

Towards Non-quadratic Absolute Stability Theory

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Plan of The Talk

Non-quadratic Lyapunov functions: Motivation

Lur'e systems and classical S-lemma

General norms as Lyapunov functions: Extended S-lemma

Absolute stability in non-Euclidean norms.

Non-Quadratic Lyapunov Functions



- systems, LPV systems etc. polyhedral and other LFs
- Still underrepresented; regular design methods are still missing.

F. Bullo, Contraction Theory for Dynamical Systems, Kindle Direct Publishing, Edition 1.1, Mar 1, 2023 F. Bullo, Lectures on Network Systems, Kindle Direct Publishing, Edition 1.6, Jan 1, 2022



 Non-quadratic LF prove to be useful in many applications: Models of populations (Lotka-Volterra etc.), monotone systems, cell transmission models, compartmental

• This work: revise one of the oldest application of quadratic LF (Lur'e systems stability/contraction) and expand the design approach to some non-quadratic LF.



Contraction in "Non-Standard" Norms: Resilience



- Noises are naturally characterized in non-Euclidean norms (standard or weighted ()
- Lipschitz constants are also mainly interesting in l_{∞}
- are too large.

Liang, Huang, Large Norms of CNN Layers Do Not Hurt Adversarial Robustness//2021, AAAI Conference on Artificial Intelligence, 35(10), 8565-8573. Davydov et al., Non-Euclidean Contraction Analysis of Continuous-Time Neural Networks, IEEE TAC 2025 (online) Jafarpour et al., Robust Implicit Networks via Non-Euclidean Contractions//Adv. Neural Information Processing Systems 34, 2021

Resilience and regularization of CNNs, RNNs, GNNs to adversarial attacks, efficient Lipschitz constants

Slight perturbation of an image leads to incorrect classification: "adversarial examples"

Computation of Lipschitz constants can be much more efficient than for the Euclidean norm by (LP vs. SDP). Algorithms to compute fixed-points of neural nets, tight convergence bounds in l_1 and l_{∞}

Topological equivalence of norms on a space of a huge dimension is misleading: comparison factors





Lur'e Problem (1957): The Launchpad for Robust Nonlinear Control



- Absolute stability GAS of x = 0 for any nonlinear element from a given class **Absolute contractivity – contractivity for any nonlinear element from a given class** Class – usually, very broad (sector, slope or other quadratic constraint)

Lur'e, Postnikov, Some Nonlinear Problems in the Theory of Automatic Control, Her Majesty Stationary Office, 1957







Absolute Stability: Two Main Tracks in 1960-1990s

Common Lyapunov stability certificates for the state space models

Lur'e, Barbashin, Persidskii, Kalman, Rosenwasser, Yakubovich, Barabanov, Narendra,...

$$V(x) = x^{\top} H x \qquad \left[+ \int_0^y \varphi(s) ds \right]$$

- Lyapunov condition V < 0: quadratic constraints + S-Procedure

Integral operators in L2 space Popov, Desoer, Vidyasagar, Yakubovich, Zames, Falb, Rasvan, Megretskii, Rantzer,...

General Volterra equations (also, infinite-dimensional) Stability in integral L_2 norm, little information about transient process Conditions in frequency domain: hard to verify in MIMO case

(additional term, optional)

Existence of the LF -- frequency-domain condition via KYP lemma (old) or **LMIs** (modern). **Depending on a problem, entails** GAS, contractivity, output stability, instability, oscillations.



Vasile Mihai Popov (born 1928)



S-Procedure: A Simple Example



Try to prove contractivity using a quadratic (incremental) LF $V(\Delta x) = (\Delta x)^{\top} H(\Delta x) \Longrightarrow \dot{V} = 2(\Delta x)^{\top} H(A\Delta x + B\Delta w)$

Lyapunov condition for contractivity: how to get it?



S-procedure: implication (?) holds if $2(\Delta x) \cdot H(A\Delta x + B\Delta w) + \varepsilon \|x\|_2^2$ $\leq \tau \Delta w (\varkappa^{-1} \Delta w - C \Delta x)$ for some $\tau \geq 0$ and all variables

$\Delta w \in \mathbb{R}, \Delta x \in \mathbb{R}^n.$ It is an LMI on $H \succ 0, \tau \ge 0$



Slope inequality!

 $\Delta w(\varkappa^{-1}\Delta w - \Delta y) \le 0,$ $\Delta y = C\Delta x$





S-Lemma: S-Procedure is "Lossless".



The Yakubovich S-Lemma: (?) holds for all variables $\Delta w \in \mathbb{R}, \Delta x \in \mathbb{R}^n$ if and only if $\tau \ge 0$ exists satisfying the inequality

Vladimir A. Yakubovich 1926-2012

S-procedure finds all quadratic LFs helping to derive contraction from the single slope constraint.







The idea of S-procedure is inspired by Lagrange multipliers. There is an explicit relation between S-lemma and the Lagrange duality.

 $\Delta w(\varkappa^{-1}\Delta w - \Delta y) \le 0,$ $\Delta y = C \Delta x$

Further Developments of S-Lemma

- essay, Automation and Remote Control, 67 (2006), pp. 1768–1810
- I. Polik and T. Terlaky, A survey of the S-lemma, SIAM Review, 49 (2007), pp. 371–418 $x^{\top}Q_1x < 0, \dots, x^{\top}Q_nx < 0 \Longrightarrow x^{\top}Px < 0$
 - Holds if there exist multipliers $\tau_1 \ge 0$, $\tau_2 \ge 0$,..., $\tau_n \ge 0$ such that $P \le \sum_i \tau_j Q_j$
 - For usual quadratic forms, it is SDP feasibility. Can also be validated for integral functionals on L₂.
 - The "only if" part is a rather exceptional property:
 - a) n=1 (Yakubovich);

 - b) n=2 (Hermitian forms on a complex space (Yakubovich, Fradkov); c) integral functionals on L₂ (Megretsky, Treil, Yakubovich, Matveev etc.) – n arbitrary.

• S.V. Gusev, A.L. Likhtarnikov, Kalman-Popov-Yakubovich lemma and the S-procedure: A historical

Non-Quadratic Lyapunov Functions in Absolute Stability

- Special class of Non-quadratic LFs squared norms
- General results on absolute stability of differential inclusions and switching systems (E.S. Pyatnitskii et al., Barabanov N.E.): existence of the non-Euclidean LF of this structure, approximations by polyhedral norms.
- Davydov et al. work New insights about use of such LFs for contraction and stability
 - \checkmark Derive the Lyapunov condition V < 0 from "pseudo-quadratic" constraint + S-Lemma
 - ✓Existence of LF: conditions involving the log-norm ("matrix measure"). For each specific norm, convex optimization problem.
 - \checkmark Efficient stability/contractivity conditions in non-Euclidean norm, e.g., l_1 and l_{∞} (important in machine learning, e.g., robustness certificates for NN, also for systems with conserved quantities, distributed iterations)

Alexander Davydov, Saber Jafarpour, Francesco Bullo, Non-Euclidean Contraction Theory for Robust Nonlinear Stability, IEEE TAC 2022

 $V(x) = ||x||^2$









Technical Prelimianries - I



Derivative of the (differentiable) curve's norm

Compatible WP is non-unique be) chosen in such a way that

$$\mu(A) = \sup_{|x|=1} [Ax, x]$$

$$\frac{d}{dt} ||x(t)||^2 = [\dot{x}(t), x(t)] \quad \text{a.e.}$$



Technical Prelimianries - II

Norm	Weak pairing	Log norm
$\ x\ _2 = \sqrt{x^\top x}$	$[\![x,y]\!]_2 = x^\top y$	$\mu_2(A) = \frac{1}{2}$
$\ x\ _p = \left(\sum_i x_i ^p\right)^{1/p},$ 1	$ \begin{split} \llbracket x, y \rrbracket_p &= \\ \ y\ _p^{2-p} (y \circ y ^{p-2})^\top x \end{split} $	$\mu_p(A) =$
$\ x\ _1 = \sum_i x_i $	$[x, y]_1 = y _1 \operatorname{sign}(y)^\top x$	$\mu_1(A) =$

 $\|x\|_{\infty} = \max_{i} |x_{i}| \qquad [x, y]_{\infty} = \max_{i \in I_{\infty}(y)} x_{i} y_{i}$

TABLE 1 Table of norms, weak pairings, and log norms for ℓ_2 , ℓ_p for $p \in (1, \infty)$, ℓ_1 , and ℓ_∞ norms. We adopt the shorthand $I_{\infty}(x) = \{i \in \{1, ..., n\} \mid |x_i| = ||x||_{\infty}\}.$

ns and Lumer's equality

 $\frac{1}{2}\lambda_{\max}(A+A^{\top})$ $\max_{\|x\|_{2}=1}x^{\top}Ax$

 $\max_{\|x\|_p=1} (x \circ |x|^{p-2})^\top A x$

$$\max_{\substack{j \in \{1,...,n\}}} \left(a_{jj} + \sum_{i \neq j} |a_{ij}| \right)$$
$$\sup_{\|x\|_1 = 1} \operatorname{sign}(x)^\top A x$$

Easy to find: p=1,2, ∞

Quite difficult to find for a general p, leads to the non-convex optimization problem.

The operator p-norm computation is known to be NP hard (seems to be an open problem for log-norms).

$$\max_{i \in \{1,...,n\}} \left(a_{ii} + \sum_{j \neq i} |a_{ij}| \right)$$
$$\sup_{\|x\|_{\infty} = 1} \max_{i \in I_{\infty}(x)} (Ax)_{i} x_{i}$$

eral p, ization tion is b be an

"Pseudo-Quadratic" S-Lemma.

? $[Px, x] \le 0$

<u>Lemma.</u> Let the WP [,] and the log-norm μ correspond to the same vector norm $\|\cdot\|$.

The implication (?) is valid for each vector x if a parameter $au \geq 0$ exists such that $\ \mu(P- au Q) \leq 0.$

Proof: Without loss of generality (since both inequalities are homogeneous), ||x|| = 1.

 $[Px, x] < [Px - \tau Qx, x] + [\tau Qx, x] \le \mu (P - \tau Q) + \tau [Qx, x] \le \tau [Qx, x].$

Suppose that one wishes to prove the following implication with "pseudo-quadratic" forms:

$[Qx, x] \le 0$

"Pseudo-Quadratic" S-Lemma: Some Remarks

$$x^{\top} P x = [P x, x] \le 0 \quad \longleftarrow$$

$$\mu(P-\tau Q) \rightarrow$$

- The problem is convex, because the log-norm is a convex function
- special norms, e.g. l_1 , l_2 , l_{∞} .
- multipliers arise)



$x^{\top}Qx = [Qx, x] \le 0$

inf s.t. $\tau > 0$

• S-lemma in the general case reduces to optimization problem (the implication holds if inf <= 0)

• The oracle computing the function (and gradient, if needed) is of high complexity, except for

Can be trivially generalized to the case of multiple "pseudo-quadratic constraints" (several

Leads to new absolute stability and absolute contraction criteria in non-Euclidean norms.



S-procedure with a Non-Euclidean Norm



It remains to apply S-lemma!

$$\dot{V} \leq -c \|\Delta x\|_{p}^{2} \iff \\ \iff [A\Delta x + c\Delta x + B\Delta w, \Delta x]_{p} \leq 0 \\ \iff \left[\begin{pmatrix} A + cI & B \\ 0 & 0 \end{pmatrix} \begin{pmatrix} \Delta x \\ \Delta w \end{pmatrix}, \begin{pmatrix} \Delta x \\ \Delta w \end{pmatrix} \right]_{p} \leq 0$$

$V(\Delta x) = \|\Delta x\|_{p,R}^2 = \|R\Delta x\|_p^2, \ \det R \neq 0.$

Program: repeat the trick with S-lemma.

- Write the slope restriction as a "pseudo-quadratic" constraint
- Write the Lyapunov condition as a "pseudo-quadratic" constraint
- Apply S-lemma

?

- Principal difference: extended statecontrol vector needs to be used!
- For simplicity, let *R=I*.



 $0 \le \frac{\Delta w}{\Delta y} \le \varkappa \Longleftrightarrow$



Applying S-Lemma: Contraction in (Norm



Theorem. The system is contractive with respect to the norm $\|\Delta x\|_p$ and rate c if $\tau \ge 0$ exists such that

$$\mu_p \begin{pmatrix} A + cI & RB \\ \tau C & -\tau \varkappa^{-1} \end{pmatrix} \le 0$$



Remarks:

- This constraint is convex!
- However, the computation of the lognorm is troublesome (optimization with a computationally expensive oracle).
- Easily computable for:
- **p=1 or** ∞
- p=2: classical LMIs.



More General Result: Contraction in Weighted (, Norm



Theorem. The system is contractive with respect to the (non-Euclidean) norm $\|\Delta x\|_{p,R} = \|R\Delta x\|_p$

and rate c if $\tau \ge 0$ exists such that

$$\mu_p \begin{pmatrix} RAR^{-1} + cI & RB \\ \tau CR^{-1} & -\tau\varkappa^{-1} \end{pmatrix} \le 0$$

Remarks:

- For a **fixed** weight matrix, the condition is convex. For a variable weight, the constraint is non-convex!
- Sometimes, the problem reduces to quasi-convex optimization (Davydov, Proskurnikov, Bullo, IEEE TAC 2025)
- $p=1 \text{ or } \infty + \text{diagonal weight matrix } R$
- p=2: classical LMIs
 - Example (in the journal paper): strong Kalman conjecture for positive systems. If $A, A - \varkappa BC$ are Hurwitz and Metzler, then the R = R(p) exists for all p (contraction is any norm is guaranteed).









Conclusions and Future Works

- Journal Paper: A.V. Proskurnikov, A. Davydov, F. Bullo, The Yakubovich S-Lemma Revisited: Stability and Contractivity in Non-Euclidean Norms, SICON 2023
- Many details omitted in this talk
- Some examples
- Journal Paper: A.V. Proskurnikov, A. Davydov, F. Bullo, Non-Euclidean contraction analysis of continuous-time neural networks, TAC 2025
- Applications to contractivity and Lipschitz constant computation for RNNs
- Special norms: Weighted l_1 and l_{∞}

Topics for future research:

- **Efficient computational algorithms: how to validate log-norm criteria?**
- **Complicated nonlinearities:**
- NNs, dynamical blocks, optimization solvers (control allocation logic, MPC etc.)
- **Does non-quadratic norms work better? Can we outperform classical stability criteria with non-quadratic norms?**

