Multi-dimensional state estimation in adversarial environment

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- Sensor networks are becoming ubiquitous
- Sensors are usually cheap, distributed in space and physically exposed, which makes it difficult to ensure security for every single sensor
- Our goal: to design the optimal state estimator in the presence of compromised sensory data

- We assume that $x \in \mathbb{R}^n$ is the state
- *m* sensors are deployed to monitor the system. Denote $y_i \in \mathbb{R}$ as the measurement generated by sensor *i*.
- Denote $y = \begin{bmatrix} y_1 & \dots & y_m \end{bmatrix}^T$ as the collection of all sensory data.
- We assume the following sensor model

$$y=Hx+Gw+a,$$

where $||w|| \le \delta$ represents measurement noise and $||a||_0 \le l$ is the bias injected by the adversary.

- An estimator f is a mapping from sensory data y to a state estimate $\hat{x} = f(y)$.
- The estimation error can be defined as $e \triangleq x f(y)$.
- Clearly the estimation error is a function of x, w, a and our choice of estimator f.
- In this presentation, we will consider the worst-case error defined as

$$e^*(f) = \sup_{x,w,a} \|e\|$$

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- Assume that $S \subset \mathbb{R}^n$ is bounded.
- We say that a ball B(x,r) covers S if $S \subset B(x,r)$.
- For any point $x \in \mathbb{R}^n$, denote $\rho(x, S)$ as the radius of the minimum ball that centers at x and covers S.
- Define the Chebyshev center and the radius of S as

$$r(S) \triangleq \inf_{x \in \mathbb{R}^n} \rho(x, S), \ c(S) \triangleq \operatorname*{arg\,min}_{x \in \mathbb{R}^n} \rho(x, S).$$

• We further define the diameter of S as $d(S) \triangleq \sup_{x,x' \in S} \|x - x'\|$.



- A circle with radius 1.
- The radius r(S) is 1 and diameter d(S) is 2.
- Notice that the Chebyshev center may not in the set S.



- A equilateral triangle with side length 1
- The radius r(S) is $1/\sqrt{3}$ and diameter d(S) is 1.
- For general set S in \mathbb{R}^n , $r(S) \neq d(S)/2$.
- However, we can prove the following inequalities (Jung's Theorem):

$$\frac{d(S)}{2} \leq r(S) \leq \sqrt{\frac{n}{2n+2}}d(S) \leq \frac{1}{\sqrt{2}}d(S).$$

Estimator Design

- Let us denote \mathbb{Y} as the set of all feasible measurements y, i.e., there exist x, $||w|| \le \delta$ and $||a||_0 \le l$, such that y = Hx + Gw + a.
- For any y ∈ 𝔅, let us denote 𝔅(y) as the set of all feasible x that can generate y, i.e., there exist ||w|| ≤ δ and ||a||₀ ≤ I, such that Hx = y Gw a.



Figure : X(y)

- For a given $y \in \mathbb{Y}$, the worst-case error is $\sup_{x \in \mathbb{X}(y)} \|x f(y)\|$.
- If $\mathbb{X}(y)$ is bounded, then the optimal estimator should be $f(y) = c(\mathbb{X}(y))$.
- Therefore, the worst-case error is

$$e^*(f) = \sup_{y \in \mathbb{Y}} r(\mathbb{X}(y)).$$

- How to efficiently compute the Chebyshev center?
- How to characterize the performance of the optimal estimator?

- Let $\mathcal{I} = \{i_1, i_2, ..., i_j\} \subset \{1, 2, \ldots, m\}$ be an index set.
- Define

$$y_{\mathcal{I}} \triangleq \begin{bmatrix} y_{i_1} \\ y_{i_2} \\ \vdots \\ y_{i_j} \end{bmatrix}, a_{\mathcal{I}} \triangleq \begin{bmatrix} a_{i_1} \\ a_{i_2} \\ \vdots \\ a_{i_j} \end{bmatrix}, H_{\mathcal{I}} \triangleq \begin{bmatrix} h_{i_1} \\ h_{i_2} \\ \vdots \\ h_{i_j} \end{bmatrix}, G_{\mathcal{I}} \triangleq \begin{bmatrix} g_{i_1} \\ g_{i_2} \\ \vdots \\ g_{i_j} \end{bmatrix}$$

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The Shape of $\mathbb{X}(y)$

- Consider an index set $\mathcal{I} = \{i_1, \ldots, i_{m-I}\}.$
- Define set $\mathbb{X}_\mathcal{I}(y) \subset \mathbb{R}^n$ as

 $\mathbb{X}_{\mathcal{I}}(y) \triangleq \{x: \exists \|w\| \leq \delta, a_{\mathcal{I}} = 0, \text{ such that } y = Hx + Gw + a\}.$

• The set $\mathbb X$ can be seen as

$$\mathbb{X}(y) = \bigcup_{|\mathcal{I}|=m-l} \mathbb{X}_{\mathcal{I}}(y).$$

• Since $a_{\mathcal{I}} = 0$ and $a_{\mathcal{I}^c}$ could be any vector, y = Hx + Gw + a is equivalent to

$$y_{\mathcal{I}}=H_{\mathcal{I}}x+G_{\mathcal{I}}w.$$

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The Shape of $\mathbb{X}_{\mathcal{I}}(y)$

• Define

$$\begin{aligned} F_{\mathcal{I}} &\triangleq G_{\mathcal{I}} G_{\mathcal{I}}^{T}, \ K_{\mathcal{I}} \triangleq \left(H_{\mathcal{I}}^{T} F_{\mathcal{I}}^{-1} H_{\mathcal{I}} \right)^{-1} H_{\mathcal{I}}^{T} F_{\mathcal{I}}^{-1}, \\ P_{\mathcal{I}} &\triangleq \left(H_{\mathcal{I}}^{T} F_{\mathcal{I}}^{-1} H_{\mathcal{I}} \right)^{-1}, \ U_{\mathcal{I}} \triangleq \left(I - H_{\mathcal{I}} K_{\mathcal{I}} \right)^{T} F_{\mathcal{I}}^{-1} (I - H_{\mathcal{I}} K_{\mathcal{I}}). \end{aligned}$$

• Define

$$\hat{x}_{\mathcal{I}}(y) = \mathcal{K}_{\mathcal{I}} y_{\mathcal{I}}, \ \varepsilon_{\mathcal{I}}(y) = y_{\mathcal{I}}^{\mathcal{T}} \mathcal{U}_{\mathcal{I}} y_{\mathcal{I}}.$$

Theorem (The shape of $X_{\mathcal{I}}(y)$)

If $\varepsilon_{\mathcal{I}}(y) > \delta^2$, then $\mathbb{X}_{\mathcal{I}}(y)$ is an empty set. Otherwise, $\mathbb{X}_{\mathcal{I}}(y)$ is an ellipsoid given by

$$\mathbb{X}_{\mathcal{I}}(y) = \{ x : (x - \hat{x}_{\mathcal{I}}(y))^{\mathsf{T}} P_{\mathcal{I}}^{-1}(x - \hat{x}_{\mathcal{I}}(y)) \leq \delta^2 - \varepsilon_{\mathcal{I}}(y) \}.$$

How to Compute the Chebyshev Center of $\mathbb{X}(y)$.

Theorem (LMI Formulation)

A ball B(x, r) covers $\mathbb{X}(y)$ if and only if for every index set $|\mathcal{I}| = m - l$, such that

$$\varepsilon_{\mathcal{I}}(y) \leq \delta^2,$$

there exists $\tau_{\mathcal{I}} \geq 0$, such that

$$au_{\mathcal{I}}\Omega_{\mathcal{I}} \geq \begin{bmatrix} I & -x & 0 \\ -x^{T} & -r^2 & x^{T} \\ 0 & x & -I \end{bmatrix},$$

where $\Omega_{\mathcal{I}}$ is defined as,

$$\Omega_{\mathcal{I}} = \begin{bmatrix} P_{\mathcal{I}}^{-1} & -P_{\mathcal{I}}^{-1} \hat{x}_{\mathcal{I}}(y) & 0\\ -\hat{x}_{\mathcal{I}}(y)^{\mathsf{T}} P_{\mathcal{I}}^{-1} & \hat{x}_{\mathcal{I}}(y)^{\mathsf{T}} P_{\mathcal{I}}^{-1} \hat{x}_{\mathcal{I}}(y) + \varepsilon_{\mathcal{I}}(y) - \delta^2 & 0\\ 0 & 0 & 0 \end{bmatrix}.$$

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An SDP Algorithm to Compute the Chebyshev Center

The Chebyshev center of $\mathbb{X}(y)$ can be computed via the following SDP:

SDP		
	$ \min_{\hat{x}, \varphi, \tau_{\mathcal{I}}} $	arphi
	subject to	$arphi \geq 0,$
		$ au_{\mathcal{I}} \ge 0,$
		$\begin{bmatrix} I & -\hat{x} & 0 \end{bmatrix}$
		$ au_{\mathcal{I}}\Omega_{\mathcal{I}} \geq \begin{vmatrix} -\hat{x}^{\mathcal{T}} & -\varphi & \hat{x}^{\mathcal{T}} \end{vmatrix}, ext{ if } arepsilon_{\mathcal{I}}(y) \leq \delta^2.$
		$\begin{bmatrix} 0 & \hat{x} & -I \end{bmatrix}$

where the radius of the Chebyshev ball is $r = \sqrt{\varphi}$.

Theorem (Bounds on $e^*(f)$)

- If there exists an index set $\mathcal{K} \subset S$ with cardinality m 2l, such that $H_{\mathcal{K}}$ is not of full column rank, then $e^* = \infty$.
- If for all $|\mathcal{K}| = m 2I$, $H_{\mathcal{K}}$ is full column rank, then for all possible $y \in \mathbb{Y}$, we have

$$\sup_{y\in\mathbb{Y}}d(\mathbb{X}(y))=2\delta\max_{|\mathcal{K}|=m-2I}\sqrt{\sigma(P_{\mathcal{K}})}.$$

Therefore, e* satisfies

$$\max_{|\mathcal{K}|=m-2I} \delta \sqrt{\sigma(P_{\mathcal{K}})} \leq e^* \leq \max_{|\mathcal{K}|=m-2I} \delta \sqrt{2\sigma(P_{\mathcal{K}})},$$

where $\sigma(P)$ is the spectral radius of P.

Numerical Examples

• We consider the following system:

$$H = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 1 & 1 \\ 1 & -1 \end{bmatrix}, G = I.$$

- Assume 1 sensor is compromised.
- The y is chosen to maximize $r(\mathbb{X}(y))$:

$$y = \begin{bmatrix} -0.851\\ 2.753\\ 0.5257\\ 0 \end{bmatrix}$$

• The optimal state estimate is

$$\hat{x} = \begin{bmatrix} -0.851\\ 1.376 \end{bmatrix},$$

and the corresponding error is 1.618.

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Numerical Examples



Figure : The performance of the optimal state estimator. The green ellipse corresponds to $\mathbb{X}_{\{1,3,4\}}(y)$ and the red ellipse corresponds to $\mathbb{X}_{\{1,2,3\}}(y)$. The set $\mathbb{X}_{\{2,3,4\}}(y)$ and $\mathbb{X}_{\{1,2,4\}}(y)$ is empty. The black "+" is the optimal state estimate while the black dashed line is the Chebyshev ball for $\mathbb{X}(y)$.

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- We consider the problem of state estimation from static sensory data, which could be compromised by an adversary.
- We provide an SDP algorithm to compute the optimal state estimate.
- We also characterize the performance of the optimal estimator.
- We would like to consider more general sensor model (stochastic sensor noise, non-linear sensor model) and dynamic state estimation problem in the future.