A Distributed Adaptive Signal Fusion Framework for Spatial Filtering in Wireless Sensor Networks

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1. Contribution

We describe a distributed algorithm for adaptive signal fusion/spatial filtering, particularly well-suited to wireless sensor networks (WSNs). In order to cope with the bandwidth and computational limitations of a WSN, the procedure does not require any data centralization and solely relies on the exchange of linearly compressed views of the nodes' sensor data.

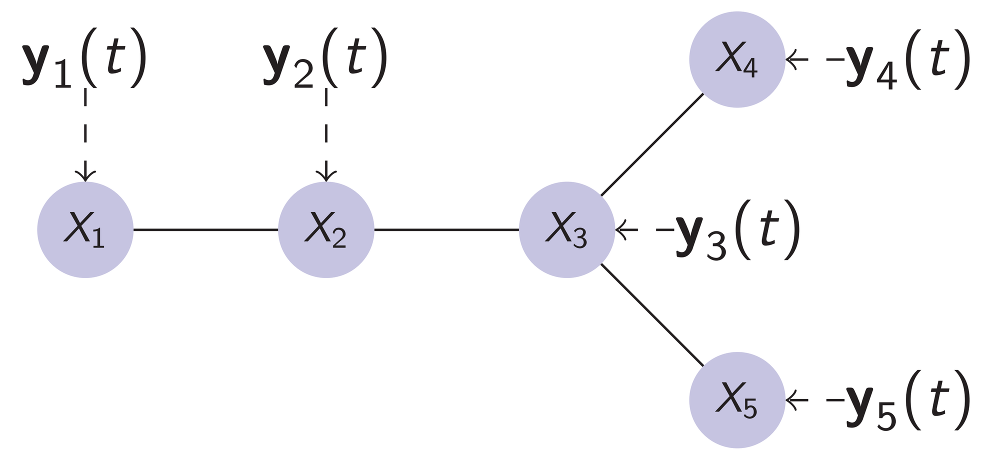
2. Problem Statement

▷ Filtering and signal fusion optimization problems

$$\min_X \varphi(X_1^T\mathbf{y}_1(t), X_2^T\mathbf{y}_2(t), \dots, X_K^T\mathbf{y}_K(t)) = f(X^T\mathbf{y}(t))$$
$$\text{s.t.} \quad \eta(X_1^T\mathbf{y}_1(t), X_2^T\mathbf{y}_2(t), \dots, X_K^T\mathbf{y}_K(t)) = g(X^T\mathbf{y}(t)) \in \mathcal{C}$$

▷ Feature-based distribution of data among nodes in a network

$$X = \begin{bmatrix} X_1 \\ X_2 \\ X_3 \\ X_4 \\ X_5 \end{bmatrix}$$



▷ Common examples

	Cost	Constraints
LCMV	$\mathbb{E}[\|\|X^T\mathbf{y}(t)\|\|^2]$	$X^TB = H$
PCA	$-\mathbb{E}[\|\|X^T\mathbf{y}(t)\|\|^2]$	$X^TX = I_Q$
LS/MMSE	$\mathbb{E}[\|\|\mathbf{d}(t) - X^T\mathbf{y}(t)\|\|^2]$	$X \in \mathbb{R}^{M\times Q}$

with $\mathbf{y}(t) = [\mathbf{y}_1(t)^T \ \mathbf{y}_2(t)^T \ \mathbf{y}_3(t)^T \ \mathbf{y}_4(t)^T \ \mathbf{y}_5(t)^T]^T$

3. From Global to Local Problems

▷ Starting from some estimate of the solution X^*, a specific node is selected (node 1 hereafter) and

$$\begin{bmatrix} X_1 \\ X_2 \\ X_3 \\ X_4 \\ X_5 \end{bmatrix} \text{ is parameterized as } \begin{bmatrix} X_1 \\ X_2^*G_2 \\ X_3^*G_3 \\ X_4^*G_4 \\ X_5^*G_5 \end{bmatrix}$$

▷ Instead of optimizing

$$\varphi\left(X_1^T\mathbf{y}_1(t), X_2^T\mathbf{y}_2(t), X_3^T\mathbf{y}_3(t), X_4^T\mathbf{y}_4(t), X_5^T\mathbf{y}_5(t)\right),$$

we optimize

$$\varphi\left(X_1^T\mathbf{y}_1(t), G_2{}^T\mathbf{z}_2(t), G_3{}^T\mathbf{z}_3(t), G_4{}^T\mathbf{z}_4(t), G_5{}^T\mathbf{z}_5(t)\right)$$

with

$$\mathbf{z}_k(t) = X_k^{*\,T}\mathbf{y}_k(t).$$

↓

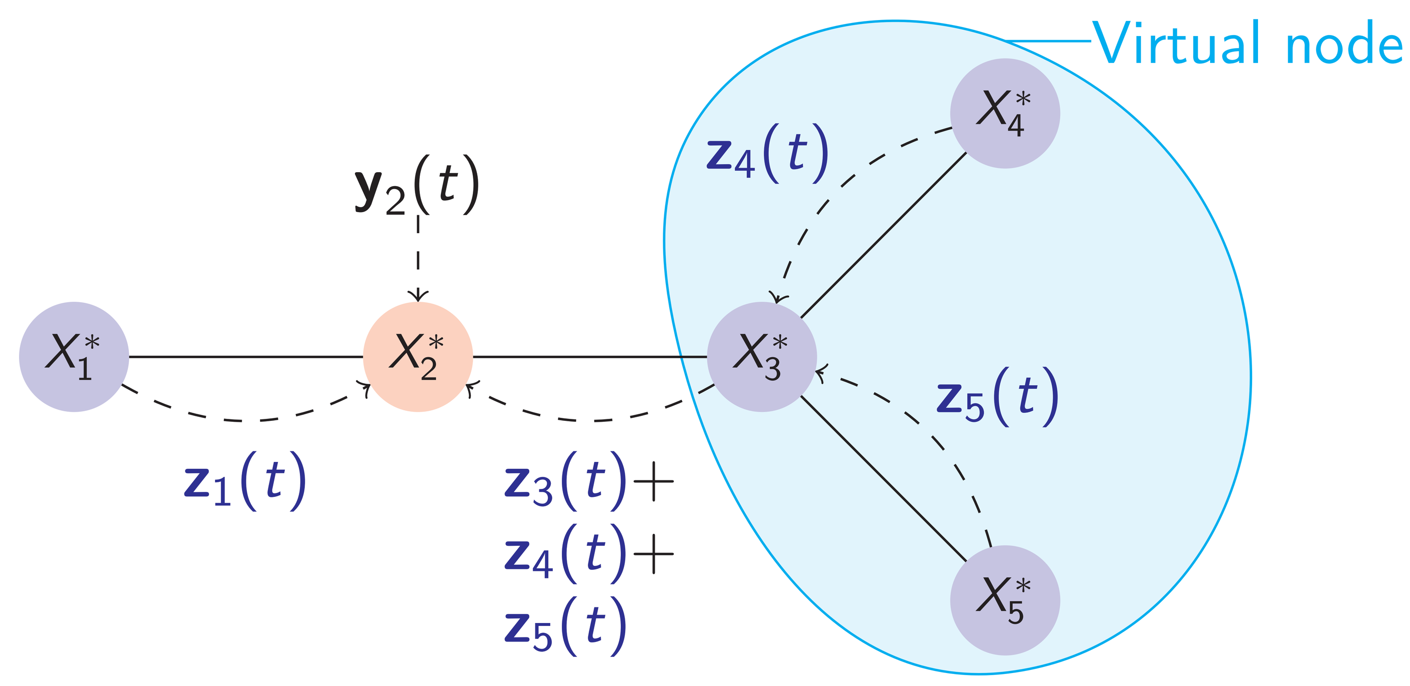
We solve the **same** problem using

linearly compressed data and **optimization variables**

$$\begin{bmatrix} \mathbf{y}_1(t) \\ \mathbf{z}_2(t) \\ \mathbf{z}_3(t) \\ \mathbf{z}_4(t) \\ \mathbf{z}_5(t) \end{bmatrix} \qquad \begin{bmatrix} X_1 \\ G_2 \\ G_3 \\ G_4 \\ G_5 \end{bmatrix}$$

4. Iterative Optimization Procedure

1. Select the updating node in a round-robin fashion
2. Aggregate the compressed variables by recursive summation



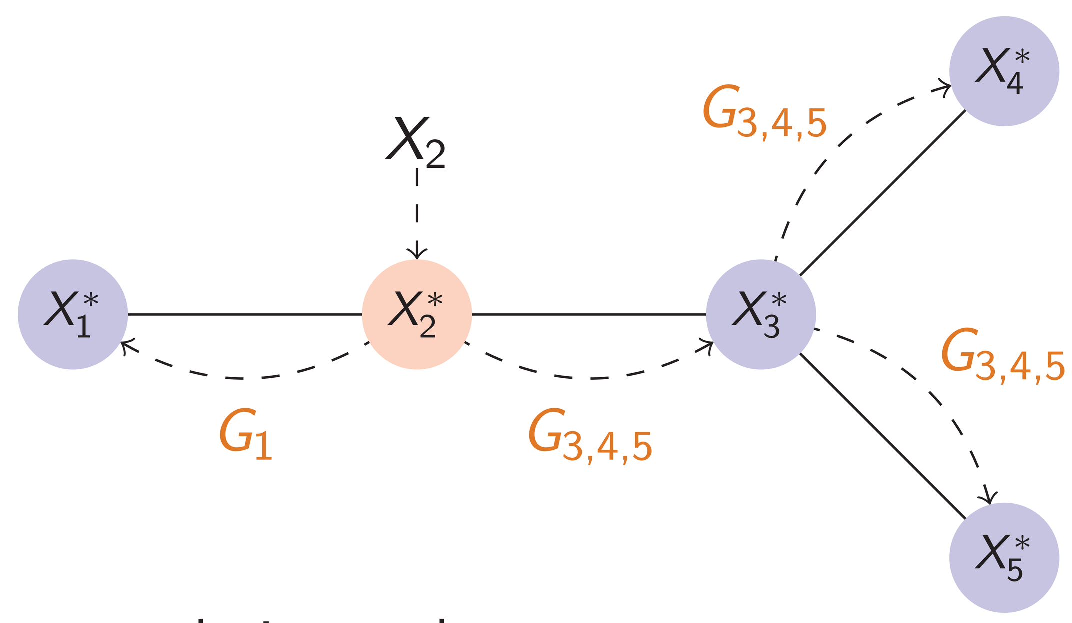
Nodes in a common branch rooted at the updating node are **fused into a single virtual node**

3. Solve the local problem

$$\min_{\{G_1, X_2, G_{3,4,5}\}} \varphi(G_1{}^T\mathbf{z}_1(t), X_2^T\mathbf{y}_2(t), G_{3,4,5}{}^T\Sigma_{k=3,4,5}\mathbf{z}_k(t))$$
$$\text{s.t.} \quad \eta(G_1{}^T\mathbf{z}_1(t), X_2^T\mathbf{y}_2(t), G_{3,4,5}{}^T\Sigma_{k=3,4,5}\mathbf{z}_k(t)) \in \mathcal{C}.$$

4. Update the estimates

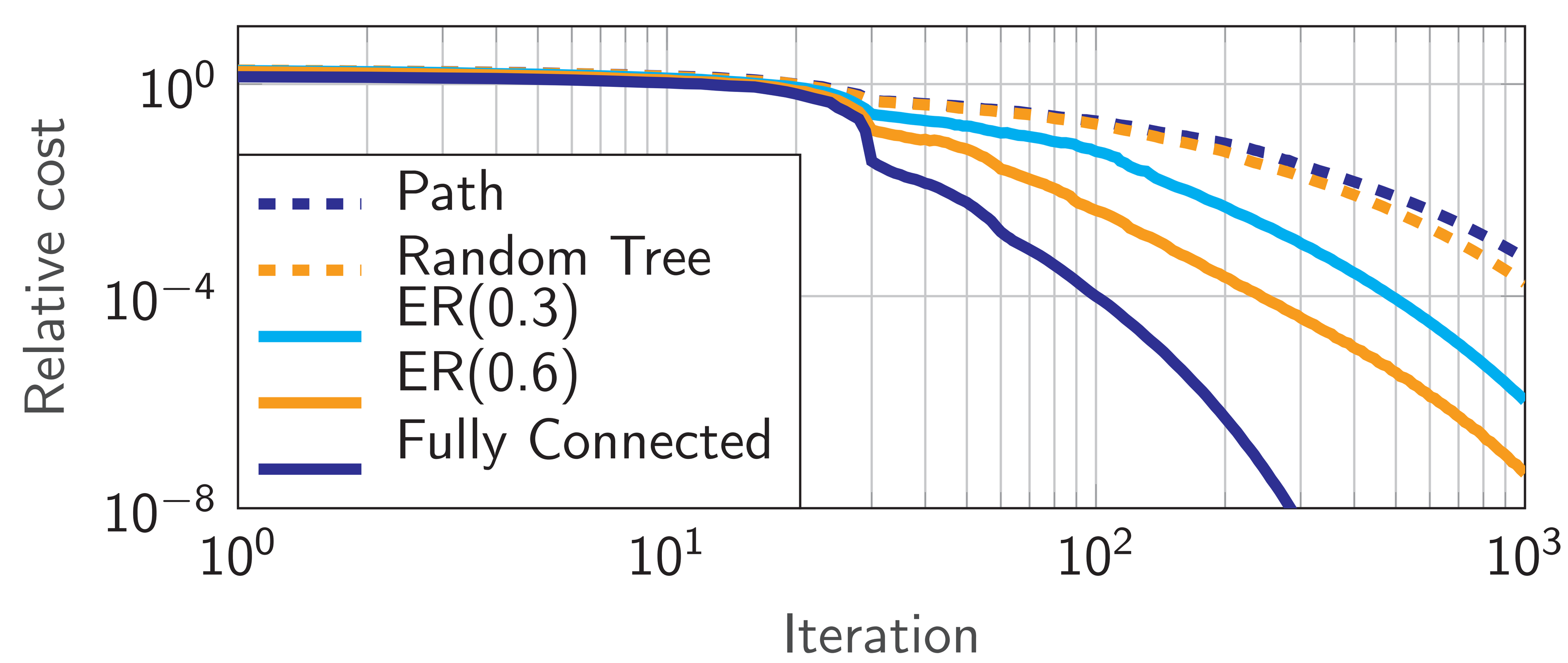
$$X_1^* \leftarrow X_1^*G_1$$
$$X_2^* \leftarrow X_2$$
$$X_3^* \leftarrow X_3^*G_{3,4,5}$$
$$X_4^* \leftarrow X_4^*G_{3,4,5}$$
$$X_5^* \leftarrow X_5^*G_{3,4,5}$$



5. Repeat with the next updating node

5. Scalability and Convergence

▷ The communication and computational cost at each node solely depends on its degree and **is independent of the total network's size**.
▷ Sparsely connected networks achieve **greater compression** at the cost of **slower convergence**.
▷ Proven convergence to a global minimum under mild assumptions.



ER(p) denotes Erdös-Rényi graphs with connection probability p.