

Enclosing Ellipsoids and Elliptic Cylinders of Semialgebraic Sets and Their Application to Error Bounds in Polynomial Optimization

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Dedicated to Professor Yoshitsugu Yamamoto
on the occasion of his 60th birthday

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Outline

- 1 Problem and Formulation
- 2 Applications to the Sensor Network Localization Problem with Exact Distance
- 3 Concluding Remarks

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- 1 **Problem and Formulation**
- 2 Applications to the Sensor Network Localization Problem with Exact Distance
- 3 Concluding Remarks

$M \in \mathbb{S}_+^n$ ($n \times n$ positive semidefinite matrices, **shape**). Define
 $\varphi(\mathbf{x}, \mathbf{c}) \equiv (\mathbf{x} - \mathbf{c})^T M (\mathbf{x} - \mathbf{c}), \forall \mathbf{x} \in \mathbb{R}^n, \forall \mathbf{c} \in \mathbb{R}^n$ (**center**),
 Ellipsoidal set $E(\mathbf{c}, \gamma) \equiv \{\mathbf{x} \in \mathbb{R}^n : \varphi(\mathbf{x}, \mathbf{c}) \leq \gamma\}, \forall \gamma > 0$ (**size**).

Problem: Given a semialgebraic set F , find a minimum (in γ) ellipsoidal set $E(\mathbf{c}, \gamma)$ which encloses F .

Application to error bounds in Polynomial Optimization Problem

POP : minimize $f_0(\mathbf{x})$ subject to $f_k(\mathbf{x}) \geq 0$ ($k = 1, 2, \dots, p$).
 Here $f_k : \mathbb{R}^n \rightarrow \mathbb{R}$: a polynomial ($k = 0, 1, \dots, p$).

$\hat{\mathbf{x}}$: an approx. opt. solution; $f_k(\hat{\mathbf{x}}) \geq 0$ ($k = 1, 2, \dots, p$). Let

$$F = \{\mathbf{x} \in \mathbb{R}^n : f_k(\mathbf{x}) \geq 0, (k = 1, 2, \dots, p), f_0(\mathbf{x}) \leq f_0(\hat{\mathbf{x}})\}.$$

$F \subset E(\mathbf{c}, \gamma) \implies E(\mathbf{c}, \gamma)$ contains $\hat{\mathbf{x}}$, all opt. sol. of POP.

$$M = I \implies \|\mathbf{x} - \mathbf{c}\|^2 \leq \gamma \text{ for } \forall \text{ opt. sol. } \mathbf{x}$$

$$M = \text{diag}(1, 0, \dots, 0) \implies |x_1 - c_1|^2 \leq \gamma \text{ for } \forall \text{ opt. sol. } \mathbf{x}$$

- Implemented in the Matlab software SparsePOP (Waki et.al) for solving POPs by **the sparse SDP relaxation**.

$M \in \mathbb{S}_+^n$ ($n \times n$ positive semidefinite matrices, **shape**). Define

$$\varphi(\mathbf{x}, \mathbf{c}) \equiv (\mathbf{x} - \mathbf{c})^T M (\mathbf{x} - \mathbf{c}), \forall \mathbf{x} \in \mathbb{R}^n, \forall \mathbf{c} \in \mathbb{R}^n \text{ (center),}$$

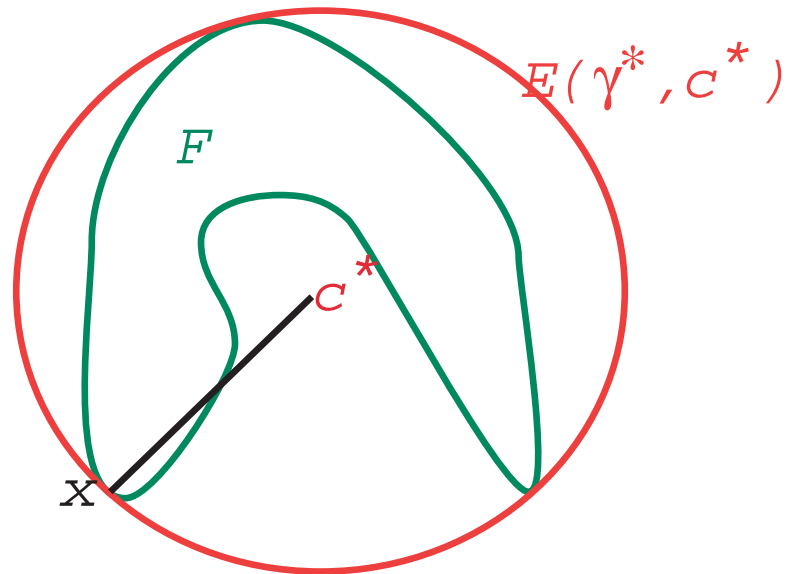
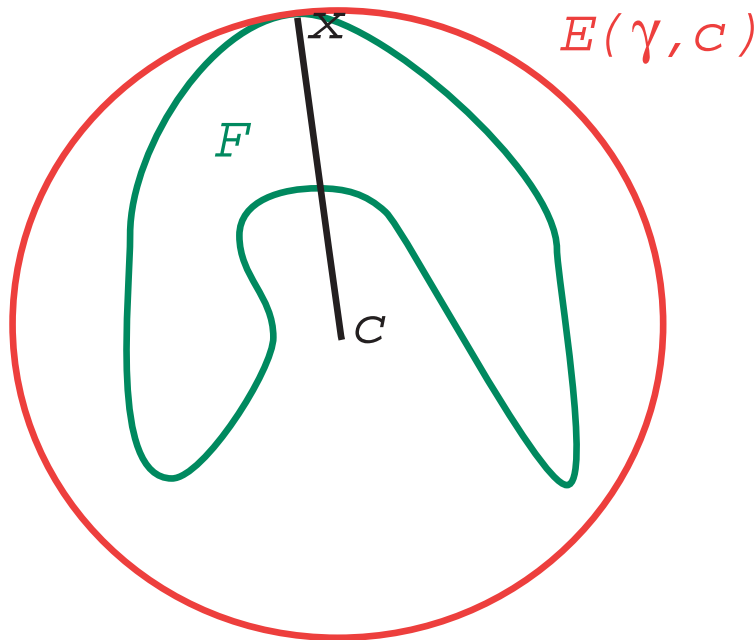
Ellipsoidal set $E(\mathbf{c}, \gamma) \equiv \{\mathbf{x} \in \mathbb{R}^n : \varphi(\mathbf{x}, \mathbf{c}) \leq \gamma\}$, $\forall \gamma > 0$ (**size**).

F : a semialgebraic subset of \mathbb{R}^n .

min-max
formulation

$$\gamma^* = \min_{\mathbf{c} \in \mathbb{R}^n} \max_{\mathbf{x} \in F} \varphi(\mathbf{x}, \mathbf{c}) = \max_{\mathbf{x} \in F} \varphi(\mathbf{x}, \mathbf{c}^*).$$

Suppose that M = the 2×2 identity matrix



$M \in \mathbb{S}_+^n$ ($n \times n$ positive semidefinite matrices, **shape**). Define

$$\varphi(\mathbf{x}, \mathbf{c}) \equiv (\mathbf{x} - \mathbf{c})^T M (\mathbf{x} - \mathbf{c}), \forall \mathbf{x} \in \mathbb{R}^n, \forall \mathbf{c} \in \mathbb{R}^n \text{ (center),}$$

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Lifting

\Rightarrow

$\hat{C} \equiv$ the convex hull of $\{(\mathbf{x}, \mathbf{W}) = (\mathbf{x}, \mathbf{x}\mathbf{x}^T) \in \mathbb{R}^n \times \mathbb{S}^n : \mathbf{x} \in F\}$.

\Updownarrow "min-max = max min" in the lifting space

concave maximization

$$\gamma^* = \max_{(\mathbf{x}, \mathbf{W}) \in \hat{C}} M \bullet \mathbf{W} - \mathbf{x}^T M \mathbf{x}.$$

$M \bullet \mathbf{W}$: the inner product of M and \mathbf{W} , i.e. $\sum_{i,j} M_{ij} W_{ij}$.

Relax the intractable \hat{C} by a tractable convex C ;

$$\Downarrow \quad \hat{C} \subset C \subset \left\{ (\mathbf{x}, \mathbf{W}) \in \mathbb{R}^n \times \mathbb{S}^n : \begin{pmatrix} 1 & \mathbf{x}^T \\ \mathbf{x} & \mathbf{W} \end{pmatrix} \succeq \mathbf{O} \right\}.$$

SDP-SOCP

$$\hat{\gamma} = \max_{(\mathbf{x}, \mathbf{W}) \in C} M \bullet \mathbf{W} - \mathbf{x}^T M \mathbf{x} \quad \Rightarrow \quad \gamma^* \leq \hat{\gamma}.$$

$M \in \mathbb{S}_+^n$ ($n \times n$ positive semidefinite matrices, **shape**). Define

$$\varphi(\mathbf{x}, \mathbf{c}) \equiv (\mathbf{x} - \mathbf{c})^T M (\mathbf{x} - \mathbf{c}), \forall \mathbf{x} \in \mathbb{R}^n, \forall \mathbf{c} \in \mathbb{R}^n \text{ (center),}$$

Ellipsoidal set $E(\mathbf{c}, \gamma) \equiv \{\mathbf{x} \in \mathbb{R}^n : \varphi(\mathbf{x}, \mathbf{c}) \leq \gamma\}, \forall \gamma > 0$ (**size**).

F described by quadratic inequalities

$$F = \left\{ \mathbf{x} \in \mathbb{R}^n : \alpha_k + 2\mathbf{b}_k^T \mathbf{x} + \mathbf{x}^T \mathbf{Q}_k \mathbf{x} \geq 0 \ (1 \leq k \leq p) \right\}$$

$$= \left\{ \mathbf{x} \in \mathbb{R}^n : \begin{pmatrix} \alpha_k & \mathbf{b}_k^T \\ \mathbf{b}_k & \mathbf{Q}_k \end{pmatrix} \bullet \begin{pmatrix} 1 & \mathbf{x}^T \\ \mathbf{x} & \mathbf{x}\mathbf{x}^T \end{pmatrix} \geq 0 \ (1 \leq k \leq p) \right\},$$

$$\hat{C} = \text{convex hull of } \{(\mathbf{x}, \mathbf{x}\mathbf{x}^T) : \mathbf{x} \in F\} \subset C, \text{ where}$$

$$C = \left\{ (\mathbf{x}, \mathbf{W}) : \begin{pmatrix} \alpha_k & \mathbf{b}_k^T \\ \mathbf{b}_k & \mathbf{Q}_k \end{pmatrix} \bullet \begin{pmatrix} 1 & \mathbf{x}^T \\ \mathbf{x} & \mathbf{W} \end{pmatrix} \geq 0 \ (1 \leq k \leq p), \right. \\ \left. \begin{pmatrix} 1 & \mathbf{x}^T \\ \mathbf{x} & \mathbf{W} \end{pmatrix} \succeq \mathbf{O} \right\},$$

**SDP-
SOCP**

$$\hat{\gamma} = \max_{(\mathbf{x}, \mathbf{W}) \in C} M \bullet \mathbf{W} - \mathbf{x}^T M \mathbf{x} = M \bullet \widehat{\mathbf{W}} - \hat{\mathbf{c}}^T M \hat{\mathbf{c}}$$

$\implies F \subset E(\hat{\mathbf{c}}, \hat{\gamma})$. Replace ≥ 0 by $= 0 \implies$ Next applications!

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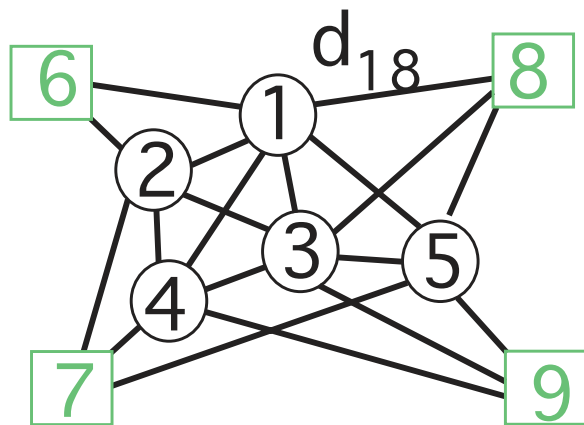
A Sensor Network Localization Problem with Exact Distance

- $\mathbf{x}^p \in \mathbb{R}^s$: unknown location of sensors ($p = 1, 2, \dots, m$),
 $\mathbf{x}^r = \mathbf{a}^r \in \mathbb{R}^s$: known location of anchors ($r = m + 1, \dots, n$),
 $d_{pq}^2 = \|\mathbf{x}^p - \mathbf{x}^q\|^2$ — given for $(p, q) \in \mathcal{N}$ (1)
 $\mathcal{N} = \{(p, q) : \|\mathbf{x}^p - \mathbf{x}^q\| \leq \rho = \text{a given radio range}\}$

$m = 5, n = 9$.

1, ..., 5: sensors

6, 7, 8, 9: anchors



Anchors' positions are known.

A distance is given for \forall edge.

Compute locations of sensors.

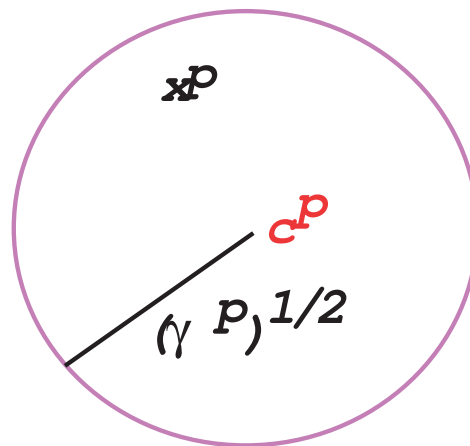
\Rightarrow Nonconvex QOPs

- SDP relaxation — FSDP by Biswas-Ye '06.
- **SFSDP** by Kim, Kojima, Waki '09 = a sparse version of FSDP .
- ...

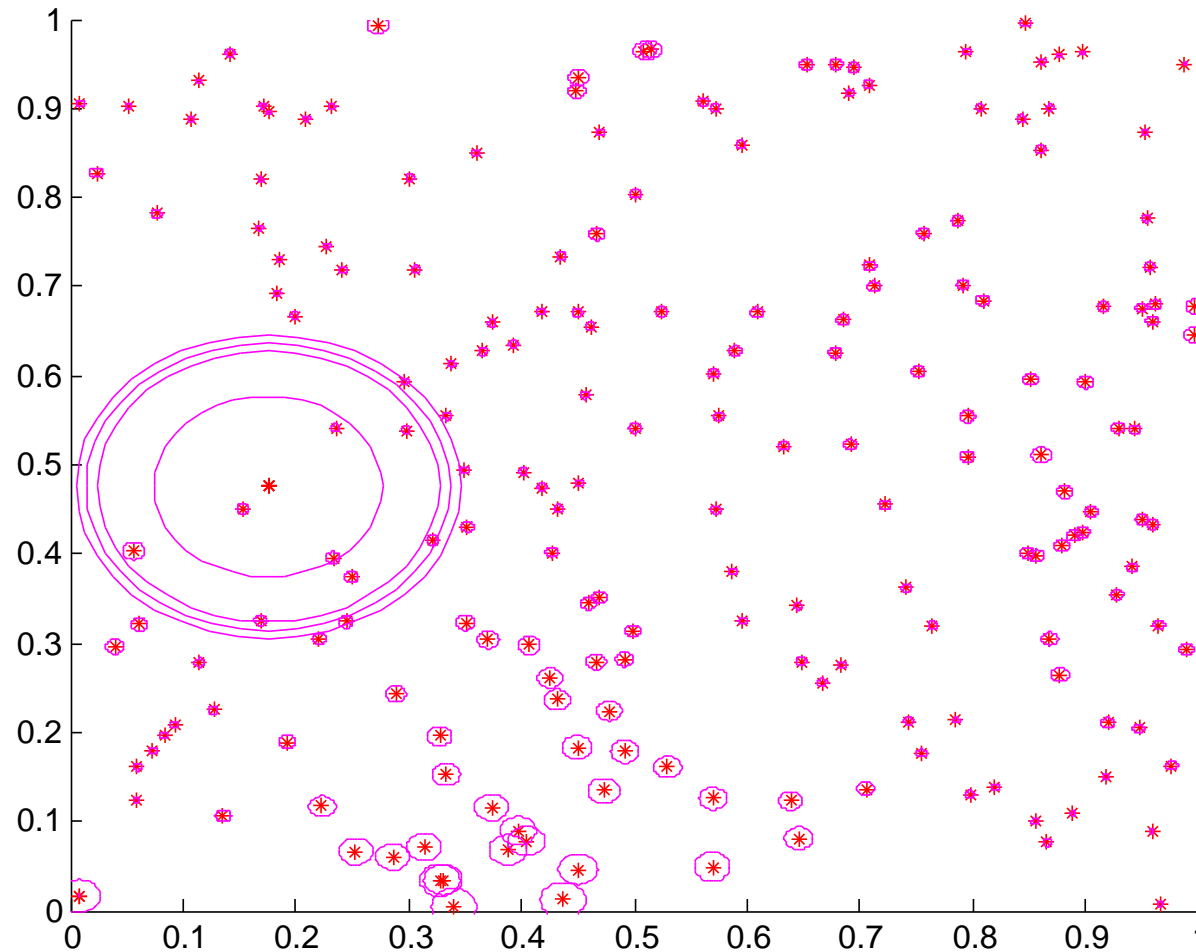
A Sensor Network Localization Problem with Exact Distance

$$\begin{aligned} \mathbf{x}^p \in \mathbb{R}^s & : \text{ unknown location of sensors } (p = 1, 2, \dots, m), \\ \mathbf{x}^r = \mathbf{a}^r \in \mathbb{R}^s & : \text{ known location of anchors } (r = m + 1, \dots, n), \\ d_{pq}^2 & = \|\mathbf{x}^p - \mathbf{x}^q\|^2 \text{ — given for } (p, q) \in \mathcal{N} \quad (1) \\ \mathcal{N} & = \{(p, q) : \|\mathbf{x}^p - \mathbf{x}^q\| \leq \rho = \text{a given radio range}\} \end{aligned}$$

- When ρ is not large enough or \mathcal{N} does not contain enough number of pairs of p and q , **the system of quadratic equations (1)** is underdetermined and/or **its SDP relaxation** is too weak to locate all sensors uniquely.
- Our method computes $\mathbf{c}^p \in \mathbb{R}^s$ and $\gamma^p > 0$ for each sensor p such that the distance from \mathbf{c}^p to its unknown location \mathbf{x}^p is bounded by $(\gamma^p)^{1/2}$.



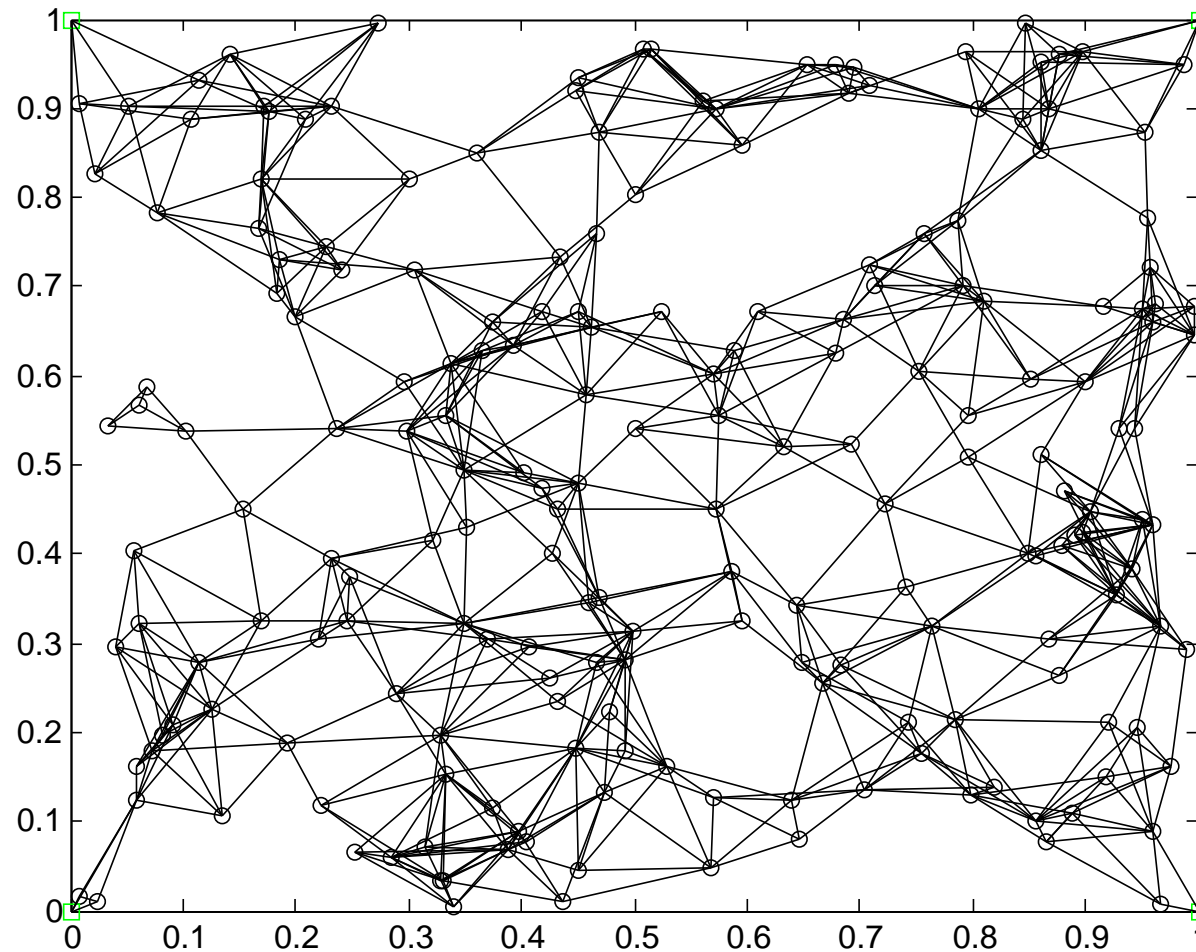
$m = 200$ sensors randomly distributed in $[0, 1]^2$, $n - m = 4$ anchors at the corner of $[0, 1]^2$, $\rho = 0.14$.



* : c^p = a computed location of sensor p .

the true location of sensor p is within $(\gamma^p)^{1/2} \leq 0.18$ from c^p

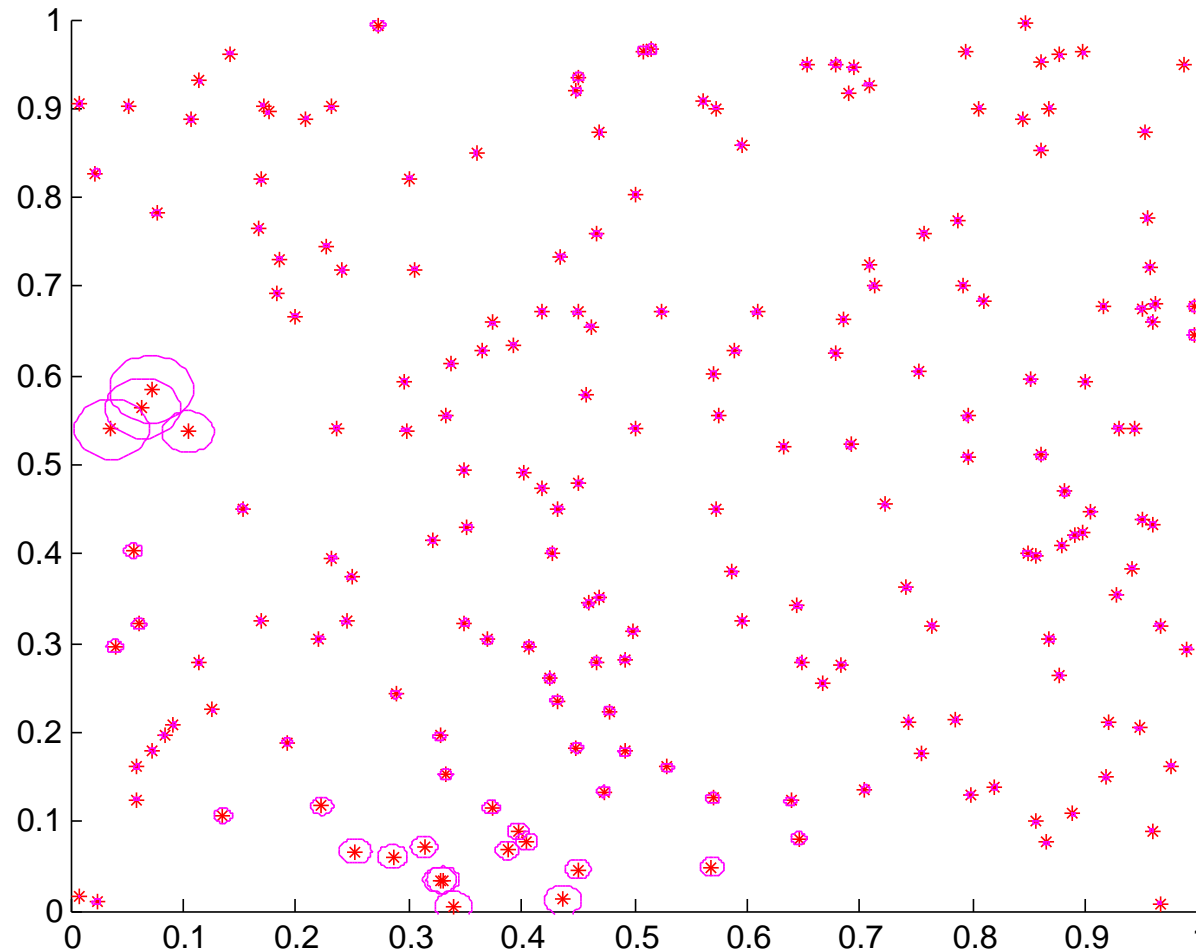
$m = 200$ sensors randomly distributed in $[0, 1]^2$, $n - m = 4$ anchors at the corner of $[0, 1]^2$, $\rho = 0.14$.



the true location \circ of sensor p

\circ — \circ : the edge (x^p, x^q) with a given exact distance

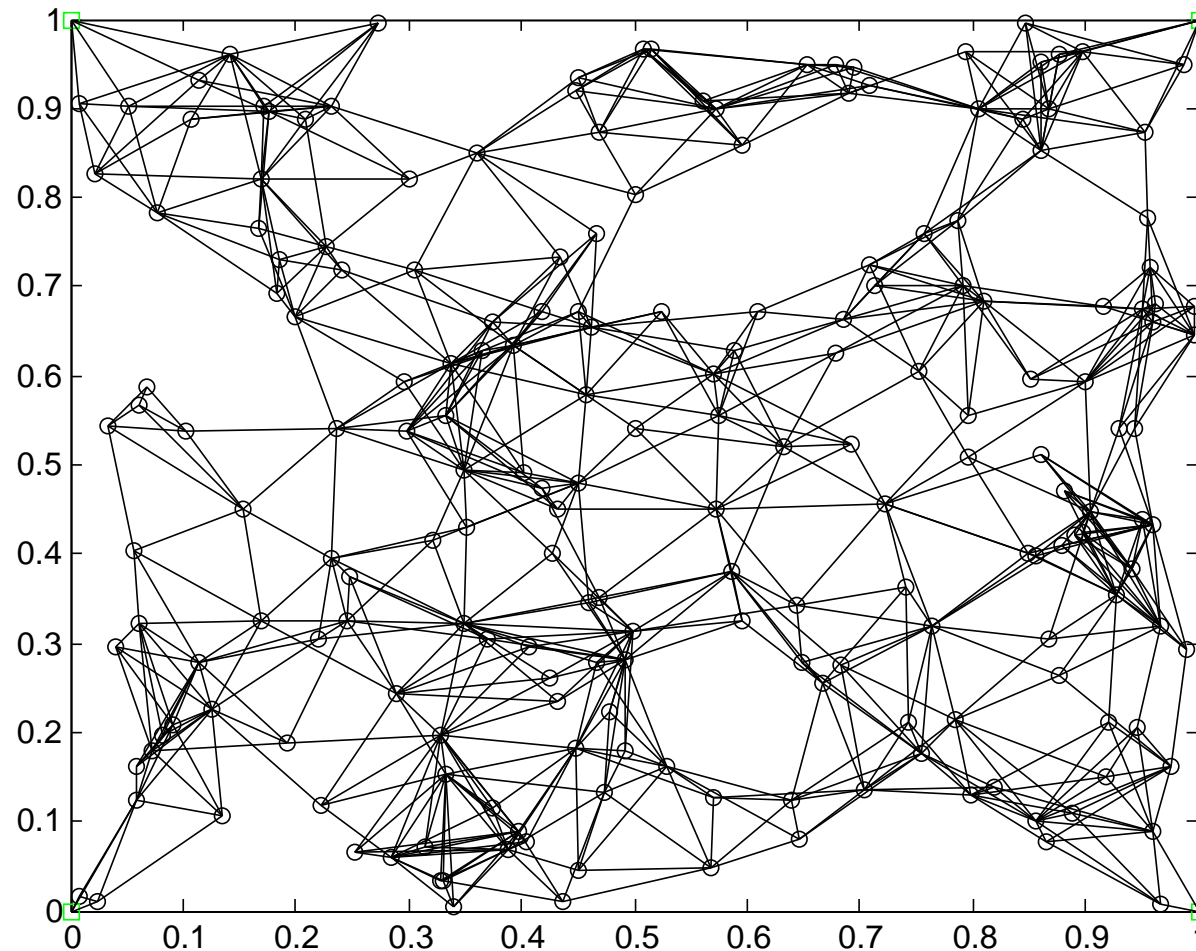
$m = 200$ sensors randomly distributed in $[0, 1]^2$, $n - m = 4$ anchors at the corner of $[0, 1]^2$, $\rho = 0.15$.



* : c^p = a computed location of sensor p .

the true location of sensor p is within $(\gamma^p)^{1/2} \leq 0.04$ from c^p

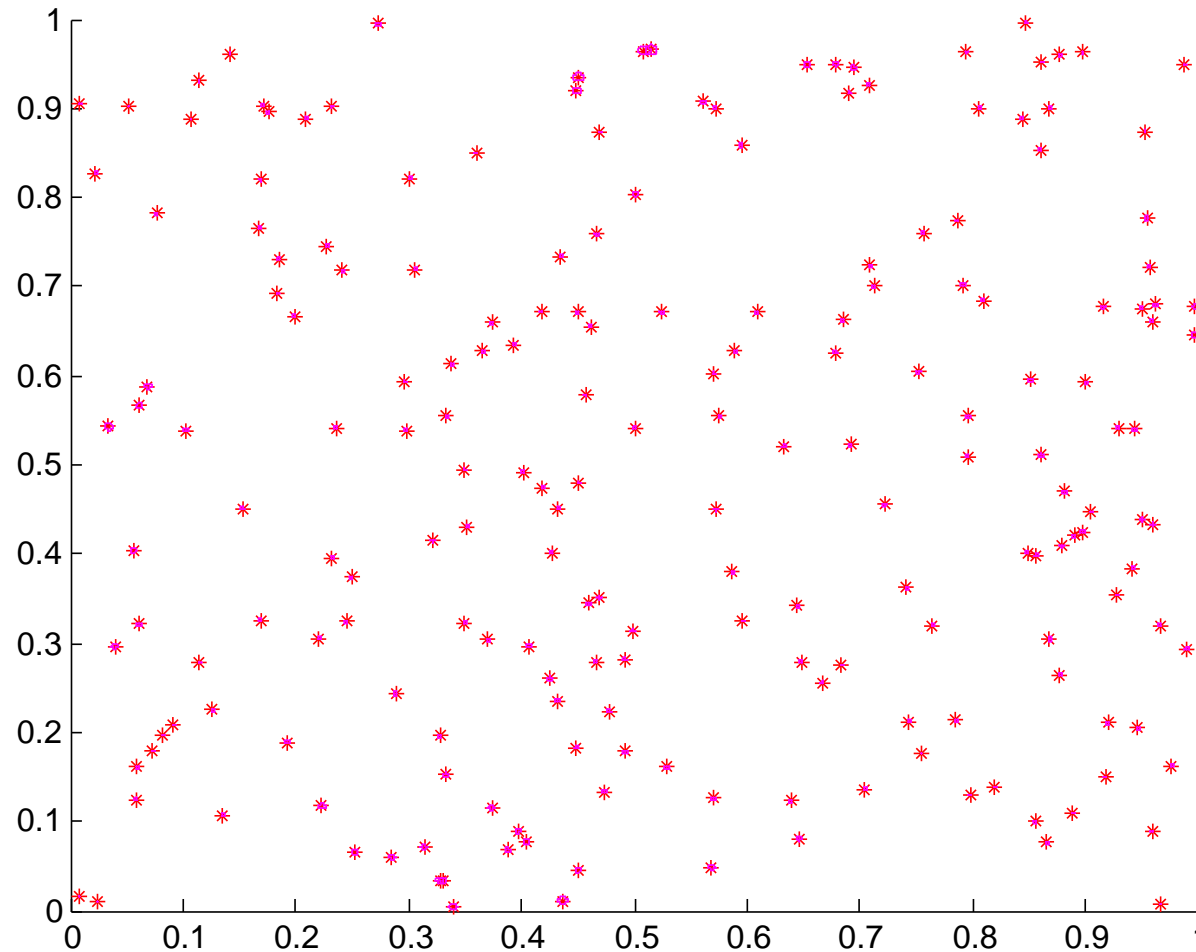
$m = 200$ sensors randomly distributed in $[0, 1]^2$, $n - m = 4$ anchors at the corner of $[0, 1]^2$, $\rho = 0.15$.



the true location \circ of sensor p

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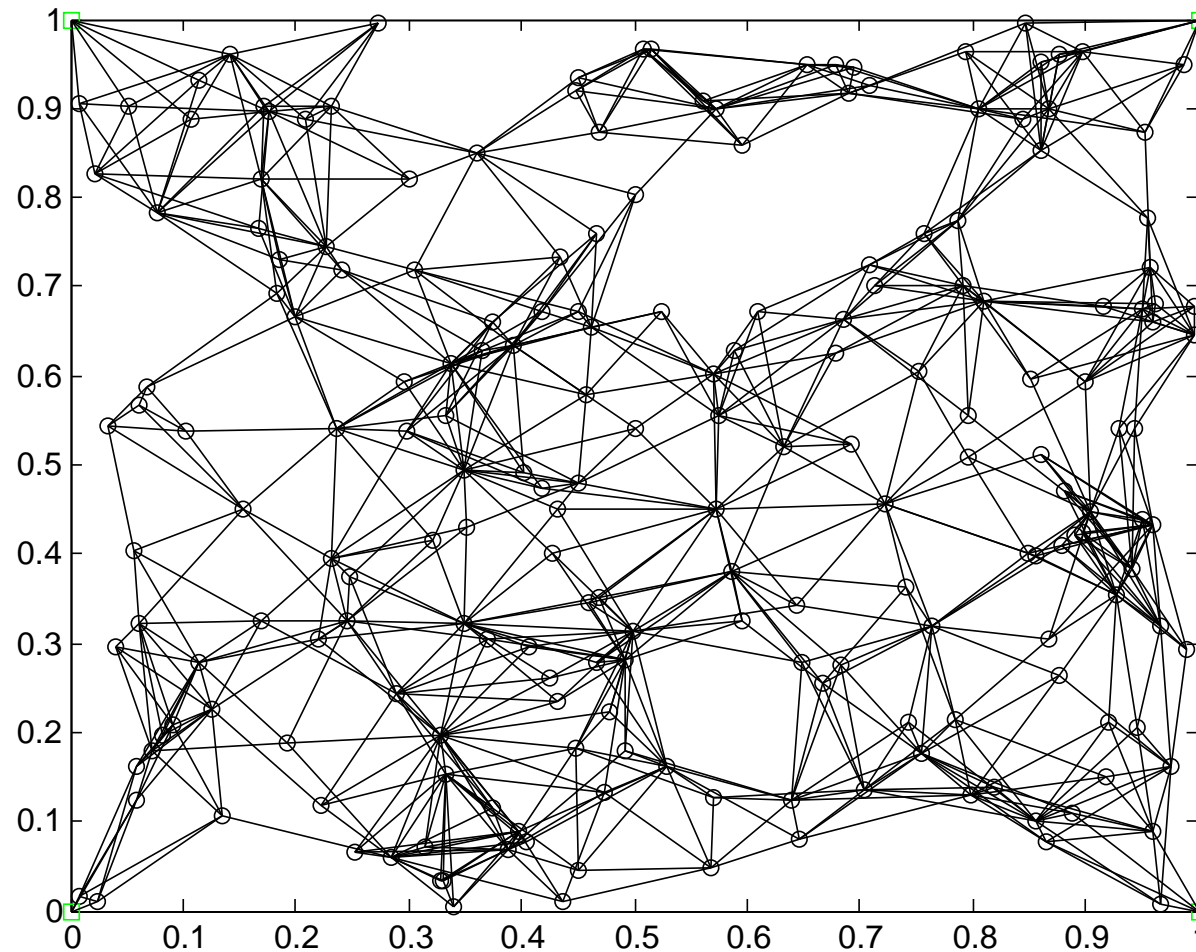
$m = 200$ sensors randomly distributed in $[0, 1]^2$, $n - m = 4$ anchors at the corner of $[0, 1]^2$, $\rho = 0.16$.



* : c^p = a computed location of sensor p .

the true location of sensor p is within $(\gamma^p)^{1/2} \leq 6.0e-3$ from c^p

$m = 200$ sensors randomly distributed in $[0, 1]^2$, $n - m = 4$ anchors at the corner of $[0, 1]^2$, $\rho = 0.16$.



the true location \circ of sensor p

\circ — \circ : the edge (x^p, x^q) with a given exact distance

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Concluding Remarks

We can apply the proposed method to:

- Sensor network localization problems with **inexact distance involving measurement error** (but the results are not sharp).
- Polynomial optimization problems involving a 0-1 variable x to determine whether $x = 0$ or $x = 1$.
- Polynomial optimization problems involving a pair of variables $x \geq 0, y \geq 0$ with complementarity $xy = 0$ to determine whether $x > 0$ or $y > 0$.