Secure state-estimation for dynamical systems under active adversaries

Hamza Fawzi

Joint work with Paulo Tabuada and Suhas Diggavi





Why security for control systems?

 Control systems are *physical* processes (chemical plants, power grid, mechanical system, etc.)



- Control systems becoming larger (large sensor networks) and increasingly open to the *cyber*-world (e.g., internet) ⇒ increased vulnerability to attacks
- Examples of real attacks: Sewage control system (Queensland, Australia, 2000), Natural gas pipelines (Russia, 2000), Stuxnet (2010), ...
- Need efficient ways to detect attacks on control systems...

For more info on security for control systems see [Cardenas, Amin, Sastry, 2008]

• (Some of the) existing works on adversarial, malicious attacks:

- Optimal control in the presence of intelligent jammer (cf. Gupta, Langbort and Basar, 2010)
 - game-theoretic approach; attacker's objective is to maximize cost function
- Secure state-estimation for power network against malicious attacks (cf. Pasqualetti, Dorfler, Bullo (2011))
 - attack-detection filter is proposed, but computationally expensive (combinatorial, test all possible attack sets)
- This talk: efficient algorithm to estimate the state of a linear dynamical system when sensors are attacked

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- ► Objective: Given observations y⁽⁰⁾,..., y^(T-1): recover state x⁽⁰⁾ of physical plant from observations (attack set K is unknown)

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- Note:

can correct q = 0 errors \equiv can recover $x^{(0)}$ from $(Cx^{(0)}, \ldots, CA^{T-1}x^{(0)}) \equiv (A, C)$ observable

Let T > 0 be fixed. Then q errors are correctable after T steps iff

$$\forall x \neq 0, \ |\mathsf{supp}(Cx) \cup \mathsf{supp}(CAx) \cup \dots \cup \mathsf{supp}(CA^{T-1}x)| > 2q$$
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Example of a very bad pair (A, C): A = identity, C = identity (easy to see that even q = 1 does not satisfy condition above: take x to be supported on one component)

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- $\blacktriangleright \Rightarrow q = 1$ error is NOT correctable in this case

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For almost all systems (A, C), the number of correctable errors is maximal (equal to $\lceil p/2 - 1 \rceil$).

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- Given a specific system (A, C), what is the number of correctable errors q?
 - Unfortunately, this is still unsolved and is likely to be hard:

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If q errors can be corrected by some decoder, then the above decoder can correct q errors.

- Interpretation: The above decoder is, in some sense, unbeatable...
- One little problem: It is NP-hard... :-(

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- ► Let's rewrite the previous "unbeatable" decoder using these notations:
 - smallest number of attacked sensors that explain the received observations:

$$\underset{x}{\text{minimize}} \| \underbrace{Y^{(T)} - \Phi^{(T)}}_{E^{(T)}} x \|_{\ell_0}$$

$$\min_{x} \|Y^{(T)} - \Phi^{(T)}x\|_{\ell_0}$$

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• Magnitude of a row of $E^{(T)}$ measured by its ℓ_r norm (in \mathbf{R}^T), for any $r \ge 1$.

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- ▶ Relaxation idea: Instead of " ℓ_0 norm" (intractable), use ℓ_1 norm (convex program, tractable)
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- Magnitude of a row of $E^{(T)}$ measured by its ℓ_r norm (in \mathbf{R}^T), for any $r \ge 1$.
- ℓ₀ → ℓ₁ relaxation idea used in compressed sensing (recovery of sparse signals), and error correction over the reals (cf. Candes, Tao, Donoho, etc.)

Numerical example 1

- Randomly generated system (A, C) with n = 30 and p = 20 (Gaussian entries)
- Used ℓ_1/ℓ_2 decoder



Figure: (a) Fraction of initial conditions (out of 20) that were correctly recovered in less than T = 20 time steps, for different values of q. (b) Average number of time steps it took to correctly recover the initial state, as a function of the number of corrupted components.

Numerical example 2

Electric power network: IEEE 14-bus power network (5 generators, 14 buses)

- $n = 2 \times 5 = 10$ states for the rotor angles δ_i and the frequencies $d\delta_i/dt$ of each generator *i*
- p = 35 sensors to measure: real power injections at every bus (14 sensors), real power flows along every branch (20 sensors), rotor angle at generator 1 (1 sensor)¹

Used ℓ_1/ℓ_∞ decoder



Figure: (a) IEEE 14-bus power network (b) Fraction of initial conditions that were correctly recovered in less than T = 10 steps. For each value of q, 200 simulations were carried out with different initial conditions and different sets of attacked sensors.

¹cf. [Pasqualetti, Dorfler, Bullo 2010]. Thanks to Fabio Pasqualetti from UCSB for the data!

The ℓ_1/ℓ_r decoder

• How suboptimal is the ℓ_1/ℓ_r decoder compared to the ℓ_0 decoder?

Proposition

Let T > 0 be fixed. Then the ℓ_1/ℓ_r decoder can correct q errors after T steps iff

 $\|(\Phi x)_{\mathcal{K}}\|_{\ell_1/\ell_r} < \|(\Phi x)_{\mathcal{K}^c}\|_{\ell_1/\ell_r} \quad \forall x \neq 0 \; \forall \mathcal{K} \; \text{s.t.} \; |\mathcal{K}| = q$

(recall that
$$\Phi_X = \begin{bmatrix} C_X & \dots & CA^{T-1}_X \end{bmatrix}$$
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- ▶ Question: Given (A, C) how to check above condition? no known efficient way...

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- ► Find efficient way to compute the maximum number of errors that can be corrected for a given system (A, C) (i.e., number of errors that the ℓ₀ decoder can handle).
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Extensions:

- Generalize to control systems with inputs
- Study robustness (noise in unattacked sensors, disturbance in state-evolution equation, etc.)

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Thank you!

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► ℓ₁-relaxation:

 $\min_{\hat{x}} \|y - C\hat{x}\|_{\ell_1}$

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