Zeno-free, distributed event-triggered coordination for multi-agent average consensus

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Consider

- N agents with state $x = (x_1, \ldots, x_N) \in \mathbb{R}^N$
- each agent *i* can **communicate with neighbors** $j \in \mathcal{N}_i$ in undirected communication graph \mathcal{G}

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- Continuous local state information
- Continuous communication
- Continuous actuation

-25

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Notice that this is different from the **idealistic** system

 $\dot{x} = f(x, k(x))$



Most existing control theory was developed ignoring the implementation details

$$\begin{array}{c} -25 \text{ freed putter } \textbf{\textit{k}}(\textbf{\textit{x}}) \\ \dot{x} = f(x, u) \end{array} \qquad \not \longrightarrow \qquad \dot{x} = f(x, k(x)) \end{array}$$

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As long as k(x) is updated **sufficiently fast**, everything will be okay

-Time-triggered- control

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Drawbacks:

- controller is often designed assuming perfect information
- state is sampled and controllers are updated periodically
- robustness analysis done a posteriori

Consider a linear system

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If we can now **enforce** that

$$|e|| \le \sigma \frac{a}{b} \|x\|$$

for some $\sigma \in (0, 1)$, then

$$\dot{V} \le -(1-\sigma)a||x||^2 < 0$$

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Still requires continuous communication in a network



- 2 Problem statement
- Event-triggered design
 Simulations



Problem statement

The distributed, continuous control law

$$u_i^*(t) = -\sum_{j \in \mathcal{N}_i} (x_i(t) - x_j(t))$$

is **well known** to have each agent state asymptotically converge to the initial average of all agent states.

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Problem (Multi-agent average consensus)

How should agents decide to broadcast their state to ensure their state converges to the initial average of all agent states?

Cameron Nowzari (Penn)

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Implementable controller

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$$\mathcal{L}_{u^*}V(x) = x^T L \dot{x} \qquad \qquad \mathcal{L}_u V(x) = x^T L \dot{x}$$

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$$u_{i}^{*}(t) = -\sum_{j \in \mathcal{N}_{i}} (x_{i}(t) - x_{j}(t)) \qquad u_{i}(t) = -\sum_{j \in \mathcal{N}_{i}} (\hat{x}_{i}(t) - \hat{x}_{j}(t)) u^{*} = -Lx \qquad u = -L\hat{x}$$

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So how can we do this in a **distributed** way?

Let $e = \hat{x} - x$, then

$$\dot{V} = -(\hat{x} - e)^T L L \hat{x}$$
$$= -\|L \hat{x}\|^2 + (L \hat{x})^T L e$$

Let $\hat{z} = L\hat{x}$, then

$$\dot{V} = -\sum_{i=1}^{N} \hat{z}_{i}^{2} + \sum_{i=1}^{N} \sum_{j \in \mathcal{N}_{i}} \hat{z}_{i}(e_{i} - e_{j})$$

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By Young's inequality,

$$\sum_{i=1}^{N} |\mathcal{N}_i| \hat{z}_i e_i \le \sum_{i=1}^{N} \left(\frac{1}{2} |\mathcal{N}_i| \hat{z}_i a + \frac{1}{2a} |\mathcal{N}_i| e_i^2\right)$$

and

$$-\sum_{i=1}^{N}\sum_{j\in\mathcal{N}_{i}}\hat{z}_{i}e_{j}\leq\sum_{i=1}^{N}\sum_{j\in\mathcal{N}_{i}}\left(\frac{1}{2}\hat{z}_{i}^{2}a+\frac{1}{2a}e_{j}^{2}\right)$$

So we can bound

$$\dot{V} \le -\sum_{i=1}^{N} \hat{z}_{i}^{2} + \sum_{i=1}^{N} \left(\frac{1}{2} |\mathcal{N}_{i}| \hat{z}_{i}a + \frac{1}{2a} |\mathcal{N}_{i}| e_{i}^{2} \right) + \sum_{i=1}^{N} \sum_{j \in \mathcal{N}_{i}} \left(\frac{1}{2} \hat{z}_{i}^{2}a + \frac{1}{2a} e_{j}^{2} \right)$$

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Since the graph is undirected, we know

$$\sum_{i=1}^{N} \sum_{j \in \mathcal{N}_i} \frac{1}{2a} e_j^2 = \sum_{i=1}^{N} \sum_{j \in \mathcal{N}_i} \frac{1}{2a} e_i^2 = \sum_{i=1}^{N} \frac{1}{2a} |\mathcal{N}_i| e_i^2$$

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Then,

$$\dot{V} \le \sum_{i=1}^{N} (a|\mathcal{N}_i| - 1)\hat{z}_i^2 + \frac{1}{a}|\mathcal{N}_i|e_i^2$$

We can now present the distributed event-triggering condition as

$$e_i^2 = \frac{a(1-a|\mathcal{N}_i|)}{|\mathcal{N}_i|}\sigma_i \hat{z}_i^2$$

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at all times, then

$$\dot{V} \le -\sum_{i=1}^{N} (1 - \sigma_i)(1 - a|\mathcal{N}_i|)\hat{z}_i^2 \le 0 \quad \text{for} \quad a < \min_{i \in \{1, \dots, N\}} \frac{1}{|\mathcal{N}_i|}$$

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Theorem (E. Garcia et al. 2013)

The inter-event times for each agent $i = \{1, \ldots, N\}$ are strictly positive.

Main trigger

$$e_i^2 \ge \sigma_i \frac{a_i}{|\mathcal{N}_i|} \left(1 - \frac{1}{2} a_i |\mathcal{N}_i| - \frac{1}{2} \sum_{j \in \mathcal{N}_i} a_j \right) \hat{z}_i^2$$

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Additional trigger added to ensure no Zeno behavior can occur

Theorem

The system with the described control law and modified event-triggered broadcasting algorithm exponentially converges to the average consensus state and is guaranteed to avoid Zeno executions.

- Simulation with N = 5 agents
- $a_1 = a_3 = a_5 = 0.3$
- $a_2 = a_4 = 0.2$
- $\sigma_i = 0.999$ for all agents

Evolution of state trajectories

Number of events triggered

Evolution of Lyapunov function ${\cal V}$

Distributed event-triggered broadcasting and control algorithm

- does not require any global a priori knowledge
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- exponential convergence rate
- extension to **time-varying topologies**

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Future work:

- sampled-data implementations
- directed graphs
- more general algorithms

Thank You!