

Optimal localized feedback design for multi-vehicle systems

Fu Lin

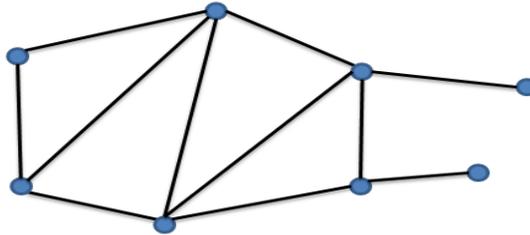
joint work with:

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Problem setup

A network (graph) \mathcal{G} of n vehicles (nodes)



Single-integrator dynamics

$$\dot{x}_i = u_i + d_i, \quad d_i \text{ disturbance}$$

Relative information exchange with neighbors

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

Vector form $\dot{x}(t) = -L(k)x(t) + d(t)$

Structured matrix $L(k)$ depends on graph topology

Problem setup

Structured matrix

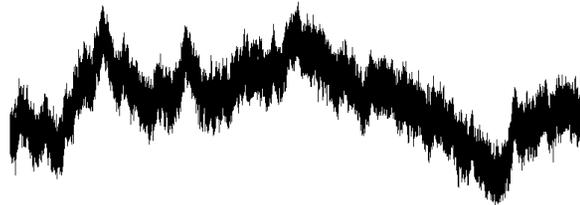
$$L(k)\mathbf{1} = 0 \cdot \mathbf{1} \quad \mathbf{1} \text{ is vector of all 1}$$

Independent of graph topology and feedback gains $\{k_{ij}\}$

$$\dot{x}(t) = -L(k)x(t) + d(t)$$

Average mode

$$\bar{x}(t) = (1/n) \sum x_i(t) \quad \text{undergoes random walk}$$



If other modes are stable, $x_i(t)$ fluctuates around $\bar{x}(t)$

Deviation from average $\tilde{x}(t)$

$$\tilde{x}_i(t) = x_i(t) - \bar{x}(t)$$

Steady-state variance

$$\lim_{t \rightarrow \infty} \mathcal{E}\{\tilde{x}^T(t)\tilde{x}(t)\} \quad \text{quantifies consensus performance}$$

Optimal control problem

What graph topologies lead to small variance?

How to design feedback gains to minimize variance? (In this talk)

- Choose feedback gains $\{k_{ij}\}$ to minimize H_2 norm $\|d \rightarrow z\|_2^2$

$$\begin{aligned} \dot{x} &= -L(k)x + d \\ z &= \begin{bmatrix} \tilde{x} \\ u \end{bmatrix} = \begin{bmatrix} x - \bar{x} \mathbf{1} \\ -L(k)x \end{bmatrix} \end{aligned}$$

Assumptions:

- Bi-directional interaction between vehicles (undirected graphs)
- Symmetric feedback gains $k_{ij} = k_{ji}$ (interpreted as spring constant)

$$L(k) = L^T(k)$$

Need some stuffs to express $L(k)$ explicitly

Incidence matrix

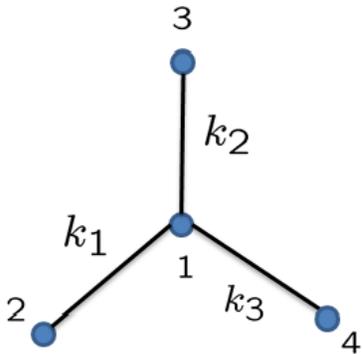
Edge $l \sim (i, j)$ connects nodes i and j

Define $e_l \in \mathbb{R}^n$ with only two nonzero entries

$$(e_l)_i = 1 \quad (e_l)_j = -1$$

Incidence matrix

$$E = [e_1 \cdots e_m]$$



$$E = \begin{bmatrix} 1 & 1 & 1 \\ -1 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & -1 \end{bmatrix} \quad E^T \mathbf{1} = 0$$

Edge $l \sim (i, j)$ $k_l := k_{ij} = k_{ji}$

Structured matrix

$$L(K) = EKE^T \quad K = \begin{bmatrix} k_1 & & \\ & \ddots & \\ & & k_m \end{bmatrix}$$

Unobservable mode

$$\dot{x} = -EKE^T x + d$$

$$z = \begin{bmatrix} \tilde{x} \\ u \end{bmatrix} = \begin{bmatrix} x - \bar{x}\mathbf{1} \\ -EKE^T x \end{bmatrix}$$

Deviation from average

$$x - \bar{x}\mathbf{1} = (I - (1/n)\mathbf{1}\mathbf{1}^T)x$$

Can be verified

$$(I - (1/n)\mathbf{1}\mathbf{1}^T)\mathbf{1} = 0$$

and

$$-EKE^T\mathbf{1} = 0$$

- Average mode \bar{x} is unobservable, i.e., not minimal representation

Need a change of coordinates to separate \bar{x}

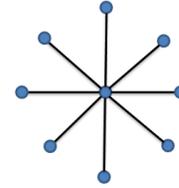
Coordinate transformation

Tree: connected graph with no loops

path



star



Incidence matrix of tree E_t

$$T = \begin{bmatrix} E_t^T \\ (1/n)\mathbf{1}^T \end{bmatrix} \quad T^{-1} = \begin{bmatrix} E_t (E_t^T E_t)^{-1} & \mathbf{1} \end{bmatrix}$$

Zelazo & Mesbahi CDC'09

$$Tx := \begin{bmatrix} \psi \\ \bar{x} \end{bmatrix}$$

For tree graphs $L = E_t K E_t^T$

$$\begin{bmatrix} E_t^T \\ (1/n)\mathbf{1}^T \end{bmatrix} E_t K E_t^T \begin{bmatrix} E_t (E_t^T E_t)^{-1} & \mathbf{1} \end{bmatrix} = \begin{bmatrix} E_t^T E_t K & 0 \\ 0 & 0 \end{bmatrix}$$

Tree graphs

$$\dot{\psi} = -E_t^T E_t K \psi + E_t^T d$$

$$z = \begin{bmatrix} \tilde{x} \\ u \end{bmatrix} = \begin{bmatrix} E_t (E_t^T E_t)^{-1} \\ -E_t K \end{bmatrix} \psi$$

H_2 norm $\|d \rightarrow z\|_2^2$

$$J(K) = \frac{1}{2} \text{trace} \left((E_t^T E_t)^{-1} K^{-1} + K E_t^T E_t \right)$$

Diagonal matrix

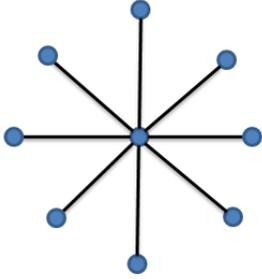
$$K = \begin{bmatrix} k_1 & & \\ & \ddots & \\ & & k_{n-1} \end{bmatrix}$$

- Optimal localized feedback gains

$$k_i = \sqrt{\frac{(E_t^T E_t)^{-1}_{ii}}{2}} \quad i = 1, \dots, n-1$$

Two simple examples

• Star

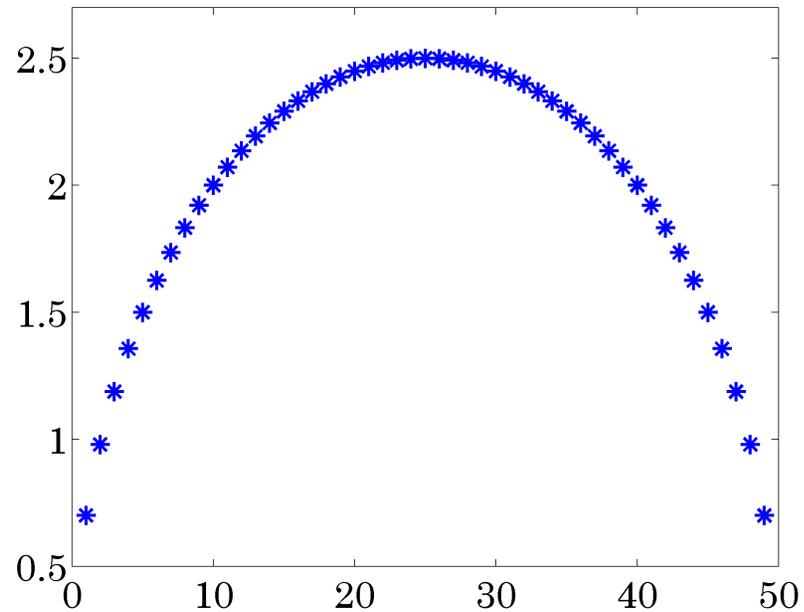


uniform gain $k = \sqrt{\frac{n-1}{2n}} \approx \frac{1}{\sqrt{2}}$ for large n

• Path:



$$k_i = \sqrt{\frac{i(n-i)}{2n}}$$



larger gains in the center

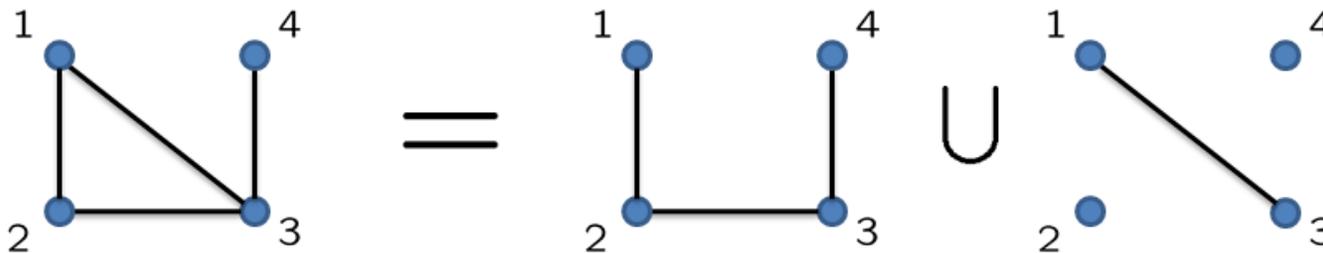
General graphs

Decompose \mathcal{G} into a tree subgraph \mathcal{T} and remaining edges \mathcal{C}

(Does not depend on the choice of tree subgraph)

Form corresponding incidence matrix

$$E = [E_t \quad E_c]$$



$$\begin{bmatrix} 1 & 0 & 0 & 1 \\ -1 & 1 & 0 & 0 \\ 0 & -1 & 1 & -1 \\ 0 & 0 & -1 & 0 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ -1 & 1 & 0 \\ 0 & -1 & 1 \\ 0 & 0 & -1 \end{bmatrix} \cup \begin{bmatrix} 1 \\ 0 \\ -1 \\ 0 \end{bmatrix}$$

$$E = [E_t \quad E_c] = E_t [I \quad (E_t^T E_t)^{-1} E_t^T E_c] = E_t \Gamma$$

General graphs

$$\dot{\psi} = -E_t^T E_t \Gamma K \Gamma^T \psi + E_t^T d$$

$$z = \begin{bmatrix} \tilde{x} \\ u \end{bmatrix} = \begin{bmatrix} E_t (E_t^T E_t)^{-1} \\ -E_t \Gamma K \Gamma^T \end{bmatrix} \psi$$

$$J(K) = \frac{1}{2} \text{trace} \left((E_t^T E_t)^{-1} (\Gamma K \Gamma^T)^{-1} + \Gamma K \Gamma^T E_t^T E_t \right)$$

Tree graphs $\Gamma = I$

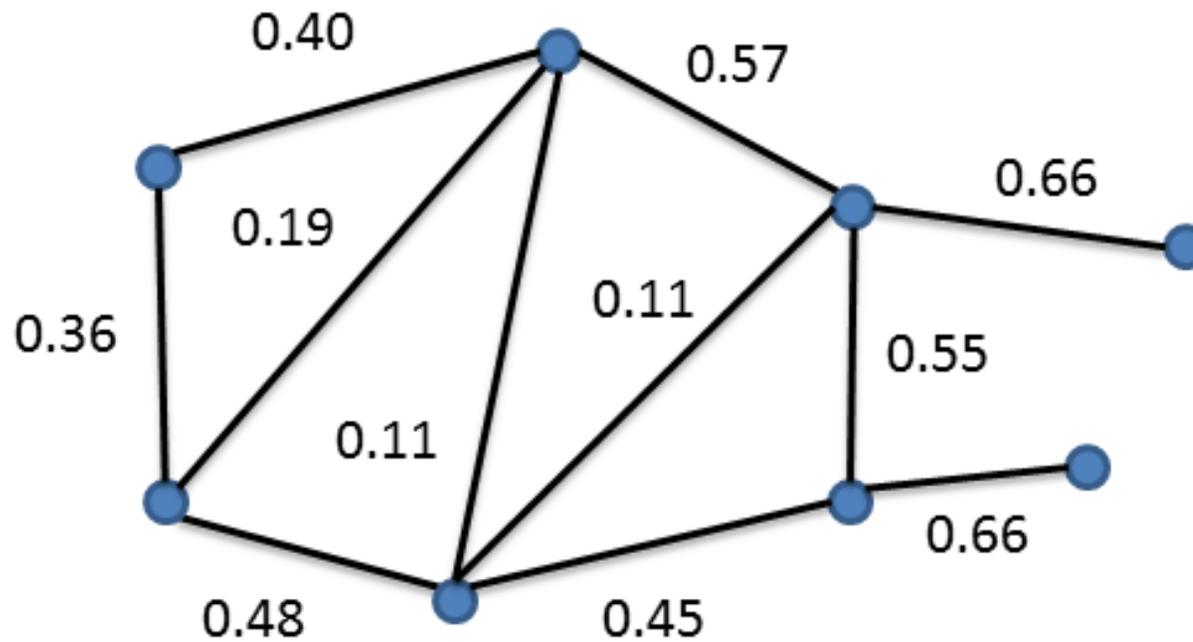
Main results:

- Closed-loop stability $\iff \Gamma K \Gamma^T > 0$
- $J(K)$ is convex function if $\Gamma K \Gamma^T > 0$

Can be formulated as a semi-definite program

- ★ $W_1 > 0, W_2 = W_2^T$, then $\lambda(-W_1 W_2) < 0$ if and only if $W_2 > 0$
- ★ $\text{trace}(W^{-1})$ is convex for $W > 0$

Example



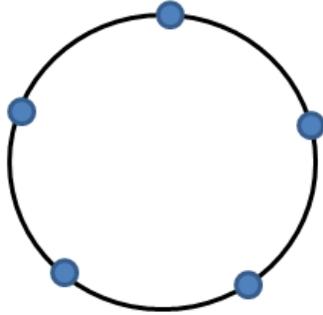
- Compared with performance of uniform gain design

J^*	$J(k = 1)$	$(J - J^*)/J^*$
9.1050	13.1929	45%

Two examples

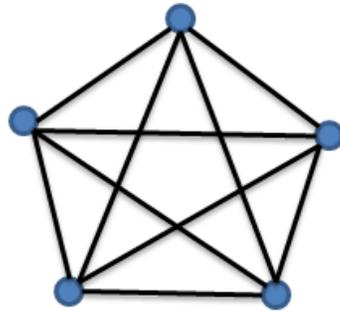
Analytical solutions for some simple graphs

- Circle



uniform gain $k = \sqrt{\frac{n^2 - 1}{24n}}$

- Complete graph

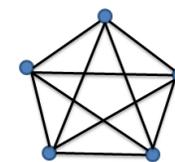
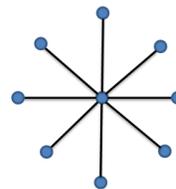
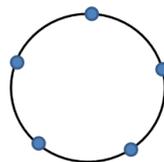
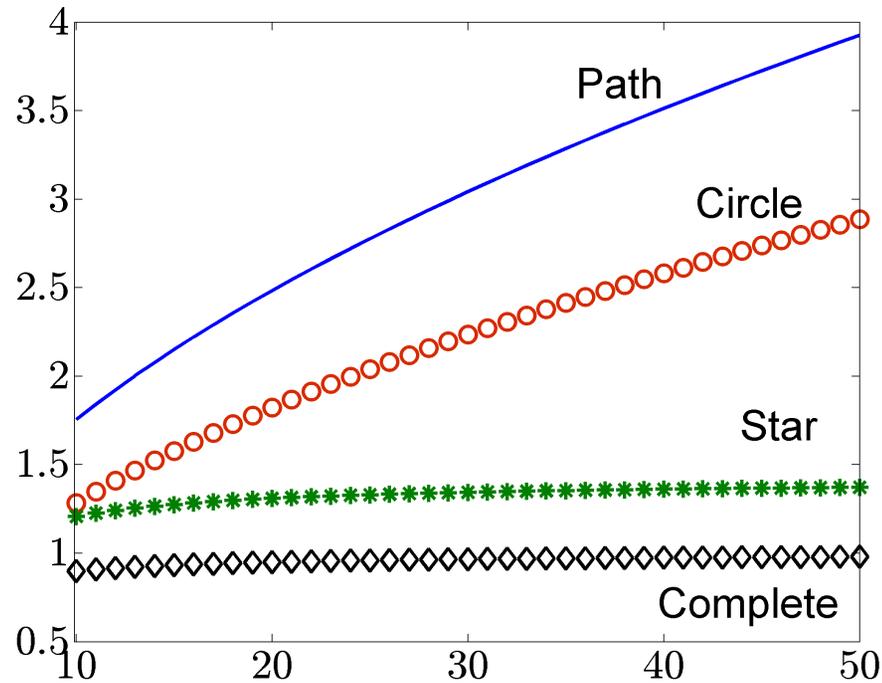


uniform gain $k = \frac{2}{n}$

Performance vs. size

H_2 norm $\|d \rightarrow z\|_2^2$ normalized by the number of nodes

	path	circle	star	complete
$\frac{1}{n} J^*(K)$	$\frac{\pi}{8} \sqrt{2n}$	$\sqrt{\frac{n^2 - 1}{6n}}$	$\sqrt{\frac{2(n - 1)^3}{n^3}}$	$\frac{n - 1}{n}$



Concluding remarks

Optimal localized feedback gain design

- Analytical solutions for tree graphs
- Characterize stabilizing feedback gains
- Convex problem for general graphs

Ongoing work:

- Feedback gain design of directed graphs
Hard problem in general, analytical solutions? hidden convexity? etc...
- Is it possible to have sparse feedback gains, i.e., few edges?
Identify sparsity patterns...
Fardad, Lin, Jovanović ACC'11 (submitted)