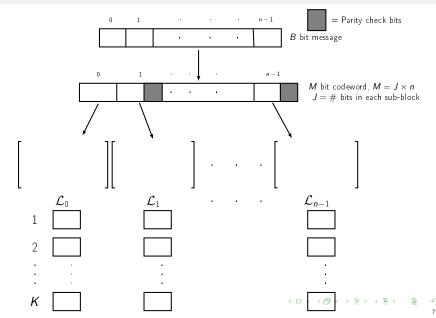


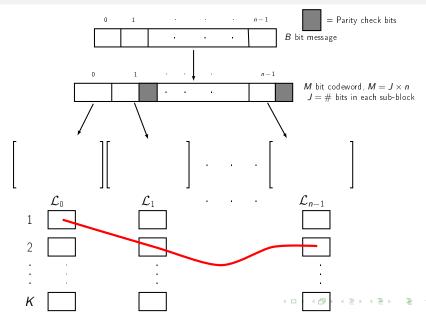


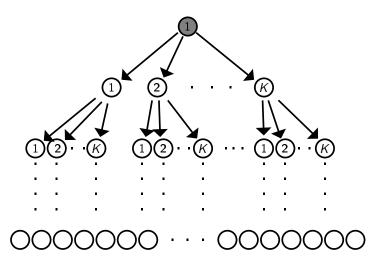


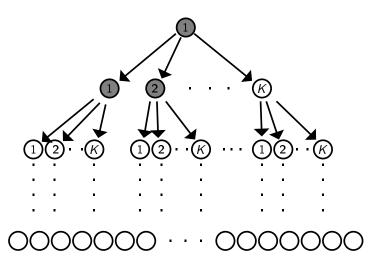


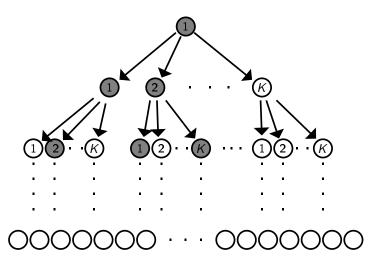


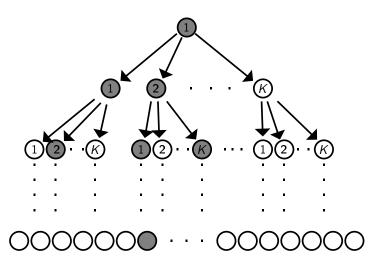


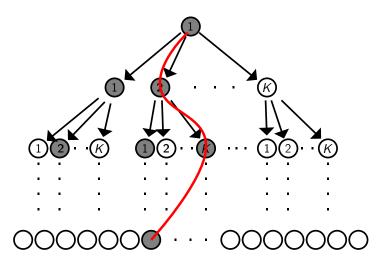












#### Iterative Extension

- Contribution of columns identified by tree decoder as transmitted vectors is cancelled from the received signal.
- ► Subsequent iterations: Reduced sparsity sub-problems are solved followed by tree decoding.

▶  $I_i$ : #parity bits in sub-block  $i \in [1:n-1]$ ,

- ▶  $l_i$ : #parity bits in sub-block  $i \in [1:n-1]$ ,
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#### Expressions for $\mathbb{E}[L_i]$ and C

▶  $L_i|L_{i-1} \sim B((L_{i-1}+1)K-1,p_i), p_i = \frac{1}{2^{l_i}}, q_i = 1-p_i,$ 

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$$\mathbb{E}[L_{i}] = \mathbb{E}[\mathbb{E}[L_{i}|L_{i-1}]]$$

$$= \mathbb{E}[((L_{i-1}+1)K-1)p_{i}]$$

$$= p_{i}K\mathbb{E}[L_{i-1}] + p_{i}(K-1),$$

$$= \sum_{m=1}^{i} \left[K^{i-m}(K-1)\prod_{j=m}^{i} p_{j}\right]$$

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$$= \mathbb{E}[((L_{i-1}+1)K-1)p_i] = p_i K \mathbb{E}[L_{i-1}] + p_i (K-1), = \sum_{m=1}^{i} \left[ K^{i-m} (K-1) \prod_{j=m}^{i} p_j \right]$$

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- $ightharpoonup C = K + \sum_{i=1}^{n-2} [(L_i + 1)K]$
- $ightharpoonup \mathbb{E}[C]$  can be computed using the expression for  $\mathbb{E}[L_i]$

## Performance Analysis

► 
$$L_i|L_{i-1} \sim B((L_{i-1}+1)K-1, p_i), p_i = \frac{1}{2^{l_i}}, q_i = 1 - p_i$$

• 
$$G_{L_{n-1}}(z) = \mathbb{E}[z^{L_{n-1}}] = \sum_{k=0}^{K^{n-1}-1} P(L_{n-1} = k)z^k$$

#### Probability of error for the tree decoder

$$P(L_{n-1} \ge 1) = 1 - G_{L_{n-1}}(0),$$
 where  $G_{L_{n-1}}(z) = \prod_{i=0}^{n-2} f_{n-1-i}^{K-1}(z),$   $f_k(z) = egin{cases} q_k + p_k f_{k+1}^K(z), & 1 \le k \le n-1 \ z^{rac{1}{K}}, & k = n, \end{cases}$ 

#### Overall probability of error

 $ightharpoonup p_{cs}$ : Probability of error of compressed sensor at sub-block level

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#### Overall probability of error

- $\triangleright$   $p_{cs}$ : Probability of error of compressed sensor at sub-block level
- $P_e = 1 (1 P(L_{n-1} \ge 1))(1 p_{cs})^n$

# Optimization of Parity Lengths

```
 \begin{array}{ll} \underset{(I_1,I_2,\dots I_{n-1})}{\text{minimize}} & \mathbb{E}[C] \\ \text{subject to} & P(L_{n-1} \geq 1) \leq \varepsilon_{\mathsf{tree}}, \\ & \sum_{i=1}^{n-1} I_i = M - B, \\ & I_i \in \{0,1,\dots J\} \ \forall \ i \in [1:n-1]. \end{array}
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- ► Geometric programming opt. problem
- ► Can be solved using any standard convex solver (ex. CVX).

# Choice of Parity Lengths

$$K = 200, n = 11, J = 15$$

$arepsilon_{tree}$	$\mathbb{E}[C]$	Parity Lengths
0.006	Infeasible	Infeasible
0.0061930	$3.2357 \times 10^{11}$	[0,0,0,0,15,15,15,15,15,15]
0.0061931	3357300	[0, 3, 8, 8, 8, 8, 10, 15, 15, 15]
0.0061932	1737000	[0, 4, 8, 8, 8, 8, 9, 15, 15, 15]
0.0061933	926990	[0, 5, 8, 8, 8, 8, 8, 15, 15, 15]
0.0061935	467060	[1, 8, 8, 8, 8, 8, 8, 11, 15, 15]
0.0062	79634	[1, 8, 8, 8, 8, 8, 8, 11, 15, 15]
0.007	7357.8	[6, 8, 8, 8, 8, 8, 8, 8, 13, 15]
0.008	6152.7	[7,8,8,8,8,8,8,12,15]
0.02	5022.9	[6, 8, 8, 9, 9, 9, 9, 9, 14]
0.04	4158	[7, 8, 8, 9, 9, 9, 9, 9, 13]
0.6378	3066.3	[9, 9, 9, 9, 9, 9, 9, 9, 9]

## Choice of Sensing Matrix

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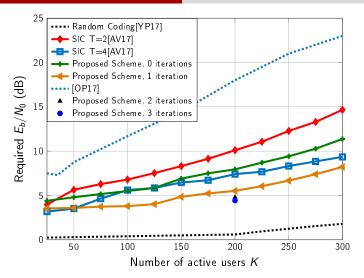
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- ▶  $A = [\vec{a_0}, \vec{a_1}, \cdots, \vec{a_{2^J-1}}]$ , where  $\vec{a_i} = \sqrt{P(2\vec{c_i} 1)}, \vec{c_i} \in C^0 \ \forall \ i \in [0:2^J 1]$ .

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## Decoding Algorithm

- ► Non-negative least squares
- ▶ Take top K + 10 elements



- ► B = 75, N = 22517
- ► Only 4.3 dB away from Polyanksiy's achievability result

#### Conclusion

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- ► Sub-linear time complexity
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#### Open Problems

- ► A strict FBL lower bound for GMAC?
- ▶ Design of optimal sensing matrix for the K-sparse CS problem
- ► Solve a generic CS problem of huge dimensions using this framework: Bounds for sample and computational complexities.

# Questions?

# Thank you!