

ALGEBRAICALLY-INITIALIZED EXPECTATION MAXIMIZATION FOR HEADER-FREE COMMUNICATION

Liangzu Peng, Xuming Song, Manolis C. Tsakiris, Hayoung Choi, Laurent Kneip, and Yuanning Shi

School of Information Science and Technology, ShanghaiTech University, Shanghai 201210, China

Introduction

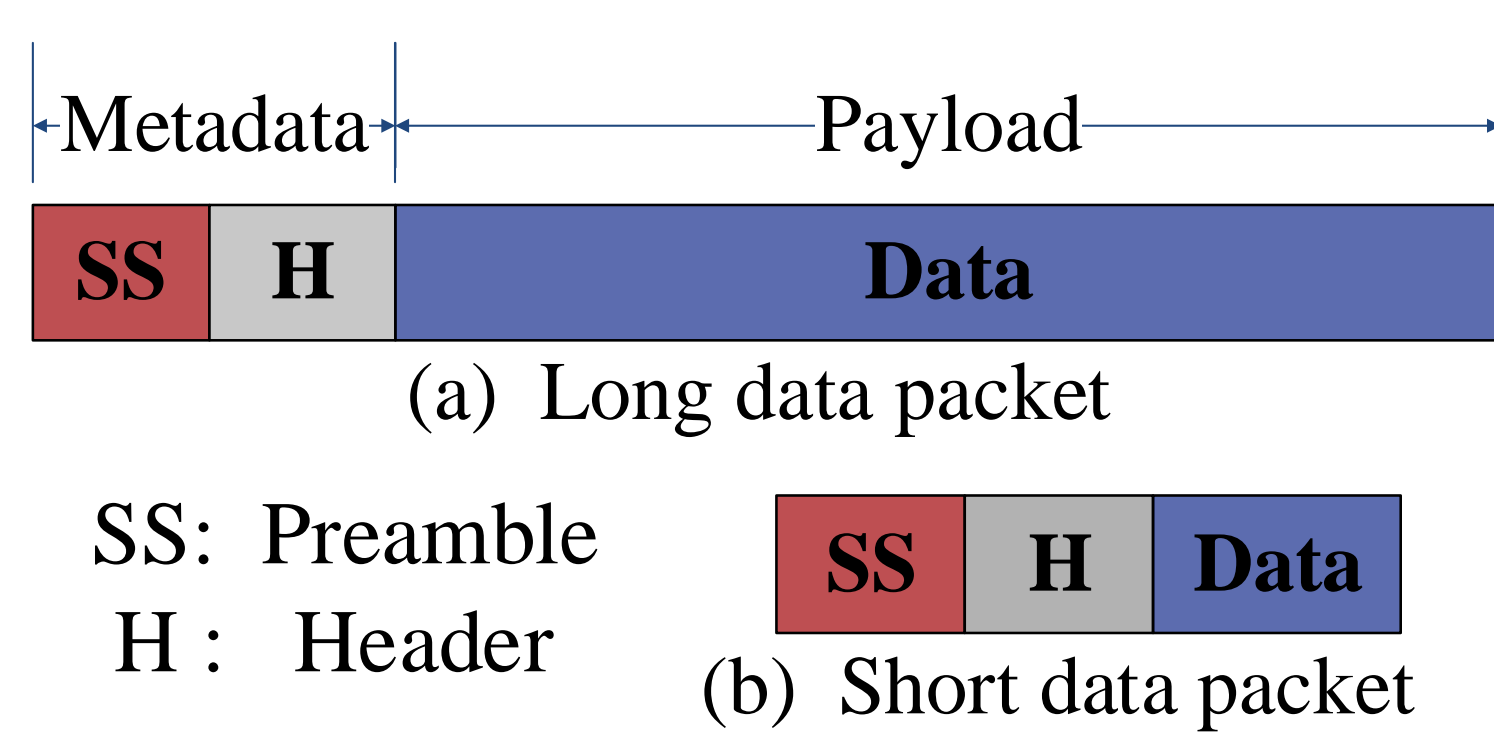


Figure 1: Example of the long and short data packet.

- It has been a trend to have low latency in wireless communication systems.
 - **Example.** URLLC, MM2M [1].
- Transmission latency may be highly suboptimal when applying traditional methods to transmit short packets [2].
- One simple solution is to exclude the header, i.e.,
 - **H** in Figure 1.
- Such an exclusion leads to the so-called *header-free communication*.

Application Context

- Figure 2 depicts an application of header-free communication in massive IoT networks.

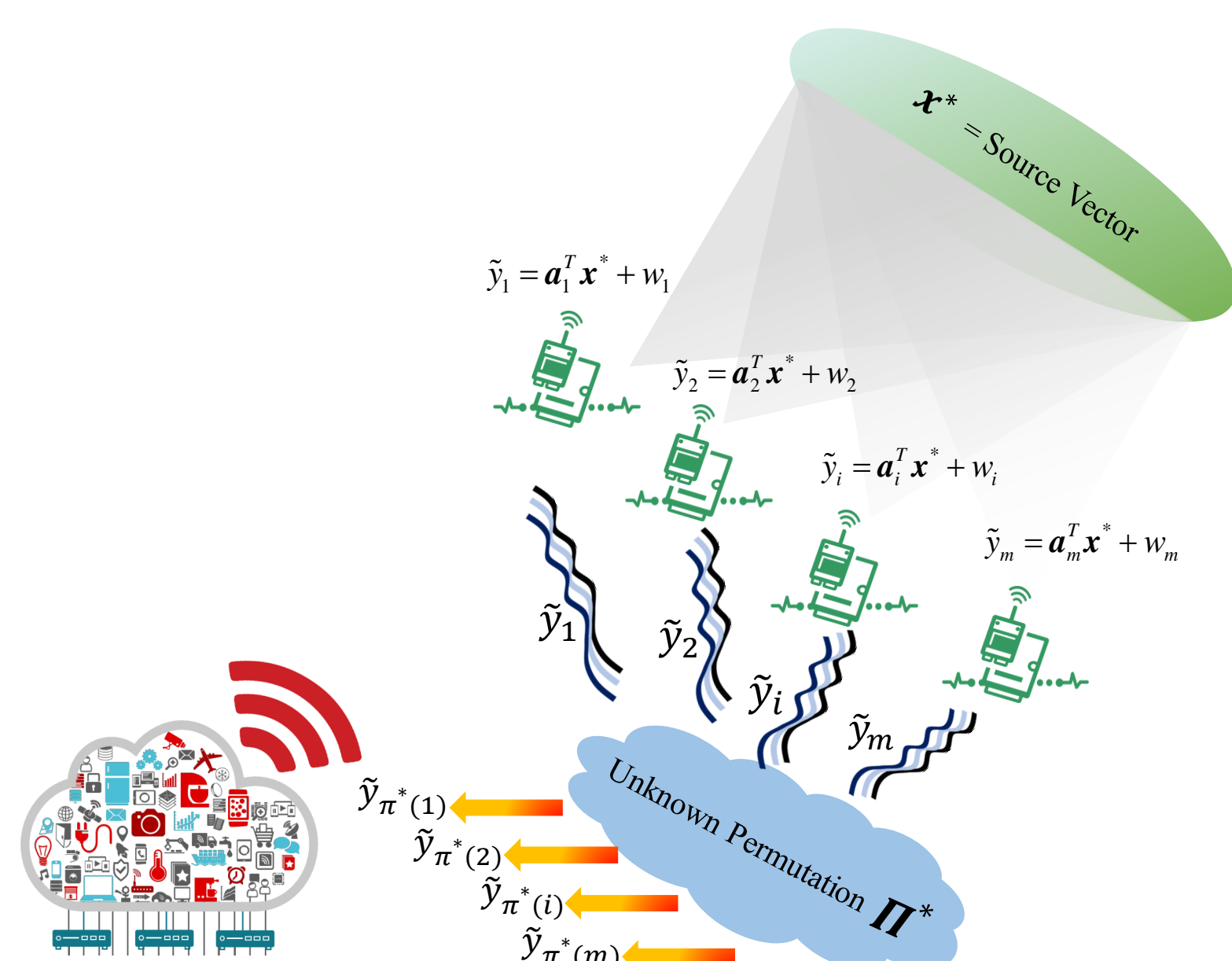


Figure 2: IoT networks with header-free communication.

Modeling

- each sensor $s_i, i \in \{1, \dots, m\} =: [m]$ has a corrupted measurement $x_j^* + w_{i,j}$ at time j for $j \in [n]$, where $w_{i,j} \in \mathbb{R}$ is noise.
- sensor s_i sends the weighted average

$$a_{i,1}(x_1 + w_{i,1}) + \dots + a_{i,n}(x_n + w_{i,n}) \quad (1)$$
 to the fusion center, where $a_{i,j}$'s are weights.
- the center receives

$$\tilde{\mathbf{y}}_i := \mathbf{a}_i^\top \mathbf{x}^* + w_i. \quad (2)$$
- packets sent with headers:

$$\tilde{\mathbf{y}} = \mathbf{A}\mathbf{x}^* + \mathbf{w}. \quad (\text{Linear Regression}) \quad (3)$$
- header-free communication ($\mathbf{y} = \Pi^\top \tilde{\mathbf{y}}$ received):

$$\Pi \mathbf{y} = \mathbf{A}\mathbf{x}^* + \mathbf{w}. \quad (\text{Shuffled Linear Regression}) \quad (4)$$

Power Sum Polynomial System

- Power Sum Polynomials:

$$p_k(\mathbf{z}) = \sum_{i=1}^m z_i^k, \forall k \in [n]. \quad (5)$$
- (5) is permutation invariant:

$$p(\mathbf{z}) = p(z_{\pi(1)}, \dots, z_{\pi(m)}) =: p(\Pi \mathbf{z}), \quad (6)$$
- hence

$$p_k(\mathbf{A}\mathbf{x}^* + \mathbf{w}) = p_k(\Pi^* \mathbf{y}) = p_k(\mathbf{y}) \quad (7)$$

$$\iff p_k(\mathbf{A}\mathbf{x}^* + \mathbf{w}) - p_k(\mathbf{y}) = 0. \quad (8)$$
- Power Sum Polynomial System $\hat{\mathcal{P}}$:

$$\hat{p}_k(\mathbf{x}) := p_k(\mathbf{A}\mathbf{x}) - p_k(\mathbf{y}) = 0, k \in [n]. \quad (9)$$
- (9) is solvable by standard algorithms in computational algebraic geometry, yielding finitely many solutions [3].

Future Work

- Shuffle Linear Regression in high dimension
- Extension to other applications, such as
 - multi-target tracking
 - genome-assembly

References

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- [4] Abubakar Abid and James Zou. Stochastic em for shuffled linear regression. *arXiv e-print*, 2018.
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Contributions

- a working algorithm for the noisy shuffled linear regression problem for small dimensions (n).
 - at a complexity linear in the number m of sensors.
- suitable for massive IoT sensor networks with header-free communication.

The AIEM Algorithm

Algebraic Initialization.

- 1 $\{\hat{\mathbf{x}}_i\}_{i=1}^L \leftarrow$ solutions of $\hat{\mathcal{P}}$ (9);
- 2 take the real parts of the roots:

$$\{(\hat{\mathbf{x}}_i)_{\mathbb{R}}\}_{i=1}^L \leftarrow \{a : a + ib \in \{\hat{\mathbf{x}}_i\}_{i=1}^L\}. \quad (10)$$
- 3 extract the most *suitable* one:

$$\hat{\mathbf{x}}_0 \leftarrow \operatorname{argmin}_{i \in [L]} \{\min_{\Pi} \|\Pi \mathbf{y} - \mathbf{A}(\hat{\mathbf{x}}_i)_{\mathbb{R}}\|_2\}. \quad (11)$$

Expectation Maximization.

- iteratively solve (12) via sorting, and

$$\Pi_t \leftarrow \operatorname{argmin}_{\Pi} \|\Pi \mathbf{y} - \mathbf{A}\mathbf{x}_{t-1}\|_2 \quad (12)$$
- solve (13) via least-squares until convergence.

$$\mathbf{x}_t \leftarrow \operatorname{argmin}_{\mathbf{x} \in \mathbb{R}^n} \|\Pi_t \mathbf{y} - \mathbf{A}\mathbf{x}\|_2 \quad (13)$$
- return the final estimate, say $\mathbf{x}_T =: \hat{\mathbf{x}}$, for \mathbf{x}^* .

Results

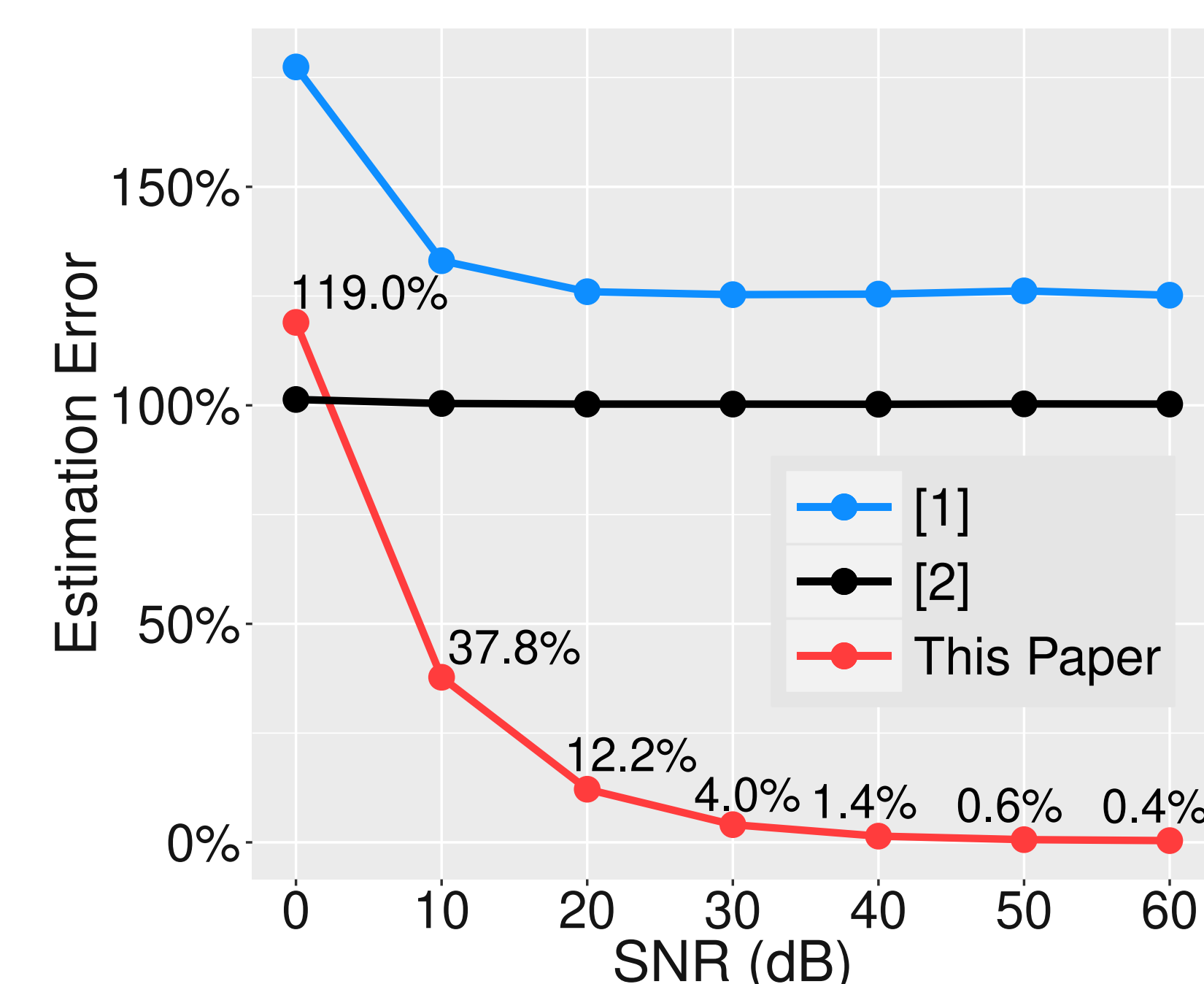


Figure 3: Estimation error $100 \times \frac{\|\mathbf{x}^* - \hat{\mathbf{x}}\|_2}{\|\mathbf{x}^*\|_2} \%$.

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Contact Information

Liangzu Peng
 • Email: penglz@shanghaitech.edu.cn

