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CDC-2024
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Stability of Nonexpansive Monotone Systems and Application to Recurrent Neural Networks

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IEEE 63rd Conference on Decision and Control 2024 – December 16-19 – Milan, Italy

Outline

- ① Introduction
- ② Main Results
- ③ Application to Recurrent Neural Networks
- ④ Conclusions

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Definition: Subtopical systems

A dynamical system with state $x(t) \in \mathbb{R}^n$ at time t , and solution $\varphi(t, x_0) = x(t)$ from the initial condition $x(0) = x_0$, is said to be *topical* if it is:

- **Monotone**., i.e., solutions preserve the ordering between the initial conditions:

$$y_0 \leq z_0 \Rightarrow \varphi(t, y_0) \leq \varphi(t, z_0), \quad \forall y_0, z_0 \in \mathbb{R}^n, t \geq 0;$$

- **1-(sub)homogeneous**, i.e., solutions are (sub)invariant to rigid transformations:

$$\varphi(t, x_0 + \alpha \mathbf{1}) \leq \varphi(t, x_0) + \alpha \mathbf{1}, \quad \forall x_0 \in \mathbb{R}^n, \alpha \geq 0, t \geq 0.$$

Known fact: trajectories of these systems always converge to equilibrium points (if any exist).

D. Deplano, M. Franceschelli, and A. Giua, “*Novel Stability Conditions for Nonlinear Monotone Systems and Consensus in Multi-Agent Networks*”, in IEEE Transaction on Automatic Control (2023)

Main question: does the result hold for general η -subhomogeneity with $\eta \in \mathbb{R}_+^n$?

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Multi-Robot Systems



Peer-to-Peer Networks



Chemical Reaction Networks



Neural Networks

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Result 1

A smooth monotone system $\dot{x}(t) = f(x(t))$ is η -subhomogeneous with $\eta \in \mathbb{R}_+^n$ if and only if it is nonexpansive w.r.t. the diagonally weighted supremum norm

$$\|x\|_{\infty, [\eta]^{-1}} = \max_{i=1, \dots, n} \frac{1}{\eta_i} |x_i|.$$

Sketch of the proof:

- Change of variable $z(t) = [\eta]^{-1} x(t)$ where $[\eta]$ denotes a diagonal matrix with the entries of η ;
- The new system $z(t)$ is monotone and 1-subhomogeneous;
- Under monotonicity, 1-subhomogeneous is equivalent to nonexpansiveness w.r.t. $\|\cdot\|_{\infty}$ [R1];
- One-to-one relation between trajectories $x(t)$ and $z(t)$;
- The system $x(t)$ is nonexpansive w.r.t. $\|\cdot\|_{\infty, [\eta]^{-1}}$ iff the system $z(t)$ is nonexpansive w.r.t. $\|\cdot\|_{\infty}$.

[R1] B. Lemmens and R. Nussbaum, Nonlinear Perron-Frobenius Theory. Cambridge University Press, 2012.

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Result 2

Consider a smooth system $\dot{x}(t) = f(x(t))$ satisfying the following:

- the system is monotone and nonexpansive w.r.t. $\|\cdot\|_{\infty, [\eta]}^{-1}$;
- the set of equilibrium points $\mathcal{F}(f) \neq \emptyset$ is not empty.

Then all equilibrium points are stable and each trajectory converges asymptotically to one of them.

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[R2] D. Deplano, M. Franceschelli, and A. Giua, "Novel stability conditions for nonlinear monotone systems and consensus in multi-agent networks", IEEE Transactions on Automatic Control (2023).

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How to practically use these results?

Result 3

For a smooth monotone system $\dot{x}(t) = f(x(t))$, the following statements are equivalent:

- (a) The system is nonexpansive w.r.t. $\|\cdot\|_{\infty, [\eta]^{-1}}$;
- (b) the system is η -subhomogeneous;
- (c) the vector field satisfies $f(x + \alpha\eta) \leq f(x)$, $\forall x \in \mathbb{R}^n, \alpha \geq 0$;
- (d) the Jacobian satisfies $Df(x)\eta \leq 0$, $\forall x \in \mathbb{R}^n$.

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Result 3

For a smooth monotone system $\dot{\mathbf{x}}(t) = f(\mathbf{x}(t))$, the following statements are equivalent:

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- (d) the Jacobian satisfies $Df(\mathbf{x})\boldsymbol{\eta} \leq \mathbf{0}$, $\forall \mathbf{x} \in \mathbb{R}^n$.

A simple example

Consider the class of dynamical systems $\dot{x}(t) = f(x(t))$ on \mathbb{R}^2 with dynamics:

$$\dot{x}(t) = \begin{bmatrix} \dot{x}_1(t) \\ \dot{x}_2(t) \end{bmatrix} = \begin{bmatrix} -x_1(t) + \alpha x_2(t) - \gamma g(x_1) \\ \beta x_1(t) - x_2(t) \end{bmatrix}$$

where $\alpha, \beta, \gamma \geq 0$ and $g: \mathbb{R} \mapsto \mathbb{R}_{\geq 0}$ is C^1 such that $g(0) = 0$ and $g'(x) \geq 0$ for all $x \in \mathbb{R}$.

- **Monotonicity** holds because the Jacobian $Df(x(t))$ of the vector field is Metzler, indeed,

$$Df(x_1, x_2) = \begin{bmatrix} -1 - \gamma \frac{d}{dt} g(x_1) & \alpha \\ \beta & -1 \end{bmatrix}.$$

- **η -subhomogeneity** holds for $\alpha\beta \leq 1$, indeed,

$$\begin{cases} -(1 + \gamma \frac{d}{dt} g(x_1(t)))\eta_1 + \alpha\eta_2 \leq 0 \\ \beta\eta_1 - \eta_2 \leq 0 \end{cases} \Rightarrow \eta_2 \in [\beta\eta_1, \frac{1}{\alpha}\eta_1].$$

NB: For $\alpha = 0.5$ and $\beta = 2$ the system is nonexpansive but “**non-contracting**”.
Yet, the system converges to one of the equilibrium points.

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We consider two models of RNNs [R3], the Hopfield and the firing-rate models, with dynamics

$$\dot{\mathbf{x}}(t) = f_H(\mathbf{x}(t)) := -C\mathbf{x}(t) + A\Phi(\mathbf{x}(t)) + \mathbf{b}, \quad (1)$$

$$\dot{\mathbf{x}}(t) = f_{FR}(\mathbf{x}(t)) := -C\mathbf{x}(t) + \Phi(A\mathbf{x}(t) + \mathbf{b}), \quad (2)$$

where $C \in \mathbb{R}^{n \times n}$ is a positive diagonal matrix, $A \in \mathbb{R}^{n \times n}$ is an arbitrary matrix, $\mathbf{b} \in \mathbb{R}^n$ is a constant input, and $\Phi : \mathbb{R}^n \mapsto \mathbb{R}^n$ is an activation function satisfying the followign assumption.

Assumption 1

Activation functions are diagonal, i.e., $\Phi(\mathbf{x}) = [\phi_1(x_1), \dots, \phi_n(x_n)]^\top$ where each $\phi_i : \mathbb{R} \mapsto \mathbb{R}$ is continuously differentiable and globally Lipschitz, i.e., there exists finite $d_1 \leq d_2$ such that for all $i = 1, \dots, n$ it holds

$$\frac{d}{dx} \phi_i(x) \in [d_1, d_2], \quad \forall x \in \mathbb{R},$$

and the Lipschitz constant is given by $\bar{d} = \max\{|d_1|, |d_2|\}$.

[R3] A. Davydov, A.V. Proskurnikov, F. Bullo, “Non-Euclidean contraction analysis of continuous-time neural networks”, IEEE Transactions on Automatic Control, 2024.

Result 4

Consider Hopfield and firing-rate neural networks as in eqs. (1)-(2) with activation function satisfying Assumption 1. Let $A_\star = \min\{d_1 A, d_2 A\}$ and $A^\star = \max\{d_1 A, d_2 A\}$ satisfy the following conditions:

- A_\star is Metzler (monotonicity);
- $\exists \boldsymbol{\eta} \in \mathbb{R}_+^n : (A^\star - C)\boldsymbol{\eta} \leq \mathbf{0}$ ($\boldsymbol{\eta}$ -subhomogeneity).

Then, all their trajectories converge to some equilibrium point, if any exists.

Some examples of nonexpansive RNNs that are nonexpansive but not contracting can be found for any nonnegative matrix $A \geq 0$ and choosing:

- ① $C = \lambda_{\max} I$, where λ_{\max} is the largest eigenvalue of A . In this case, the system is nonexpansive w.r.t. $\|\cdot\|_{\infty, \mathbf{v}^{-1}}$ where \mathbf{v} is the eigenvector associated with λ_{\max} ;
- ② $C = \text{diag}(A\mathbf{1})$. In this case, the system is nonexpansive w.r.t. $\|\cdot\|_{\infty}$;
- ③ $C = \text{diag}((A\boldsymbol{\eta}))[\boldsymbol{\eta}]^{-1}$ for any $\boldsymbol{\eta} \geq 0$. In this case, the system is nonexpansive w.r.t. $\|\cdot\|_{\infty, \boldsymbol{\eta}^{-1}}$.

NB: This result holds for a class of RRNs that is not considered in the state-of-the-art.

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Contribution 1

- Smooth monotone systems are subhomogeneous if and only if they are nonexpansive w.r.t. a **diagonally weighted sup-norm**;
- Trajectories of smooth monotone systems that are nonexpansive w.r.t. a diagonally weighted sup-norm **converge toward equilibrium points**, if any exist;
- **Necessary and sufficient conditions** for subhomogeneity (and, in turn, nonexpansiveness) are given in terms of the Jacobian matrix of their vector field.

Contribution 2

Application to Recurrent Neural Networks (RNNs) with Hopfield and firing-rate dynamics:

- Monotonicity and subhomogeneity of these neural networks ensure convergence of their state trajectories **even if their dynamics are not contractive**.

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Application to Recurrent Neural Networks (RNNs) with Hopfield and firing-rate dynamics:

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Open questions and future directions

- Do these results hold also for Lipschitz dynamical systems (not necessarily continuously differentiable)?
- How nonexpansiveness is related to subhomogeneity when monotonicity does not hold?
- What is the relation with monotone operators in functional analysis?



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Thank you for your attention!

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