

Explicit Sensor Network Localization using Semidefinite Programming and Clique Reductions

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1 Sensor Network Localization (SNL)

- Introduction
- Euclidean Distance Matrices and Semidefinite Matrices

2 Clique Reductions of SNL

- Clique Reductions
- Completing the EDM

3 Algorithm

- Clique Unions and Node Absorptions
- Results

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Motivation

Many applications use **wireless sensor networks**:

- natural habitat monitoring, weather monitoring, disaster relief operations, ...

The Sensor Network Localization (SNL) Problem

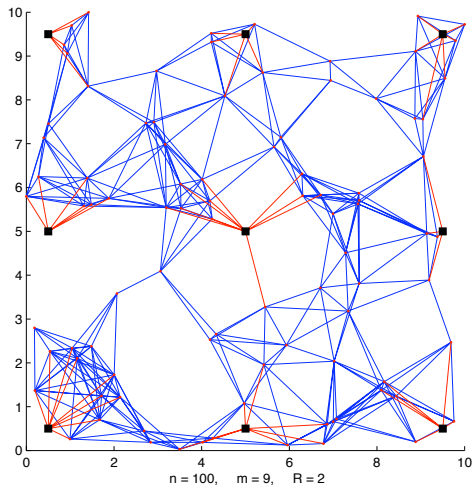
Given:

- Distances between sensors within a fixed radio range
- Positions of some fixed sensors (called **anchors**)

Goal:

- Determine locations of sensors

Introduction



Notation

- $p_1, \dots, p_{n-m} \in \mathbb{R}^r$ - unknown points (**sensors**)
- $a_1, \dots, a_m \in \mathbb{R}^r$ - known points (**anchors**)
 - anchors also labeled p_{n-m+1}, \dots, p_n

$$P = \begin{bmatrix} p_1^T \\ \vdots \\ p_n^T \end{bmatrix} = \begin{bmatrix} X \\ A \end{bmatrix} \in \mathbb{R}^{n \times r}$$

- r - embedding dimension (usually 2 or 3)
- **Assumptions:** $n \gg m > r$
- $R > 0$ - radio range

Graph Realization

- $G = (V, E, w)$ - underlying weighted graph
 - $V = \{1, \dots, n\}$
 - $(i, j) \in E$ if $w_{ij} = \|p_i - p_j\|$ is known
- Anchors form **clique**
- SNL problem \equiv find **realization** of graph in \mathbb{R}^r

Euclidean Distance Matrix (EDM) Completion

- $D_p \in \mathcal{S}^n$ - **partial** EDM:

$$(D_p)_{ij} = \begin{cases} \|p_i - p_j\|^2 & \text{if } (i, j) \in E \\ 0 & \text{otherwise} \end{cases}$$

- SNL problem \equiv find EDM **completion** with embed. dim. $= r$

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Linear Transformation \mathcal{K}

- If D is an EDM with embed. dim. r given by $P \in \mathbb{R}^{n \times r}$, then:

$$\begin{aligned} D_{ij} = \|p_i - p_j\|^2 &= p_i^T p_i + p_j^T p_j - 2p_i^T p_j \\ &= \left(\text{diag}(PP^T)e^T + e \text{diag}(PP^T)^T - 2PP^T \right)_{ij} \\ &= \mathcal{K}(PP^T)_{ij} \end{aligned}$$

- Thus $D = \mathcal{K}(Y)$, where:

$$\boxed{\mathcal{K}(Y) := \text{diag}(Y)e^T + e \text{diag}(Y)^T - 2Y} \quad \text{and} \quad Y := PP^T$$

- $Y = PP^T$ is positive semidefinite ($Y \in \mathcal{S}_+^n$ or $Y \succeq 0$), $\text{rank}(Y) = r$
- \mathcal{K} maps the semidefinite cone, \mathcal{S}_+^n , onto the EDM cone, \mathcal{E}^n

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EDMs and Semidefinite Matrices

Properties of \mathcal{K}

- Define the **centered** and **hollow** subspaces

$$\mathcal{S}_C := \{Y \in \mathcal{S}^n : Ye = 0\}$$

and

$$\mathcal{S}_H := \{D \in \mathcal{S}^n : \text{diag}(D) = 0\}$$

- $\mathcal{K}(Y) = \text{diag}(Y)e^T + e\text{diag}(Y)^T - 2Y \implies \text{range}(\mathcal{K}) = \mathcal{S}_H$
- For $D \in \mathcal{S}_H$ we have $\mathcal{K}^\dagger(D) = -\frac{1}{2}JDJ$ where $J := I - \frac{1}{n}ee^T$ is the orthogonal projection onto $\{e\}^\perp$
- \mathcal{K} and \mathcal{K}^\dagger are one-to-one and onto:

$$\mathcal{K}^\dagger(\mathcal{S}_H) = \mathcal{S}_C$$

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EDMs and Semidefinite Matrices

Vector Formulation

Find $p_1, \dots, p_n \in \mathbb{R}^r$ such that $\left\{ \begin{array}{l} \|p_i - p_j\|^2 = (D_p)_{ij}, \quad \forall (i, j) \in \mathcal{E} \\ \|p_i - p_j\|^2 \geq R^2, \quad \forall (i, j) \notin \mathcal{E} \end{array} \right\}$

Matrix Formulation

Find $P \in \mathbb{R}^{n \times r}$ such that $\left\{ \begin{array}{l} W \circ \mathcal{K}(Y) = D_p \\ H \circ \mathcal{K}(Y) \geq R^2 \end{array} \right\}$, where $Y = PP^T$

Semidefinite Programming (SDP) Relaxation

Find $Y \in \mathcal{S}_+^n \cap \mathcal{S}_C$ such that $\left\{ \begin{array}{l} W \circ \mathcal{K}(Y) = D_p \\ H \circ \mathcal{K}(Y) \geq R^2 \end{array} \right\}$

- Vector/Matrix Formulation is non-convex and NP-HARD
- SDP Relaxation is convex, but degenerate (strict feasibility fails)

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Faces of the Semidefinite Cone

- A cone $\mathcal{F} \subseteq S_+^n$ is a **face of S_+^n** (denoted $\mathcal{F} \trianglelefteq S_+^n$) if

$$X, Y \in S_+^n \quad \text{and} \quad \frac{1}{2}(X + Y) \in \mathcal{F} \quad \implies \quad X, Y \in \mathcal{F}$$

- If $S \subseteq S_+^n$, then **face(S)** is the smallest face of S_+^n containing S

Representing Faces of S_+^n

If $\mathcal{F} \trianglelefteq S_+^n$ and $X \in \text{relint}(\mathcal{F})$ with $\text{rank}(X) = t$, then

$$\mathcal{F} = US_+^t U^T$$

where $X = U\Lambda U^T$ is the compact eigenvalue decomp. with $U \in \mathbb{R}^{n \times t}$

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Clique Reductions

Theorem: Single Clique Reduction

Let:

- D_p be a partial EDM such that

$$D_p = \left[\begin{array}{c|c} \bar{D} & \cdot \\ \hline \cdot & \cdot \end{array} \right], \quad \text{for some } \bar{D} \in \mathcal{E}^k \text{ with embed. dim. } t \leq r$$

- $F := \{Y \in \mathcal{S}_+^n \cap \mathcal{S}_C : \mathcal{K}(Y[1:k]) = \bar{D}\}$ (contains SDP feas. set)
- $B := \mathcal{K}^\dagger(\bar{D})$ has eigenvectors $\bar{U} \in \mathbb{R}^{k \times t}$ (Note: $\text{rank}(B) = t$)
- $U := \left[\begin{array}{c|c} \bar{U} & \frac{1}{\sqrt{k}}e \\ \hline 0 & 0 \end{array} \middle| \begin{array}{c} 0 \\ I_{n-k} \end{array} \right]$ and $\left[V \quad \frac{U^T e}{\|U^T e\|} \right]$ be orthogonal

Then: $\text{face}(F) = \left(U \mathcal{S}_+^{n-k+t+1} U^T \right) \cap \mathcal{S}_C = (UV) \mathcal{S}_+^{n-k+t} (UV)^T$

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Clique Reductions

Corollary: Two Clique Reduction

Let $D \in \mathcal{E}^n$ with embed. dim. r . Let $\alpha_1, \alpha_2 \subseteq 1:n$ and $k := |\alpha_1 \cup \alpha_2|$. For $i = 1, 2$ let:

- $t_i :=$ embed. dim. of $D[\alpha_i] \in \mathcal{E}^{k_i}$
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- $U \in \mathbb{R}^{n \times t}$ full column rank s.t. $\text{col}(U) = \text{col}(U_1) \cap \text{col}(U_2)$
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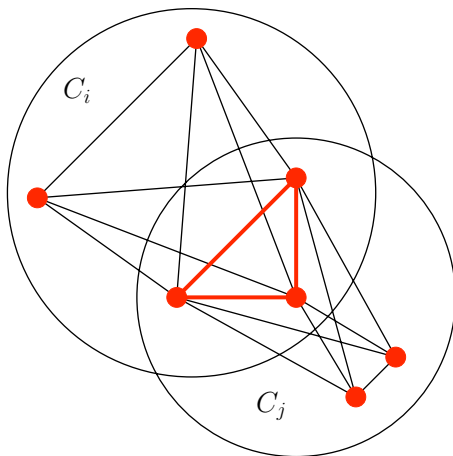
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Subspace Intersection for Two Intersecting Cliques

Suppose:

$$U_1 = \begin{bmatrix} U'_1 & 0 \\ U''_1 & 0 \\ 0 & I \end{bmatrix} \quad \text{and} \quad U_2 = \begin{bmatrix} I & 0 \\ 0 & U''_2 \\ 0 & U'_2 \end{bmatrix}$$

Then:

$$U := \begin{bmatrix} U'_1 \\ U''_1 \\ U'_2 (U''_2)^\dagger U''_1 \end{bmatrix} \quad \text{or} \quad U := \begin{bmatrix} U'_1 (U''_1)^\dagger U''_2 \\ U''_2 \\ U'_2 \end{bmatrix}$$

Satisfies:

$$\text{col}(U) = \text{col}(U_1) \cap \text{col}(U_2)$$

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 - Clique Reductions
 - **Completing the EDM**
- 3 Algorithm
 - Clique Unions and Node Absorptions
 - Results

Completing the EDM

Completing the EDM and Finding Positions

Let:

- $D \in \mathcal{E}^n$ with embed. dim. r
- $D_p := W \circ D$ be a **partial** EDM (for some 0–1 matrix W)
- $F := \{Y \in \mathcal{S}_+^n \cap \mathcal{S}_C : W \circ \mathcal{K}(Y) = D_p\}$
- $\text{face}(F) =: (UV)S_+^r(UV)^T$

If $D_p[\beta]$ is complete with embed. dim. r then:

- $(JU[\beta, :]V)Z(JU[\beta, :]V)^T = \mathcal{K}^\dagger(D_p[\beta])$ has a unique solution Z
- $D = \mathcal{K}(PP^T)$ where $P := UVZ^{\frac{1}{2}} \in \mathbb{R}^{n \times r}$

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Completing the EDM

Rotate to Align the Anchor Positions

- Given $P = \begin{bmatrix} P_1 \\ P_2 \end{bmatrix} \in \mathbb{R}^{n \times r}$ such that $D = \mathcal{K}(PP^T)$
- Solve the orthogonal Procrustes problem:

$$\begin{array}{ll} \min & \|A - P_2 Q\| \\ \text{s.t.} & Q^T Q = I \end{array}$$

using SVD (Golub/Van Loan, Algorithm 12.4.1)

- Set $X := P_1 Q$

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Algorithm

Initialize

$$C_i := \left\{ j : (D_p)_{ij} < (R/2)^2 \right\}, \quad \text{for } i = 1, \dots, n$$

Iterate

- For $|C_i \cap C_j| \geq r + 1$, do **Rigid Clique Union**
- For $|C_i \cap \mathcal{N}(j)| \geq r + 1$, do **Rigid Node Absorption**
- For $|C_i \cap C_j| = r$, do **Non-Rigid Clique Union** (lower bounds)
- For $|C_i \cap \mathcal{N}(j)| = r$, do **Non-Rigid Node Absorption** (lower bounds)

Finalize

When there is a clique containing all the **anchors**, use the computed **facial representation** and the **positions of the anchors** to solve for X

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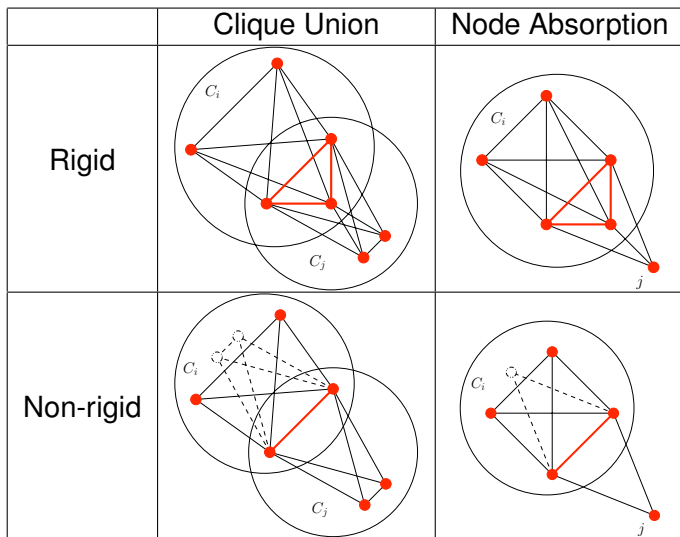
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Results

Rigid Clique Union

n / R	0.7	0.6	0.5	0.4
2000	1	7	91	362
4000	1	1	1	16
6000	1	1	1	1
8000	1	1	1	1
10000	1	1	1	1

Remaining Cliques

n / R	0.7	0.6	0.5	0.4
2000	4.8	4.6	4.2	4.1
4000	9.2	9.4	9.1	9.2
6000	16.0	14.7	15.3	14.9
8000	22.9	22.5	20.9	21.0
10000	38.3	32.7	29.1	30.7

CPU Seconds

n / R	0.7	0.6	0.5	0.4
2000	-10.1	-10.8	-	-
4000	-10.9	-11.0	-10.5	-9.6
6000	-11.6	-10.7	-10.6	-10.0
8000	-11.1	-11.0	-10.7	-9.2
10000	-11.0	-11.0	-10.2	-10.4

Max log(Error)

Rigid Clique Union and Node Absorption

n / R	0.7	0.6	0.5	0.4
2000	1	1	2	78
4000	1	1	1	1
6000	1	1	1	1
8000	1	1	1	1
10000	1	1	1	1

Remaining Cliques

n / R	0.7	0.6	0.5	0.4
2000	4.9	4.9	6.1	13.2
4000	9.2	9.5	9.1	9.8
6000	16.1	15.1	15.1	14.8
8000	22.7	22.4	21.0	21.3
10000	32.5	32.4	28.8	30.6

CPU Seconds

n / R	0.7	0.6	0.5	0.4
2000	-10.1	-10.8	-9.8	-8.8
4000	-10.9	-11.0	-10.5	-9.6
6000	-11.6	-10.7	-10.6	-10.0
8000	-11.1	-11.0	-10.7	-9.2
10000	-11.0	-11.0	-10.2	-10.4

Max log(Error)

- SDP relaxation of SNL is highly degenerate: The feasible set of this SDP is restricted to a low dimensional face of the SDP cone, causing the Slater constraint qualification (strict feasibility) to fail
- We take advantage of this degeneracy by finding explicit representations of the faces of the SDP cone corresponding to unions of intersecting cliques
- Without using an SDP-solver (eg. SeDuMi or SDPT3), we quickly compute the exact solution to the SDP relaxation (except for round-off error from computing eigenvectors, etc.)

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