

# FAST DISTRIBUTED SUBSPACE PROJECTION VIA GRAPH FILTERS

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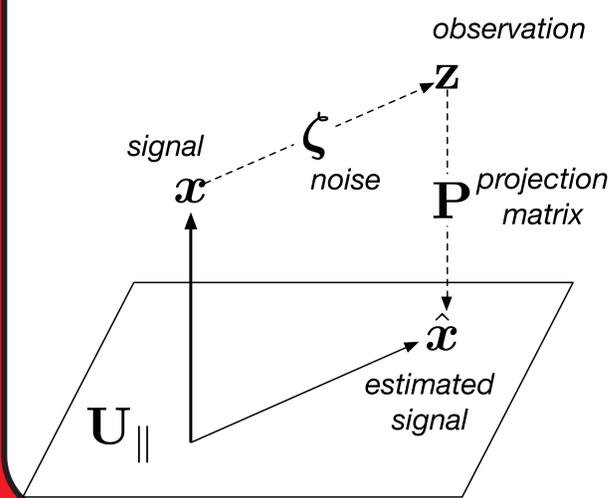
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## Contributions

**Result:** Subspace projection  
 - in a decentralized fashion  
 - in a finite number of iterations.

**Novelty:** Based on Graph filters  
 - finds valid shift matrix when it exists and  
 - is the one that approximately minimizes order  
 → number of communications between nodes.

## Subspace projection example



## Problem formulation

A graph  $\mathcal{G}(\mathcal{V}, \mathcal{E})$  is considered  
 -  $\mathcal{V} = \{v_1, \dots, v_N\}$  represent  $N$  sensors  
 - edge  $(v_n, v_{n'})$  iff sensors communicate.  
 - self loops  $(v_n, v_n) \in \mathcal{E}$ ,  $n = 1, \dots, N$  included.

$\mathbf{A}$  is the adjacency matrix:  
 -  $(\mathbf{A})_{n,n'} = 1$  if  $(v_n, v_{n'}) \in \mathcal{E}$   
 -  $(\mathbf{A})_{n,n'} = 0$  otherwise.

**Goal:** estimate signal vector  $\mathbf{x} \in \mathbb{R}^N$  from observation vector  $\mathbf{z} = [z_1, \dots, z_N]^T = \mathbf{x} + \boldsymbol{\zeta}$   
 -  $z_n \in \mathbb{R}$  denotes observation of node  $v_n \in \mathcal{V}$   
 -  $\boldsymbol{\zeta} \in \mathbb{R}^N$  stands for additive noise.

**Knowledge:**  $\mathbf{x}$  is known to lie in the subspace spanned by  $\mathbf{U}_{\parallel} \in \mathbb{R}^{N \times r}$ , where  $r < N$ ;  
 →  $\mathbf{x} = \mathbf{U}_{\parallel} \boldsymbol{\alpha}$  for some  $\boldsymbol{\alpha} \in \mathbb{R}^r$ .

**Problem:** find  $\hat{\mathbf{x}} \triangleq [\hat{x}_1, \dots, \hat{x}_N]^T = \mathbf{U}_{\parallel} \mathbf{U}_{\parallel}^T \mathbf{z} \triangleq \mathbf{Pz}$  given  $\mathbf{z}$  and  $\mathbf{U}_{\parallel}$  in a decentralized fashion.

## Motivation

Least squares estimation, denoising, weighted consensus, and distributed detection, can be cast as **subspace projection**.

Robustness, scalability, and energy consumption motivate **decentralized algorithms**.

Existing approaches:

- (i) Only converges asymptotically to desired result or
- (ii) Do not provide shift matrix and do not consider number of steps to converge.

## Proposed methodology

**Previous work:** have shown that a graph filter allows decentralized implementation.

**Problem reduced to:** find a graph filter  $\mathbf{H} := c_0 \mathbf{I} + \sum_{l=1}^{L-1} c_l \mathbf{S}^l$  such that  $\mathbf{Pz} = \mathbf{Hz}$ ,  $\forall \mathbf{z}$ .

**Our solution:** find shift matrix  $\mathbf{S}$  and filter coefficients  $c_l$  that ensure  $L$  nearly minimal.

**First step:** characterize set of feasible shift matrices

$$\mathcal{S} = \{ \mathbf{S} \in \mathbb{R}^{N \times N} : \mathbf{S} = \mathbf{S}^T, (\mathbf{S})_{n,n'} = 0 \text{ if } (v_n, v_{n'}) \notin \mathcal{E}, \\ \exists \mathbf{c} = [c_0, \dots, c_{N-1}]^T \text{ satisfying } \mathbf{U}_{\parallel} \mathbf{U}_{\parallel}^T = c_0 \mathbf{I} + \sum_{l=1}^{N-1} c_l \mathbf{S}^l \}$$

**Key point 1:** Matrices in  $\mathcal{S}$  can be expressed as  $\mathbf{S} = \mathbf{S}_{\parallel} + \mathbf{S}_{\perp}$

- $\mathbf{S}_{\perp}$  is a symmetric matrix satisfying  $\mathbf{S}_{\perp}^T \mathbf{U}_{\parallel} = \mathbf{0}$
- $\mathbf{S}_{\parallel} = \mathbf{U}_{\parallel} \mathbf{F} \mathbf{U}_{\parallel}^T$  for some symmetric  $\mathbf{F} \in \mathbb{R}^{r \times r}$ .

**Second step:** Ensure  $L$  is nearly minimal

- Requirement: Given a minimal  $L$ , filter  $\mathbf{Hz} = \mathbf{Pz} \forall \mathbf{z}$  must exist.
- Initial result: Minimal  $L$  equals the number of different eigenvalues of  $\mathbf{F}$  plus  $\mathbf{S}_{\perp}$ .
- Difficulty: finding  $\mathbf{F}$  and  $\mathbf{S}_{\perp}$  minimizing number of different eigenvalues is non-convex.

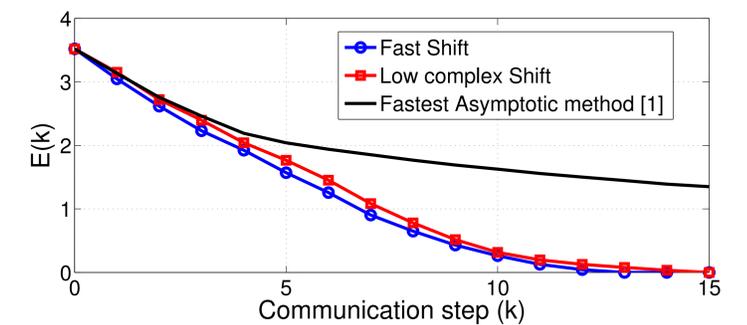
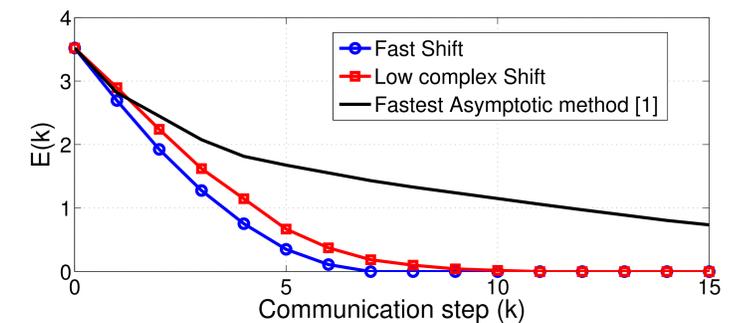
**Key point 2:** convex surrogate for objective. Similar to  $\ell_1$ -norm replacing zero norm.

**Solution:** convex problem:

$$\begin{aligned} & \underset{\mathbf{F}, \mathbf{S}, \mathbf{S}_{\parallel}, \mathbf{S}_{\perp}}{\text{minimize}} && \|\mathbf{F} \otimes \mathbf{I} - \mathbf{I} \otimes \mathbf{F}\|_* + \|\mathbf{S}_{\perp} \otimes \mathbf{I} - \mathbf{I} \otimes \mathbf{S}_{\perp}\|_* \\ & \text{s. t.} && (\mathbf{S})_{n,n'} = 0 \text{ if } (v_n, v_{n'}) \notin \mathcal{E}, n, n' = 1, \dots, N \\ & && \mathbf{S} = \mathbf{S}_{\parallel} + \mathbf{S}_{\perp}, \quad \mathbf{S}_{\perp} = \mathbf{S}_{\perp}^T, \quad \mathbf{S}_{\parallel} = \mathbf{S}_{\parallel}^T, \quad \mathbf{S}_{\parallel} = \mathbf{U}_{\parallel} \mathbf{F} \mathbf{U}_{\parallel}^T, \quad \mathbf{S}_{\perp}^T \mathbf{U}_{\parallel} = \mathbf{0}, \\ & && \text{tr}(\mathbf{F}) = r, \quad \text{tr}(\mathbf{S}_{\perp}) \leq N - r - \epsilon \end{aligned}$$

$\epsilon > 0$  is small positive constant and last two constraints needed to avoid trivial solutions.

## Numerical Results



**Setting:** Monte Carlo simulation.

- Topology  $\mathcal{E}$  and matrix  $\mathbf{U}_{\parallel}$  random.
- $N = 25$ ,  $r = [5, 10]$ .

**What is compared:** error  $\|\mathbf{y} - \mathbf{Pz}\|_2$

- exact and approximate solutions vs
- fastest asymptotic method [1].

**Error definition:**

- For two objectives proposed

$$E(k) = \mathbb{E}_{\mathbf{A}, \mathbf{z}} \left\| \sum_{l=0}^k c_l^{(k)} \mathbf{S}^l \mathbf{z} - \mathbf{Pz} \right\|_2$$

- For approach in [1]

$$E(k) = \mathbb{E}_{\mathbf{A}, \mathbf{z}} \|\mathbf{W}^k \mathbf{z} - \mathbf{Pz}\|_2$$

**Conclusion:** Proposed shifts converge to desired projection in nearly minimal number of steps, outperforming [1].

[1] S. Barbarossa et al. Distributed signal subspace projection algorithms with maximum convergence rate for sensor networks with topological constraints. ICASSP 2009.

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