



Decentralized optimization via funnel coupling

Stephan Trenn

Jan C. Willems Center for Systems and Control

University of Groningen, Netherlands

Joint work with **Jin Gyu Lee** (U Cambridge, UK), **Thomas Berger** (U Paderborn, Germany) and
Hyungbo Shim (SNU, Korea)

DMV Annual Meeting 2020, Chemnitz, Germany (online), 15 September 2020, 12:00 - 12:30
Minisymposium “The many facets of mathematical systems theory”

The problem

Minimization problem

For some differentiable and convex $F : \mathbb{R}^n \rightarrow \mathbb{R}$ find x^* which solves

$$\min_{x \in \mathbb{R}^n} F(x)$$

Challenge

$$F(x) = \sum_{i=1}^N F_i(x)$$

Find x^* in a decentralized way with N agents who only know their $F_i : \mathbb{R}^n \rightarrow \mathbb{R}$, which are also not assumed to be convex.

Some approaches available already, new approach: Utilize ideas from funnel control

Local gradient descent and coupling

Lemma (Global gradient descent)

$$\dot{x}(t) = -\eta \nabla F(x(t)), \quad x(0) = x_0 \in \mathbb{R}^n$$

Then $x(t) \rightarrow x^*$ for all x_0 and all $\eta > 0$,

Local gradient descent + coupling

$$\dot{x}_i = -\nabla F_i(x_i) + \textcolor{red}{u}_i \quad x_i(0) = x_{0,i} \in \mathbb{R}^n$$

Find suitable control law

$x_i(t) \xrightarrow{\textcolor{red}{u}_i} x^*$ in particular, synchronization / consensus

Contents

Decentralized optimization

Synchronization of heterogenous agents

Funnel coupling

Decentralized optimization via edge-wise funnel coupling

Problem statement

Given

- › N agents with **individual** n -dimensional dynamics:

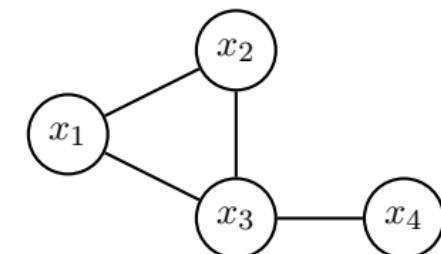
$$\dot{x}_i = f_i(t, x_i) + u_i$$

- › undirected connected coupling-graph $G = (V, E)$
- › **local** feedback $u_i = \gamma_i(x_i, x_{\mathcal{N}_i})$

Desired

Control design for practical synchronization

$$x_1 \approx x_2 \approx \dots \approx x_n$$



$$u_1 = \gamma_1(x_1, x_2, x_3)$$

$$u_2 = \gamma_2(x_2, x_1, x_3)$$

$$u_3 = \gamma_3(x_3, x_1, x_2)$$

$$u_4 = \gamma_4(x_4, x_3)$$

A „high-gain“ result

Let $\mathcal{N}_i := \{j \in V \mid (j, i) \in E\}$ and $d_i := |\mathcal{N}_i|$ and \mathcal{L} be the Laplacian of G .

Diffusive coupling

$$u_i = -k \sum_{j \in \mathcal{N}_i} (x_i - x_j) \quad \text{or, equivalently,} \quad \mathbf{u} = -k \mathcal{L} \mathbf{x}$$

Theorem (Practical synchronization¹)

Assumptions: G connected, all solutions of **average dynamics**

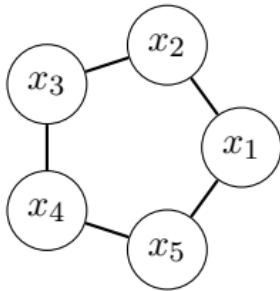
$$\dot{s}(t) = \frac{1}{N} \sum_{i=1}^N f_i(t, s(t))$$

remain **bounded**. Then $\forall \varepsilon > 0 \exists K_\varepsilon > 0 \forall k \geq K_\varepsilon$: Diffusive coupling results in

$$\boxed{\limsup_{t \rightarrow \infty} \|x_i(t) - x_j(t)\| < \varepsilon \quad \forall i, j \in V}$$

¹ J. Kim, J. Yang, H. Shim, J.-S. Kim, and J.H. Seo. IEEE Transactions on Automatic Control 2016.

Example²



Simulations in the following for $N = 5$ agents with dynamics

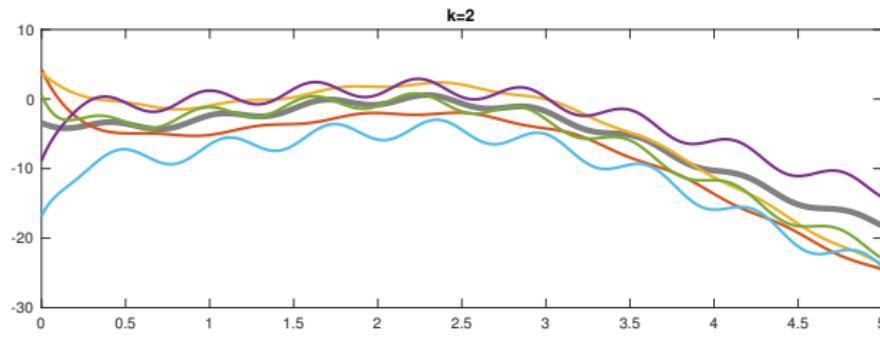
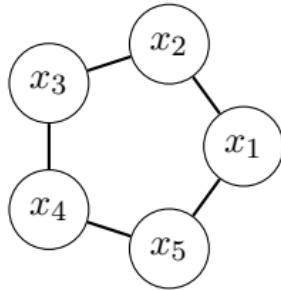
$$f_i(t, x_i) = (-1 + \delta_i)x_i + 10 \sin t + 10m_i^1 \sin(0.1t + \theta_i^1) + 10m_i^2 \sin(10t + \theta_i^2),$$

with randomly chosen parameters $\delta_i, m_i^1, m_i^2 \in \mathbb{R}$ and $\theta_i^1, \theta_i^2 \in [0, 2\pi]$.

Parameters identical in all following simulations, in particular $\delta_2 > 1$, hence agent 2 has **unstable dynamics** (without coupling).

² Shim, H. and Trenn, S. Proc. 54th IEEE Conf. Decision Control (CDC) 2015.

Example²

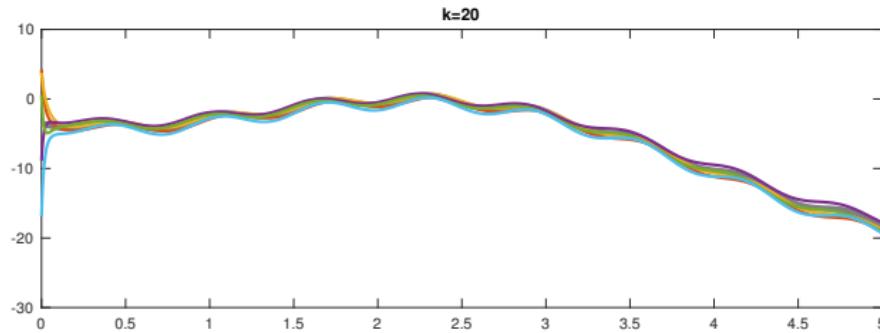


$$u = -k \mathcal{L} x$$

gray curve:

$$\dot{s}(t) = \frac{1}{N} \sum_{i=1}^N f_i(t, s(t))$$

$$s(0) = \frac{1}{N} \sum_{i=1}^N x_i(0)$$



² Shim, H. and Trenn, S. Proc. 54th IEEE Conf. Decision Control (CDC) 2015.

Application to decentralized optimization

Limit trajectory

$$\dot{s}(t) = \frac{1}{N} \sum_{i=1}^N f_i(t, s(t))$$

In fact: $\limsup_{t \rightarrow \infty} |x_i(t) - s(t)| < \varepsilon \quad \forall i \in V$

Average dynamics for local gradient descent

For $f_i(t, s) = -\nabla F_i(s)$ we have

$$\dot{s}(t) = -\frac{1}{N} \sum_{i=1}^N \nabla F_i(s(t)) = -\frac{1}{N} \nabla F(s(t))$$

↪ Average dynamics = **global** gradient descent

Corollary

For sufficiently large diffusive coupling gain: $x_i(t) \rightarrow \mathbb{B}_\varepsilon(x^*)$

Remaining problems

Problems

- › necessary gain depends on **global** network structure
- › all agents must use the **same** gain
- › no direct control over **convergence rate**
- › only practical synchronization, **no asymptotic convergence**

Contents

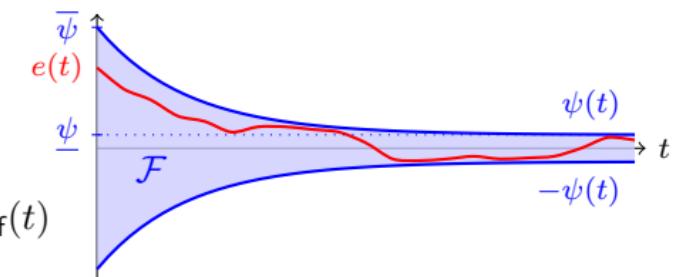
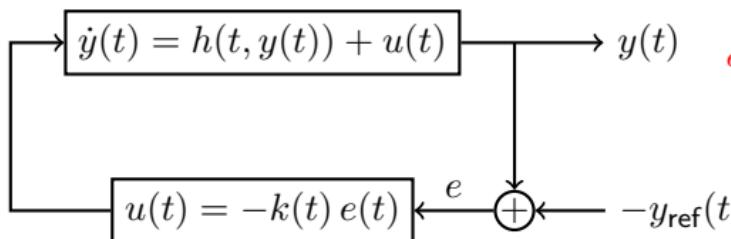
Decentralized optimization

Synchronization of heterogenous agents

Funnel coupling

Decentralized optimization via edge-wise funnel coupling

Reminder Funnel Controller



Theorem (Practical tracking³)

Funnel Control

$$k(t) = \frac{1}{\psi(t) - |e(t)|}$$

works, in particular, errors remains within funnel for all times.

Basic idea for funnel coupling

$$u = -k \mathcal{L} x \quad \longrightarrow \quad u = -k(t) \mathcal{L} x$$

³ A. Ilchmann, E.P. Ryan and C.J. Sangwin. ESAIM: Control, Opt. Calc. Variations, 2002

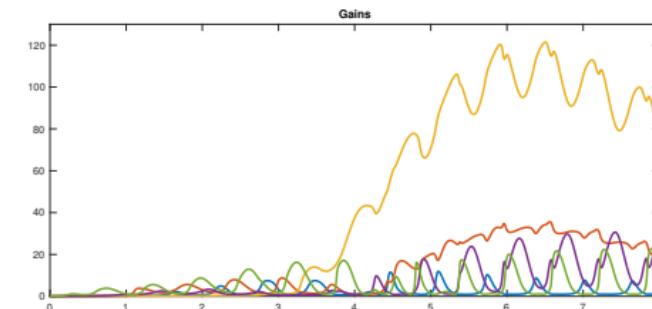
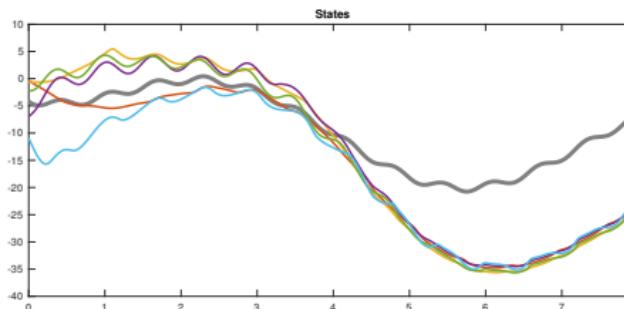
Node-wise funnel coupling approach²

Local error

$$u_i = -k \sum_{j \in \mathcal{N}_i} (x_i - x_j) = -k \left(d_i x_i - \sum_{j \in \mathcal{N}_i} x_j \right) =: -k d_i (x_i - \bar{x}_i) =: -k_i e_i$$

Funnel coupling rule

$$u_i(t) = -k_i(t) e_i(t) \quad \text{with} \quad k_i(t) = \frac{1}{\psi(t) - |e_i(t)|}$$



Edgewise Funnel coupling

Diffusive coupling → edgewise Funnel coupling

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

Edgewise funnel gain

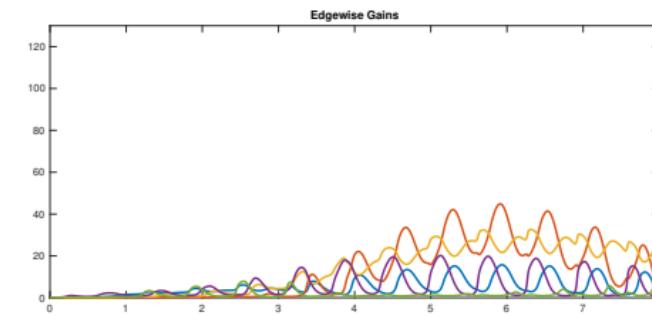
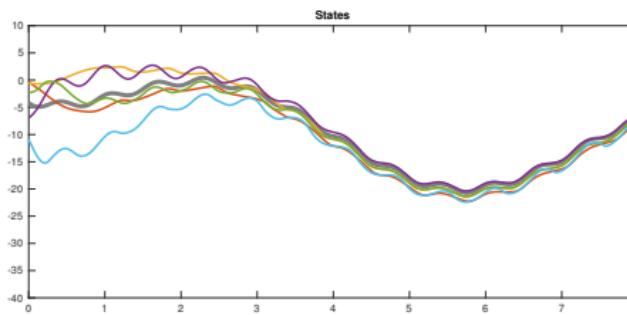
$$k_{ij}(t) = \frac{1}{\psi(t) - |e_{ij}|}, \quad \text{with} \quad e_{ij} := x_i - x_j$$

Properties:

- › **Decentralized**, i.e. u_i only depends on state of neighbors
- › **Symmetry**, $k_{ij} = k_{ji}$
- › **Laplacian feedback**, $u = -\mathcal{L}_K(t, x)x$



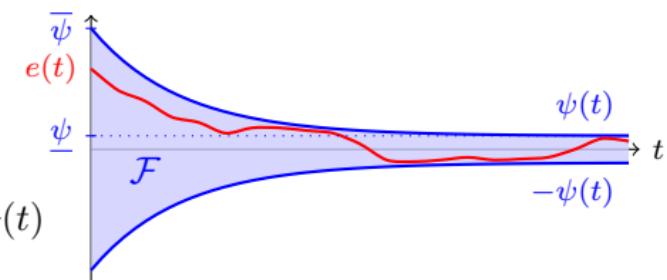
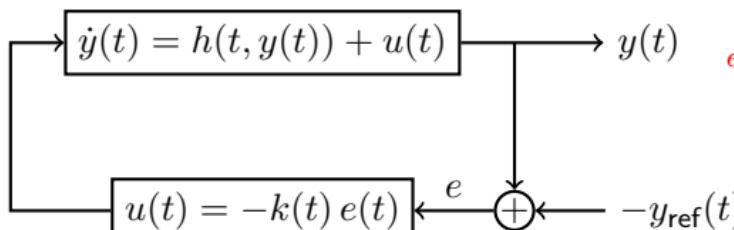
Simulation



Properties

- + Synchronization occurs
- + Predictable limit trajectory (given by average dynamics)
- + Local feedback law
- No asymptotic convergence towards limit trajectory

Funnel control and asymptotic tracking



Asymptotic tracking only with unbounded gain

$$\begin{aligned} \text{Asymptotic tracking} &\Leftrightarrow \psi(t) \xrightarrow[t \rightarrow \infty]{} 0 \Rightarrow \psi(t) - \|e(t)\| \xrightarrow[t \rightarrow \infty]{} 0 \\ &\Leftrightarrow k(t) = \frac{1}{\psi(t) - \|e(t)\|} \xrightarrow[t \rightarrow \infty]{} \infty \end{aligned}$$

Conclusion: Funnel control and asymptotic tracking **not compatible** ?

Rewrite rule for funnel control

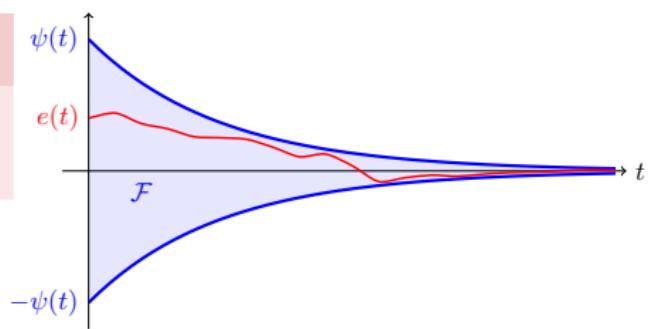
Important observation: $\psi(t) \rightarrow 0 \implies \|e(t)\| \rightarrow 0$

Hence $u(t) = -k(t)e(t) \rightarrow \infty \cdot 0$ not necessarily unbounded!

$$u(t) = -\frac{1}{\psi(t) - \|e(t)\|} e(t) = -\frac{1}{1 - \left\| \frac{e(t)}{\psi(t)} \right\|} \frac{e(t)}{\psi(t)} =: -\alpha(\eta(t)) \cdot \eta(t) \text{ where } \eta(t) := \frac{e(t)}{\psi(t)}$$

Asymptotic funnel control possible⁵

Rewriting classical funnel control rule
 $\hookrightarrow \psi(t) \rightarrow 0$ allowed!



⁵ Lee, J.G. and Trenn, S.: Asymptotic tracking via funnel control. Proc. 58th IEEE Conf. Decision Control (CDC) 2019, pp. 4228–4233, Nice, France, 2019.

Contents

Decentralized optimization

Synchronization of heterogenous agents

Funnel coupling

Decentralized optimization via edge-wise funnel coupling

Back to optimization problem

$$\min_{x \in \mathbb{R}^n} F(x)$$

F convex & differentiable

$$F(x) = \sum_{i=1}^N F_i(x)$$

Gradient descent = **average dynamics**

$$\dot{s} = -\frac{1}{N} \sum_{i=1}^N \nabla F_i(s)$$

Theorem (Optimization via high gain coupling⁶)

$$\dot{x}_i = -\nabla F_i(x_i) + u_i \quad u_i = -\bar{k} \sum_{j \in \mathcal{N}_i} (x_i - x_j)$$

Then $\limsup_{t \rightarrow \infty} \|x_i(t) - s(t)\| < \varepsilon(\bar{k})$ and $s(t) \rightarrow x^*$

⁶ J.G. Lee and H. Shim. Automatica 2020.

Replacing constant gain by edge-wise funnel gain

Replace $u_i = -\bar{k} \sum_{j \in \mathcal{N}_i} (x_i - x_j)$ by **edgewise funnel coupling**

$$u_i(t) = - \sum_{j \in \mathcal{N}_i} \alpha \left(\frac{x_i(t) - x_j(t)}{\psi(t)} \right) \frac{x_i - x_j}{\psi(t)}$$

with

$$\alpha : \mathbb{R}^n \rightarrow \mathbb{R}^{n \times n}, \eta = (\eta^1, \dots, \eta^n) \mapsto \begin{bmatrix} \frac{1}{1-|\eta^1|} & & & \\ & \frac{1}{1-|\eta^2|} & & \\ & & \ddots & \\ & & & \frac{1}{1-|\eta^n|} \end{bmatrix}$$

or, by introducing $(e_{ij}^1, e_{ij}^2, \dots, e_{ij}^n)^\top = e_{ij} := x_i - x_j$

$$u_i(t) = - \sum_{j \in \mathcal{N}_i} \left(\frac{e_{ij}^1}{\psi - |e_{ij}^1|}, \frac{e_{ij}^2}{\psi - |e_{ij}^2|}, \dots, \frac{e_{ij}^n}{\psi - |e_{ij}^n|} \right)^\top$$

Decentralized optimization via funnel coupling

$$\boxed{\min_{x \in \mathbb{R}^n} F(x)}$$

$$F(x) = \sum_{i=1}^N F_i(x) \quad \text{unique minimizer } x^* \in \mathbb{R}^n$$

$$\dot{x}_i = -\nabla F_i(x) - \sum_{j \in \mathcal{N}_i} \left(\frac{e_{ij}^1}{\psi - |e_{ij}^1|}, \frac{e_{ij}^2}{\psi - |e_{ij}^2|}, \dots, \frac{e_{ij}^n}{\psi - |e_{ij}^n|} \right)^\top, \quad x_i(0) = x_{i,0} \in \mathbb{R}^n, \quad i \in \mathcal{V}$$

Theorem (Decentralized optimization via funnel coupling⁷)

Assume ∇F_i is globally Lipschitz and coupling graph is undirected and connected, funnel boundary $\psi \in W^{1,\infty}(\mathbb{R}_{\geq 0} \rightarrow \mathbb{R}_{>0})$ with $\psi(t) \rightarrow 0$ as $t \rightarrow \infty$ and $\|x_{i,0} - x_{j,0}\| < \psi(0) \forall (i,j) \in \mathcal{E}$. Then edge-wise funnel coupling yields

$$\lim x_i(t) = x^*$$

⁷ J.G. Lee, T. Berger, S. Trenn and H. Shim. Proc. European Control Conference (ECC) 2020.

Main steps of proof

▶ Skip Proof

Step 1: Show that solution of closed loop exists on $[0, \infty)$, in particular

$$\|x_i(t) - x_j(t)\|_\infty < \psi(t) \quad \forall t \geq 0$$

Step 2: Write $x_i = x_{\text{avg}} + (\mathbf{t}_i^\top \otimes I_n) \tilde{x}$, where \mathbf{t}_i^\top is the i -th row of $T(T^\top T)^{-1}$, T is the incidence matrix of a **spanning tree** and

$$x_{\text{avg}} = \frac{1}{N} \sum_{i=1}^N x_i \quad \text{and} \quad \tilde{x} = (T^\top \otimes I_n)(x_1^\top, \dots, x_N^\top)^\top$$

Then $\|\tilde{x}(t)\|_\infty < \psi(t)$, in particular, $x_i(t) \rightarrow x_{\text{avg}}(t)$

Step 3: Use **Lyapunov function** $V(x_{\text{avg}}) := F(x_{\text{avg}}) - F(x^*)$ to show convergence of x_{avg} towards x^* .

Convergence rate

Average dynamics = gradient descent

$$\dot{s} = -\frac{1}{N} \sum_{i=1}^N F_i(s)$$

Convergence towards x^* **not influenced** by choice of coupling rule

Edge-wise funnel coupling

$$x_i(t) - s(t) \rightarrow 0 \quad \text{as } t \rightarrow \infty$$

Convergence rate (and transient behavior) directly **influenceable** by choice of ψ

Example: Distributed Least-square solver

Problem

Find least-square solution of $\textcolor{red}{Ax = b}$, where $A \in \mathbb{R}^{M \times n}$ with $M = \sum_{i=1}^N m_i$. Then

$$\frac{1}{2} \|Ax - b\|_2^2 = \sum_{i=1}^N \frac{1}{2} \|A_i x - b_i\|_2^2$$

where $A_i \in \mathbb{R}^{m_i \times n}$, $b_i \in \mathbb{R}^{m_i}$ are the corresponding block rows of A and b .

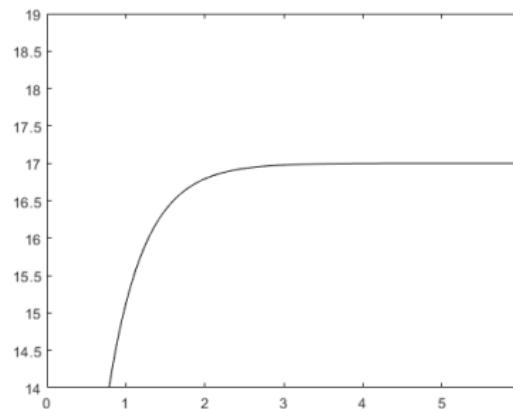
Local gradient descent with funnel coupling

$$\dot{x}_i = -A_i^\top (A_i x_i - b_i) - \sum_{j \in \mathcal{N}_i} \left(\frac{e_{ij}^1}{\psi - |e_{ij}^1|}, \frac{e_{ij}^2}{\psi - |e_{ij}^2|}, \dots, \frac{e_{ij}^n}{\psi - |e_{ij}^n|} \right)^\top$$

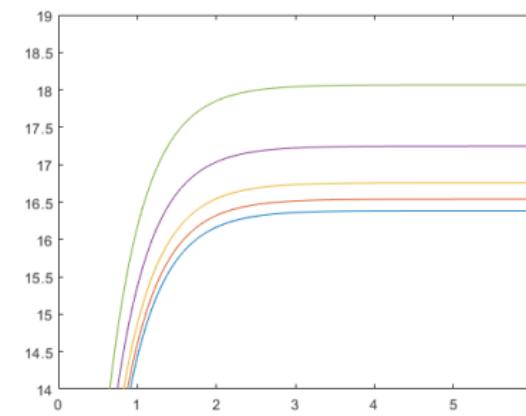
Simulation

For $A = [1, 1, 2, 2, 1]^\top$ and $b = [1, 10, 20, 18, 100]^\top$,
 $x_1(0) = 0$, $x_2(0) = -x_3(0) = 0.1$, $x_4(0) = -x_5(0) = 0.2$,
 $\psi(t) = \exp(-0.8t)$ and a line coupling we obtain

Average dynamics
= global gradient descent



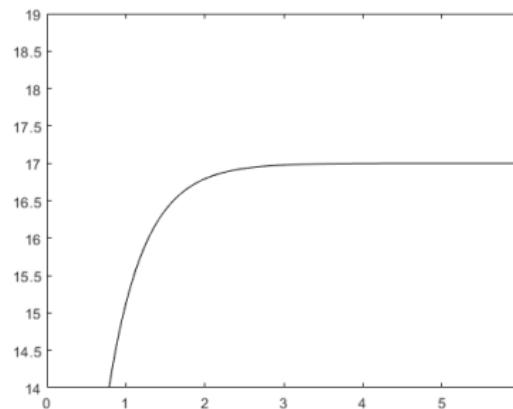
Constant gain
 $k = 100$



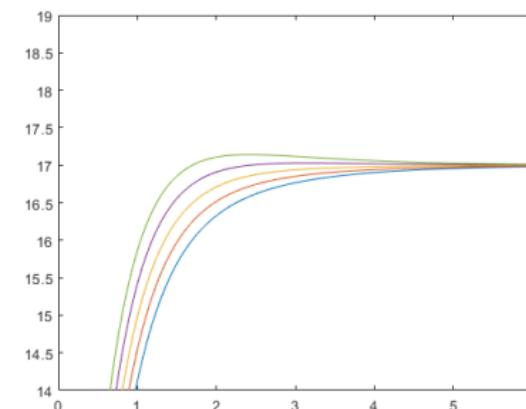
Simulation

For $A = [1, 1, 2, 2, 1]^\top$ and $b = [1, 10, 20, 18, 100]^\top$,
 $x_1(0) = 0$, $x_2(0) = -x_3(0) = 0.1$, $x_4(0) = -x_5(0) = 0.2$,
 $\psi(t) = \exp(-0.8t)$ and a line coupling we obtain

Average dynamics
= global gradient descent



Edgewise Funnel coupling



Conclusion

Optimization problem

$\min_x F(x)$ with convex $F = \sum_i F_i$ can be solved

- › completely decentralized
- › no derivatives need to be communicated
- › prespecified convergence rate (funnel)
- › asymptotic convergence

Future work

- › Decentralized optimization
 - › Constrained optimization
 - › Nonconvex cost function
- › Funnel coupling
 - › Other applications, e.g. decentralized observation/control
 - › Directed graphs