

# Computation of Lyapunov functions and contraction metrics for dynamical systems

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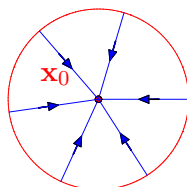
# 1. Basin of attraction of an equilibrium

System of autonomous ordinary differential equations

$$(1) \quad \begin{cases} \frac{d}{dt}\mathbf{x}(t) = \dot{\mathbf{x}}(t) = \mathbf{f}(\mathbf{x}(t)) \\ \mathbf{x}(0) = \boldsymbol{\xi} \end{cases}$$

$$\mathbf{x}(t) \in \mathbb{R}^n, \mathbf{f}: \mathbb{R}^n \rightarrow \mathbb{R}^n$$

Solution of (1) is called **flow** and denoted  $S_t \boldsymbol{\xi} := \mathbf{x}(t)$



## Assumptions

- $\mathbf{x}_0$  is **equilibrium** ( $\mathbf{f}(\mathbf{x}_0) = \mathbf{0}$ )
- $\mathbf{x}_0$  is **asymptotically stable** (eigenvalues of  $D\mathbf{f}(\mathbf{x}_0)$ )

**Definition (Basin of attraction)** The basin of attraction of  $\mathbf{x}_0$  is

$$A(\mathbf{x}_0) := \{\boldsymbol{\xi} \in \mathbb{R}^n \mid \|S_t \boldsymbol{\xi} - \mathbf{x}_0\| \xrightarrow{t \rightarrow \infty} 0\}.$$

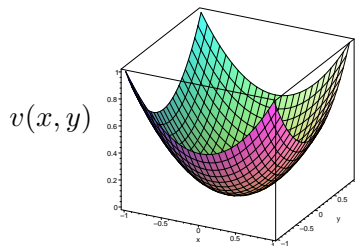
$\mathbf{x}_0$  is called globally stable, if  $A(\mathbf{x}_0) = \mathbb{R}^n$

In general difficult to determine.

**Goal:** Determine **basin of attraction**  $A(\mathbf{x}_0)$  using a **Lyapunov function**

## Idea

- Lyapunov function is like energy in dissipative system
- It implies stability of equilibrium and gives lower bound on basin of attraction
- Has minimum at equilibrium
- Is strictly decreasing along solutions



## Definition

Let  $\mathbf{x}_0$  be an equilibrium. Let

- $v \in C^1(\mathbb{R}^n, \mathbb{R})$
- $U \subset \mathbb{R}^n$  neighborhood of the equilibrium  $\mathbf{x}_0$
- $v$  has strict minimum at equilibrium:  
 $v(\mathbf{x}) \geq 0$  for all  $\mathbf{x} \in U$  and  $v(\mathbf{x}) = 0$  if and only if  $\mathbf{x} = \mathbf{x}_0$
- $v$  is strictly decreasing along trajectories:  
 $\dot{v}(\mathbf{x}) \leq 0$  for all  $\mathbf{x} \in U$  and  $\dot{v}(\mathbf{x}) = 0$  if and only if  $\mathbf{x} = \mathbf{x}_0$

Then  $v$  is called a **strict Lyapunov function** and  $\mathbf{x}_0$  is asymptotically stable.

$\dot{v}$  derivative along solutions or **orbital derivative**

## Definition (Orbital derivative)

Let  $v \in C^1(\mathbb{R}^n, \mathbb{R})$ . The derivative of  $v$  along solutions  $S_t \mathbf{x}$  of  $\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x})$ , the orbital derivative, is defined as

$$\dot{v}(\mathbf{x}) = \frac{d}{dt} v(S_t \mathbf{x}) \Big|_{t=0} = \nabla v(\mathbf{x}) \cdot \mathbf{f}(\mathbf{x}) = \sum_{i=1}^n \frac{\partial v}{\partial x_i}(\mathbf{x}) f_i(\mathbf{x})$$

## Theorem

Let  $\mathbf{x}_0$  be equilibrium,  $U$  open neighborhood of  $\mathbf{x}_0$  and  $v: \mathbb{R}^n \rightarrow \mathbb{R}$  strict Lyapunov function.

Let  $S_R = \{\mathbf{x} \in \mathbb{R}^n \mid v(\mathbf{x}) \leq R\}$  for  $R \in \mathbb{R}_0^+$  be a *sublevel set* of  $v$  and assume that

- $S_R$  is compact
- $S_R \subset U$

Then  $S_R \subset A(\mathbf{x}_0)$  and  $S_R$  is *positively invariant*.

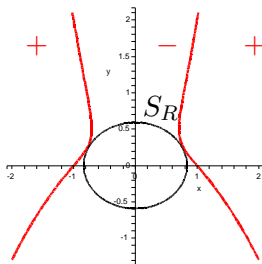
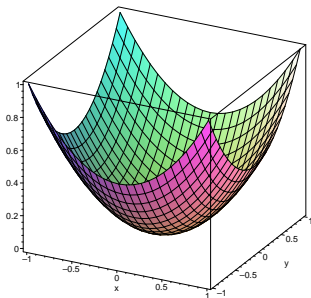
**Remark:** Positive invariance is true if  $\dot{v}(\mathbf{x}) < 0$  holds for all  $\mathbf{x} \in \partial S_R = \{\mathbf{x} \in \mathbb{R}^n \mid v(\mathbf{x}) = R\}$

# Example

$$\begin{cases} \dot{x} &= -x + x^3 \\ \dot{y} &= -\frac{1}{2}y + x^2 \end{cases}$$

$$v(x, y) = \frac{1}{2}x^2 + y^2$$

$$\begin{aligned} \text{sign of } \dot{v}(x, y) &= \nabla v(x, y) \cdot \mathbf{f}(x, y) \\ &= \begin{pmatrix} x \\ 2y \end{pmatrix} \cdot \begin{pmatrix} -x + x^3 \\ -\frac{1}{2}y + x^2 \end{pmatrix} \end{aligned}$$





## 2. Existence and construction of Lyapunov functions

- “converse Theorems” (Massera 1949) etc. – but **not constructive!**
- explicit construction possible for linear equations, special cases
- used in applications (engineering, biology)

We will present two general construction methods:

- construct continuous and piece-wise affine (CPA) Lyapunov functions
- solve a partial differential equation by meshless collocation with Radial Basis Functions (RBF)

For more methods, see review (Giesl, Hafstein 2015)

**Reminder:** for a Lyapunov function we require

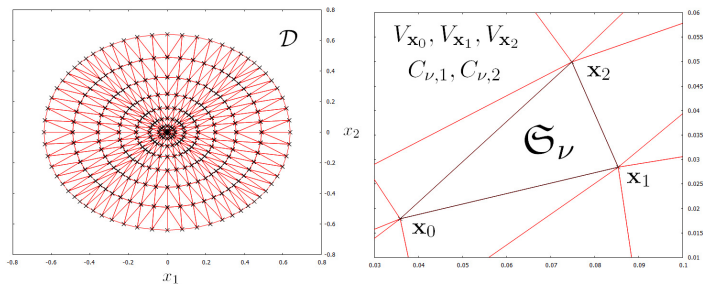
- $V(\mathbf{x}) \geq 0$
- $\dot{V}(\mathbf{x}) \leq 0$

## 2.1 CPA method

Continuous piece-wise affine function, affine on each simplex

- define triangulation: collection  $\mathcal{T}$  of simplices  $\mathcal{S} = \text{co}(\mathbf{x}_0, \mathbf{x}_1, \dots, \mathbf{x}_n)$
- vertex set  $\mathcal{V}_{\mathcal{T}}$
- $h_C$ : largest distance of vertices in a simplex

### Example of triangulation

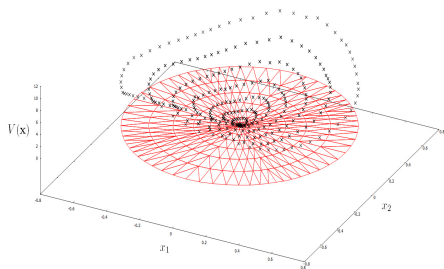


# CPA function

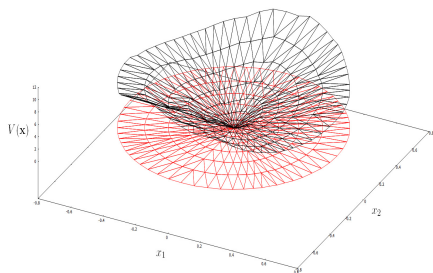
CPA function defined by values on vertices:

- i) Fix  $V_{\mathbf{x}}$  for every  $\mathbf{x} \in \mathcal{V}_{\mathcal{T}}$  (vertex set)
- ii)  $V$  is affine on every simplex  $\mathcal{S}_{\nu} \in \mathcal{T}$ , i.e.  $V(\mathbf{x}) = \mathbf{a}_{\nu}^T \mathbf{x} + b_{\nu}$  for  $\mathbf{x} \in \mathcal{S}_{\nu}$  with  $\mathbf{a}_{\nu} \in \mathbb{R}^n$ ,  $b_{\nu} \in \mathbb{R}$

## Values at vertices



## CPA function



Translate Lyapunov function conditions

- 1  $V(\mathbf{x}) \geq \|\mathbf{x}\|$
- 2  $\dot{V}(\mathbf{x}) \leq -\|\mathbf{x}\|$

into sufficient conditions on values at vertices

For every  $\mathcal{S}_\nu = \text{co}(\mathbf{x}_0, \mathbf{x}_1, \dots, \mathbf{x}_n)$  and every vertex  $\mathbf{x}_i \in \mathcal{S}_\nu$ ,

- 1  $V(\mathbf{x}_i) \geq \|\mathbf{x}_i\|$
- 2  $\dot{V}(\mathbf{x}_i) + B_\nu h_C^2 \|\nabla V_\nu\|_1 \leq -\|\mathbf{x}_i\|$  where  
 $B_\nu \geq \max_{m,r,s=1,\dots,n} \max_{\mathbf{x} \in \mathcal{S}_\nu} \left| \frac{\partial^2 f_m}{\partial x_r \partial x_s}(\mathbf{x}) \right|$ ,  $h_C$  size of simplex

## Remarks

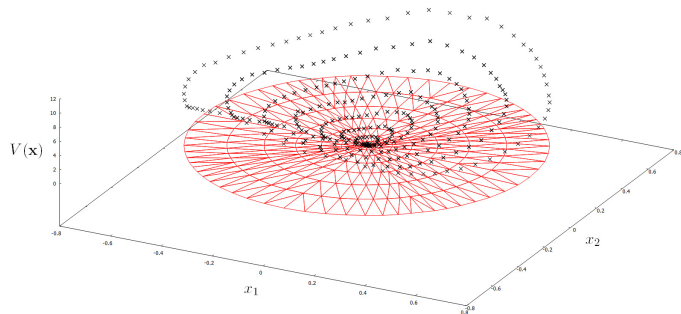
- $B_\nu$  need to be input by hand – only upper bounds necessary
- $V$  is not differentiable, but smooth on each simplex
- Constraints are linear in  $V(\mathbf{x}_i)$

# Solution to the LP problem $\implies$ CPA Lyapunov function

- Write conditions as constraints of Linear Programming (LP) problem with variables  $V_{x_i}$
- If the LP problem has a solution, then the CPA function is a Lyapunov function
- Note: not a numerical approximation,  $V$  is a Lyapunov function!
- Moreover, if the triangulation is sufficiently fine, then the method always finds a Lyapunov function

# Example

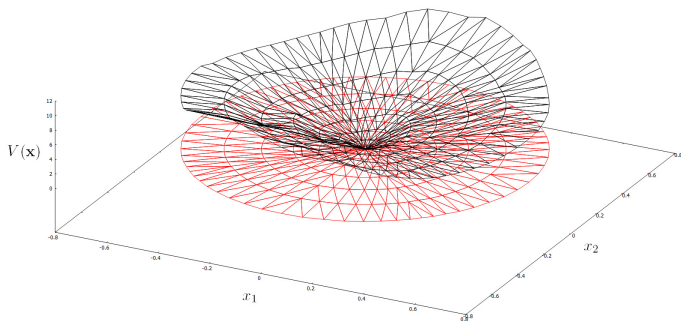
$$\begin{pmatrix} \dot{x}_1 \\ \dot{x}_2 \end{pmatrix} = \begin{pmatrix} x_2 \\ -x_1 + x_1^3/3 - x_2 \end{pmatrix}, \quad B_\nu = 2 \max_{x \in \mathcal{S}_\nu} |x_1|$$



$V_x$  solution to the LP problem

# Example

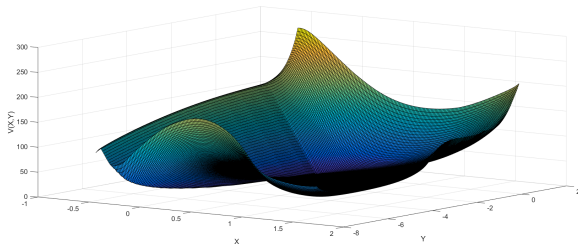
$$\begin{pmatrix} \dot{x}_1 \\ \dot{x}_2 \end{pmatrix} = \begin{pmatrix} x_2 \\ -x_1 + x_1^3/3 - x_2 \end{pmatrix}, \quad B_\nu = 2 \max_{x \in \mathcal{S}_\nu} |x_1|$$



CPA Lyapunov function

# Computing sublevel sets

- find connected component which includes equilibrium
- increase level
- until boundary of admissible area reached
- results in subset of basin of attraction
- algorithm for CPA functions





## 2.2 Meshfree collocation with Radial Basis Functions (RBF)

### Converse Theorem

#### Theorem (Existence of $V$ )

Let  $\mathbf{f} \in C^\sigma(\mathbb{R}^n, \mathbb{R}^n)$ ,  $\sigma \geq 1$ ,  $\mathbf{0}$  exponentially stable equilibrium.  
Then there exists  $V \in C^\sigma(A(\mathbf{0}), \mathbb{R})$  with

$$(2) \quad \dot{V}(\mathbf{x}) := \nabla V(\mathbf{x}) \cdot \mathbf{f}(\mathbf{x}) = -\|\mathbf{x}\|^2 \text{ for all } \mathbf{x} \in A(\mathbf{0}).$$

**Proof:**  $V(\mathbf{x}) = \int_0^\infty \|S_t \mathbf{x}\|^2 dt$

**Goal:** explicit construction of Lyapunov function

**Idea:** approximate solution of first-order linear PDE (2)

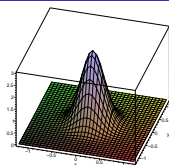
- Consider linear PDE

$$(PDE) \quad LV(\mathbf{x}) = \dot{V}(\mathbf{x}) = \sum_{i=1}^n f_i(\mathbf{x}) \frac{\partial V}{\partial x_i}(\mathbf{x}) = -\|\mathbf{x}\|^2$$

- **Approximation**  $V_R$  of  $V$  using **Meshless collocation**, in particular Radial Basis Functions (RBF)
- Approximation  $V_R$  itself **is a Lyapunov function**

# Radial Basis Functions: approximate solution of PDE

- PDE:  $LV(\mathbf{x}) = -\|\mathbf{x}\|^2$ ,  $L$  linear differential operator (**orbital derivative**)
- $\psi_k(\|\mathbf{x}\|)$  (Radial Basis Function), here:  $\psi_k$  Wendland's function (compact support)
- Corresponds to Reproducing Kernel Hilbert space  $H$  of functions with kernel  $\Phi(\mathbf{x}, \mathbf{y}) := \psi_k(\|\mathbf{x} - \mathbf{y}\|)$  (Sobolev space)
- **Collocation points**  $X_N = \{\mathbf{x}_1, \dots, \mathbf{x}_N\} \subset \mathbb{R}^n$ ,  $\lambda_i := (\delta_{\mathbf{x}_i} \circ L) \in H^*$
- Solution of problem



$$\begin{cases} \text{minimise} & \|V\|_H \\ \text{subject to} & LV(\mathbf{x}_i) = -\|\mathbf{x}_i\|^2, \forall \mathbf{x}_i \in X_N \end{cases}$$

is  $V_R(\mathbf{x}) = \sum_{j=1}^N \alpha_j \lambda_j^y \Phi(\mathbf{x}, \mathbf{y})$

- $\alpha \in \mathbb{R}^N$  determined by:  $\dot{V}_R(\mathbf{x}_j) = -\|\mathbf{x}_j\|^2$  for all  $j = 1, \dots, N$ , i.e.
- $A\alpha = r$ , where  $a_{ij} = \lambda_i^x \lambda_j^y \Phi(\mathbf{x}, \mathbf{y})$ ,  $r_i = -\|\mathbf{x}_i\|^2$
- $A$  is symmetric and positive definite  $\Rightarrow$  non-singular

$$|\dot{V}(\mathbf{x}) - \dot{V}_R(\mathbf{x})| \leq Ch_R^{k-1/2} \text{ for all } \mathbf{x} \in K$$

where

- $k$  smoothness of Radial Basis Function
- $h_R := \sup_{\mathbf{y} \in K} \min_{\mathbf{x} \in X_N} \|\mathbf{x} - \mathbf{y}\|$ : **fill distance**, measuring how dense collocation points are in  $K$

## Estimate

$V_R$  is Lyapunov function: if  $Ch_R^{k-1/2} \leq \varepsilon$ , then

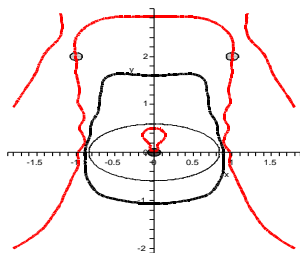
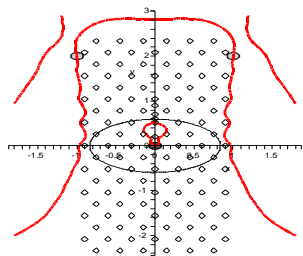
$$\dot{V}_R(\mathbf{x}) \leq \dot{V}(\mathbf{x}) + \varepsilon \leq -\|\mathbf{x}\|^2 + \varepsilon < 0$$

for  $\|\mathbf{x}\|^2 > \varepsilon$  (local problem)

# Example

$$\begin{cases} \dot{x} &= -x + x^3 \\ \dot{y} &= -\frac{1}{2}y + x^2 \end{cases}$$

Grid,  $\dot{v} = 0$ , sublevel set (thick black), previous sublevel set (thin black)



## Problem:

- How to verify  $\dot{V}_R(\mathbf{x}) < 0$  for all  $\mathbf{x} \in K$  (infinitely many)?
- Error estimate depends on  $V$  and is not known in practice

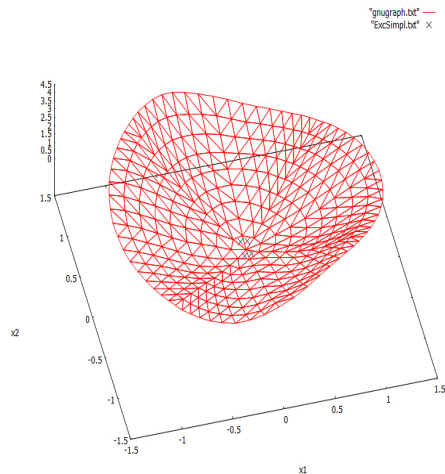
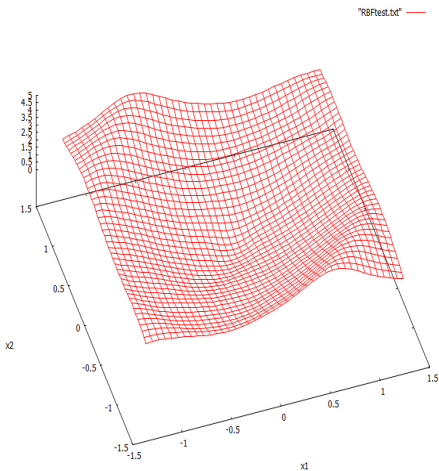
## Two methods:

- 1 Evaluate computed function at finitely many points, apply Taylor approximation with explicit bounds on derivatives.  
Many evaluation points, but verifies computed function
- 2 Use CPA (continuous piecewise affine) interpolation  $V_C$  of  $V_R$  and use verification as discussed earlier.  
Much faster, but verifies different function

Both methods can be shown to always work if evaluation/interpolation is sufficiently fine.

# Example 1: $\dot{x} = -y$ , $\dot{y} = x + y(x^2 - 1)$

RBF approximation  $19 \times 19$  – CPA interpolation,  $x -$  inequality violated  
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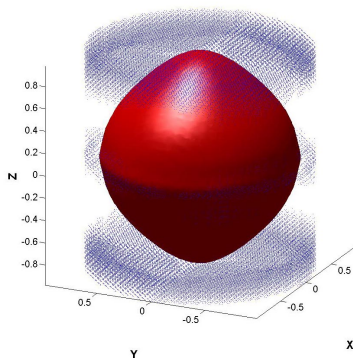


## Example 2

System:

$$\dot{\mathbf{x}} = \begin{pmatrix} x(x^2 + y^2 - 1) - y(z^2 + 1) \\ y(x^2 + y^2 - 1) + x(z^2 + 1) \\ 10z(z^2 - 1) \end{pmatrix}.$$

Level set (red); orbital derivative (of CPA interpolation) is not negative (blue dots)





## Lyapunov function

- minimum at equilibrium ( $v(\mathbf{x}) \geq 0$ )
- decreasing along solutions ( $\dot{v}(\mathbf{x}) \leq 0$ , orbital derivative)
- gives information about basin of attraction/positively invariant sets through (sub)level sets

## Construction methods

- CPA: affine function on simplices, conditions as constraints of Linear Programming problem
- RBF: smooth function, conditions as solution of linear Partial Differential Equation

# Comparison: CPA vs. RBF

- CPA and RBF work on compact set and have problems close to equilibrium
- CPA: inequalities, RBF needs equation
- CPA slow but delivers a true (nonsmooth) Lyapunov function
- RBF (comparatively) fast, smooth function, but separate verification is necessary
- CPA and RBF are guaranteed to succeed if sufficiently fine simplices/dense collocation points

## Review

- P. Giesl & S. Hafstein, Review on computational methods for Lyapunov functions, *Discrete Cont. Dyn. Syst. Ser. B*, **20** (2015), 2291–2331.

## RBF

- P. Giesl, *Construction of Global Lyapunov Functions Using Radial Basis Functions*, Lecture Notes in Math. 1904, Springer, 2007.
- P. Giesl & H. Wendland, *Meshless Collocation: Error Estimates with Application to Dynamical Systems*, *SIAM J. Numer. Anal.* 45 No. 4 (2007), 1723–1741.

## CPA

- S. Hafstein, “An algorithm for constructing Lyapunov functions”, *Electron. J. Differential Equ. Monogr.*, **8** (2007).

## RBF-CPA

- P. Giesl & S. Hafstein, Computation and Verification of Lyapunov functions, *SIAM J. Applied Dyn. Syst.*, **14** (2015), 1663–1698.

### 3. Complete Lyapunov functions

Classical Lyapunov functions: for **one** attractor, e.g. equilibrium or periodic orbit. Now consider  $\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x})$ ,  $\mathbf{x} \in \Omega \subseteq \mathbb{R}^n$ .

- Phase space can be split into **chain-recurrent set**  $\mathcal{R}$  (containing equilibria, periodic orbits, attractors, repellers, etc.) and the complement with **gradient-like flow**
- Complete Lyapunov function (Conley)  $V: \Omega \rightarrow \mathbb{R}$  satisfies
  - $\dot{V}(\mathbf{x}) < 0$  (decreasing along solutions) on gradient-like part (transient behaviour)
  - $\dot{V}(\mathbf{x}) = 0$  on chain-recurrent set, has distinct values on distinct chain-transitive components of  $\mathcal{R}$

(Conley 1978, 1988), (Hurley 1991, 1998), (Osipenko 2007), (Patrao 2011)

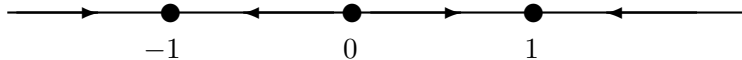
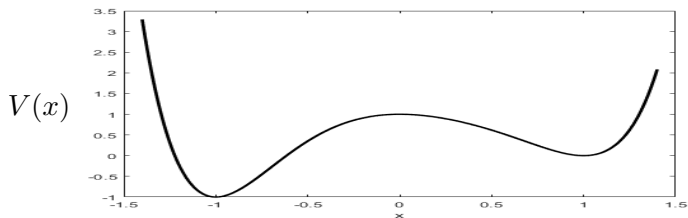
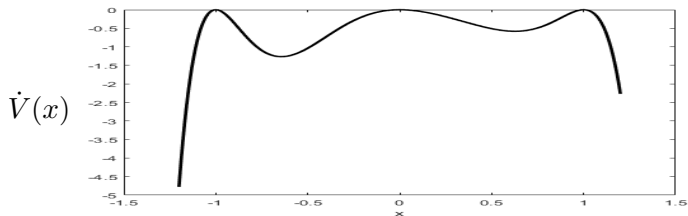
# Construction of complete Lyapunov functions

- Goal to find a (candidate) complete Lyapunov function satisfying  $\dot{V}(\mathbf{x}) \leq 0$  for all  $\mathbf{x} \in \Omega$
- with large area  $\{x \in \Omega \mid \dot{V}(\mathbf{x}) < 0\}$

Then

- $\{\mathbf{x} \in \Omega \mid \dot{V}(\mathbf{x}) = 0\}$  contains chain-recurrent set
- Maxima/minima of  $V$  indicate stability

Example:  $\dot{x} = -x(x^2 - 1)$

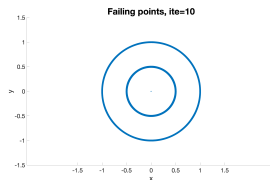
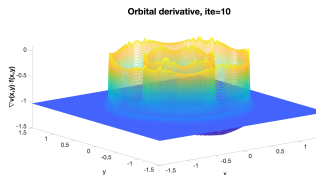


## 3.1 Numerical construction: Meshfree collocation RBF (equation)

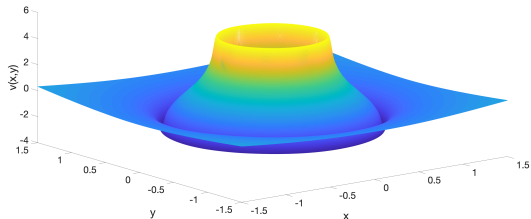
Solve  $\dot{V}(\mathbf{x}) = -1$  via meshless collocation.

- the PDE has no solution on chain-recurrent set
- meshless collocation has solution  $v$
- set where  $\dot{V}_R(\mathbf{x}) \approx 0$  approximates chain-recurrent set  $\mathcal{R}$
- iterations for better approximations
- no proof of convergence
- software LyapXool

# Complete Lyapunov function: equation



Lyapunov Function, ite=10





solve

$$\begin{cases} \text{minimise} & \|V\|_H \\ \text{subject to} & \dot{V}(\mathbf{x}) = -1 \text{ for all } \mathbf{x} \in \Gamma \\ & \dot{V}(\mathbf{x}) \leq 0 \text{ for all } \mathbf{x} \in \Omega(\setminus\Gamma) \end{cases}$$

## Remarks:

- We need to ensure  $\Gamma$  lies in the gradient-flow part
- How large does  $\Gamma$  need to be?
- Can we assume  $\dot{V}(\mathbf{x}) = -1$  in the gradient-flow part; does such a function exist?
- How do we find a (numerical) solution?

# Existence of complete Lyapunov function with prescribed derivative

## Theorem (Giesl, Suhr, Hafstein (2022))

Let  $\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x})$  define a dynamical system on an open set  $\Omega \subset \mathbb{R}^d$  with  $\mathbf{f} \in C^l(\Omega, \mathbb{R}^d)$ , where  $l \in \mathbb{N} \cup \{\infty\}$ .

Then for **every compact set**  $K \subset \Omega \setminus \mathcal{R}$  and every  $C^l$ -function  $g: \Omega_K \rightarrow (-\infty, 0)$  defined on a neighborhood  $\Omega_K \subset \Omega$  of  $K$  there exists a complete  $C^l$ -Lyapunov function  $V: \Omega \rightarrow \mathbb{R}$  with

- $\dot{V}(\mathbf{x}) = g(\mathbf{x})$  for all  $\mathbf{x} \in K$  and
- $\dot{V}(\mathbf{x}) < 0$  for all  $\mathbf{x} \in \Omega \setminus \mathcal{R}$ .

Proof is based on a modification of a  $C^\infty$  complete Lyapunov function from (Hafstein, Suhr 2021)

Hence, we can set  $g(\mathbf{x}) = -1$

## 3.2 Discretising differential inequalities

- Let  $\Gamma \subset \Omega \subset \mathbb{R}^d$
- Goal: solve

$$\begin{cases} Lv(\mathbf{x}) = -1, \forall \mathbf{x} \in \Gamma, \\ Lv(\mathbf{x}) \leq 0, \forall \mathbf{x} \in \Omega \setminus \Gamma \end{cases}$$

- $L$  is a linear (differential) operator
- Consider (Reproducing Kernel) Hilbert space  $H$  of functions  $v: \Omega \rightarrow \mathbb{R}$  with kernel  $\Phi(\mathbf{x}, \mathbf{y})$
- Optimisation problem for  $v \in H$

$$\begin{cases} \text{minimise} & \|v\|_H \\ \text{subject to} & Lv(\mathbf{x}) = -1, \forall \mathbf{x} \in \Gamma, \\ & Lv(\mathbf{x}) \leq 0, \forall \mathbf{x} \in \Omega \setminus \Gamma. \end{cases}$$

# Discretising differential inequalities: convergence

- Continuous problem:

$$(3) \quad \begin{cases} \text{minimise} & \|v\|_H \\ \text{subject to} & Lv(\mathbf{x}) = -1, \forall \mathbf{x} \in \Gamma, \\ & Lv(\mathbf{x}) \leq 0, \forall \mathbf{x} \in \Omega \setminus \Gamma. \end{cases}$$

- Meshfree collocation: discretise problem. Given discrete (regular) points  $X_\Gamma \subset \Gamma$ ,  $X_\Omega \subset \Omega \setminus \Gamma$ , solve

$$(4) \quad \begin{cases} \text{minimise} & \|v\|_H \\ \text{subject to} & Lv(\mathbf{x}_i) = -1, \forall \mathbf{x}_i \in X_\Gamma, \\ & Lv(\mathbf{x}_i) \leq 0, \forall \mathbf{x}_i \in X_\Omega. \end{cases}$$

## Results:

- (3) and (4) have unique solution
- (4) can be solved by quadratic optimisation
- Strong convergence in  $H$  of solutions of discretised problem (4) to solution of continuous system (3)

# Discretised version: quadratic optimisation

$H$  RKHS with kernel  $\Phi$ ,  $M, N \in \mathbb{N}$ ,  $\lambda_i = (\delta_{x_i} \circ L) \in H^*$ ,  
 $i = 1, \dots, M + N$  linearly independent

$$(5) \quad \begin{cases} \text{minimise} & \|v\|_H \\ \text{subject to} & \lambda_i(v) = -1, \quad i = 1, \dots, M, \\ & \lambda_{M+i}(v) \leq 0, \quad i = 1, \dots, N. \end{cases}$$

Then

- (5) has unique minimiser  $v^*(\mathbf{x}) = \sum_{j=1}^{M+N} \alpha_j \lambda_j^{\mathbf{y}} \Phi(\mathbf{x}, \mathbf{y})$
- coefficients  $\alpha_j$  are the unique solution of the minimisation problem

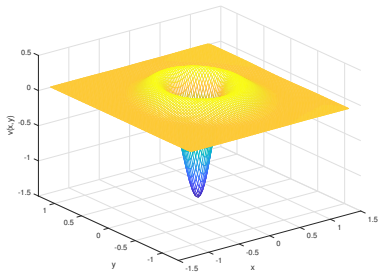
$$(6) \quad \begin{cases} \text{minimise} & \alpha^T A \alpha \\ \text{subject to} & A_1 \alpha = -\mathbf{1} \in \mathbb{R}^M \\ \text{and} & A_2 \alpha \leq \mathbf{0} \in \mathbb{R}^N. \end{cases}$$

$$A = (a_{ij}) = \begin{pmatrix} A_1 \\ A_2 \end{pmatrix}, \quad A_1 \in \mathbb{R}^{M \times (M+N)}, \quad A_2 \in \mathbb{R}^{N \times (M+N)} \quad \text{and} \\ a_{ij} = \lambda_i^{\mathbf{x}} \lambda_j^{\mathbf{y}} \Phi(\mathbf{x}, \mathbf{y})$$

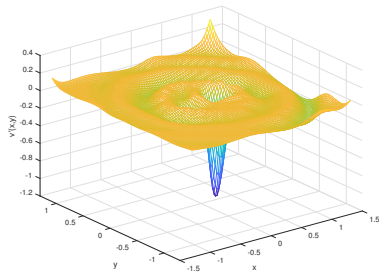
## Example 1: two periodic orbits

$$\begin{pmatrix} \dot{x} \\ \dot{y} \end{pmatrix} = \begin{pmatrix} -x(x^2 + y^2 - 1/4)(x^2 + y^2 - 1) - y \\ -y(x^2 + y^2 - 1/4)(x^2 + y^2 - 1) + x \end{pmatrix}$$

$v(x, y)$



$\dot{v}(x, y)$

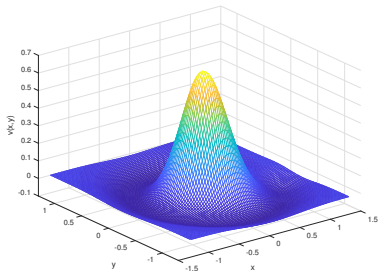


$\dot{v}(0.1846, 0) = -1$  by the equality constraint

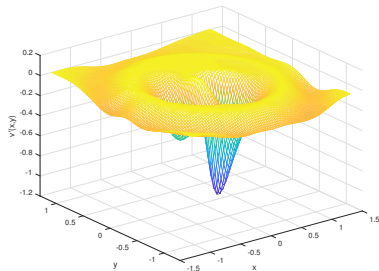
## Example 2: homoclinic orbit

$$\begin{pmatrix} \dot{x} \\ \dot{y} \end{pmatrix} = \begin{pmatrix} x(1 - x^2 - y^2) - y((x - 1)^2 + (x^2 + y^2 - 1)^2) \\ y(1 - x^2 - y^2) + x((x - 1)^2 + (x^2 + y^2 - 1)^2) \end{pmatrix}$$

$v(x, y)$



$\dot{v}(x, y)$



$\dot{v}(0.1846, 0) = -1$  by the equality constraint

### 3.3 New optimisation problem

- Drawback of previous approach: some knowledge of chain-recurrent set (for equality condition)

- $$\begin{cases} \text{minimise} & \|V\|_H \\ \text{subject to} & \dot{V}(\mathbf{x}) \leq 0 \text{ for all } \mathbf{x} \in \Omega \end{cases}$$

has trivial solution  $V \equiv 0$

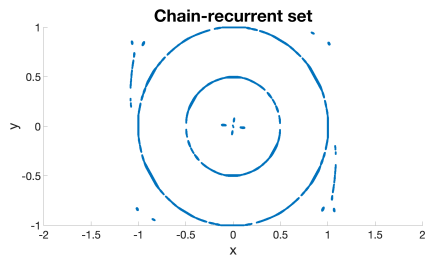
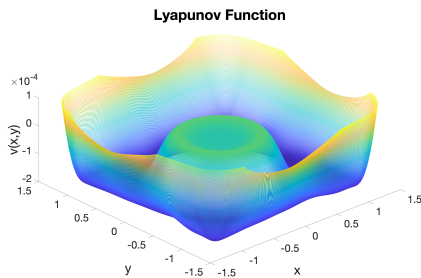
**New idea** (Giesl, Argáez, Hafstein, Wendland 2021): consider

$$\begin{cases} \text{minimise} & \|V\|_H^2 + \int_{\Omega} \dot{V}(\mathbf{x}) \, d\mathbf{x} \\ \text{subject to} & \dot{V}(\mathbf{x}) \leq 0 \text{ for all } \mathbf{x} \in \Omega \end{cases}$$

- Cost function rewards areas with negative orbital derivative
- No knowledge of gradient-like flow required
- Still leads to quadratic optimisation problem

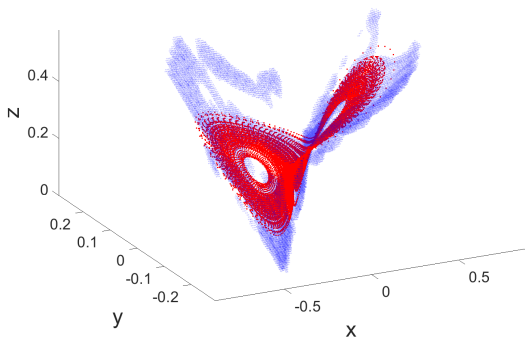


# Example 1: two periodic orbits



## Example 2: Lorenz attractor

### Chain-recurrent set



blue: computed set containing attractor, red: attractor

## Equation

- C. Arguez, P. Giesl & S. Hafstein: Complete Lyapunov Functions: Computation and Applications. In: Simulation and Modeling Methodologies, Technologies and Applications Series: Advances in Intelligent Systems and Computing 873, M. Obaidat, T. Oren, and F. De Rango (eds.), Springer, pages 200-221 (2019).
- C. Arguez, P. Giesl & S. Hafstein: Update (2.0) to LyapXool: Eigenpairs and new classification methods. *SoftwareX* 12 (2020) 100616.

## Differential inequalities

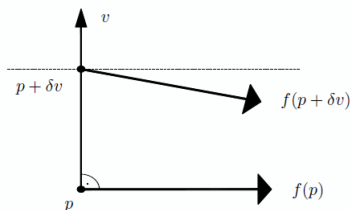
- P. Giesl, C. Arguez, S. Hafstein & H. Wendland: Construction of a complete Lyapunov function using quadratic programming. In: *Proceedings ICINCO* Vol. 1 (2018), 560-568.
- P. Giesl, C. Arguez, S. Hafstein & H. Wendland: Minimization with differential inequality constraints applied to complete Lyapunov functions. *Math. Comp.* 90 (2021), 2137-2160.

## Existence of complete Lyapunov functions

- S. Hafstein & S. Suhr: Smooth complete Lyapunov functions for ODEs. *J. Math. Anal. Appl.* **499** (2021), Article 125003.
- P. Giesl, S. Hafstein & S. Suhr: Existence of complete Lyapunov functions with prescribed orbital derivative. *Discrete Cont. Dyn. Sys. Ser. B* (2022) online

## 4. Contraction metrics

- Consider  $\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x})$
- Adjacent solutions contract with respect to contraction metric
- Can be used to show existence, uniqueness, stability and basin of attraction of equilibria/periodic orbits
- Robust with respect to perturbations of the system



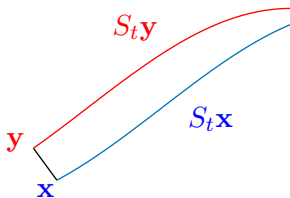
**Problem** Find Riemannian metric  $M \in C^1(\Omega; \mathbb{S}^{n \times n})$  (symmetric matrices) with scalar product  $\langle v, w \rangle_M = v^T M(\mathbf{x}) w$  such that

- $M(\mathbf{x}) \succ 0$  (positive definite)
- $LM(\mathbf{x}) := M(\mathbf{x}) D\mathbf{f}(\mathbf{x}) + \dot{M}(\mathbf{x}) + D\mathbf{f}(\mathbf{x})^T M(\mathbf{x}) \prec 0$  (negative definite)

# Idea of contraction metric

## Idea

- Solutions  $S_t \mathbf{x}$  and  $S_t \mathbf{y}$ ,  $\mathbf{y}$  near  $\mathbf{x}$
- Time-dependent distance (squared)



$$d^2(t) := (S_t \mathbf{y} - S_t \mathbf{x})^T M(S_t \mathbf{x})(S_t \mathbf{y} - S_t \mathbf{x})$$

- Derivative, denoting  $\mathbf{v} = S_t \mathbf{y} - S_t \mathbf{x}$ : exponential decay of  $d(t)$

$$\begin{aligned} \frac{d}{dt} d^2(t) &\approx (S_t \mathbf{y} - S_t \mathbf{x})^T D\mathbf{f}(S_t \mathbf{x})^T M(S_t \mathbf{x})(S_t \mathbf{y} - S_t \mathbf{x}) \\ &\quad + (S_t \mathbf{y} - S_t \mathbf{x})^T \dot{M}(S_t \mathbf{x})(S_t \mathbf{y} - S_t \mathbf{x}) \\ &\quad + (S_t \mathbf{y} - S_t \mathbf{x})^T M(S_t \mathbf{x}) D\mathbf{f}(S_t \mathbf{x})(S_t \mathbf{y} - S_t \mathbf{x}) \\ &= \mathbf{v}^T \underbrace{[M(S_t \mathbf{x}) D\mathbf{f}(S_t \mathbf{x}) + \dot{M}(S_t \mathbf{x}) + D\mathbf{f}(S_t \mathbf{x})^T M(S_t \mathbf{x})]}_{=LM(S_t \mathbf{x}) \prec -2\nu M(S_t \mathbf{x})} \mathbf{v} \\ &\leq -2\nu d^2(t) \end{aligned}$$

# Contraction metric and basin of attraction

## Theorem

- $\emptyset \neq K \subset \mathbb{R}^n$  *positively invariant, compact and connected*
- *Riemannian metric*  $M \in C^1(\mathbb{R}^n, \mathbb{S}^{n \times n})$  ( $M(\mathbf{x}) \succ 0$ )
- $LM(\mathbf{x}) = M(\mathbf{x})D\mathbf{f}(\mathbf{x}) + \dot{M}(\mathbf{x}) + D\mathbf{f}(\mathbf{x})^T M(\mathbf{x}) \prec -2\nu M(\mathbf{x})$  for all  $x \in K$  with  $\nu > 0$

Then

- *Existence and uniqueness of an exponentially asymptotically stable equilibrium*  $\mathbf{x}_0 \in K$
- $-\nu$  is *upper bound* on rate of exponential attraction
- $K \subset A(\mathbf{x}_0)$  (*basin of attraction*)

**Remark:** On compact set, it is sufficient to have

$$LM(\mathbf{x}) = M(\mathbf{x})D\mathbf{f}(\mathbf{x}) + \dot{M}(\mathbf{x}) + D\mathbf{f}(\mathbf{x})^T M(\mathbf{x}) \prec 0$$

- There exists specific contraction metric satisfying

$$LM(\mathbf{x}) := M(\mathbf{x})D\mathbf{f}(\mathbf{x}) + \dot{M}(\mathbf{x}) + D\mathbf{f}(\mathbf{x})^T M(\mathbf{x}) = -C \prec 0$$

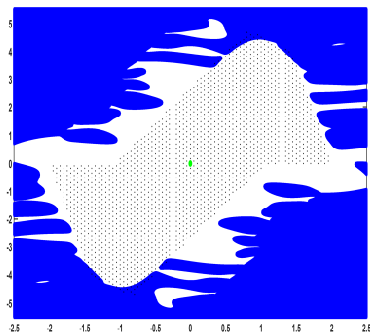
for all  $\mathbf{x} \in A(\mathbf{x}_0)$

- Approximate  $M$  satisfying equation above using meshless collocation (of matrix-valued functions)
- Interpolation with CPA metric to verify conditions

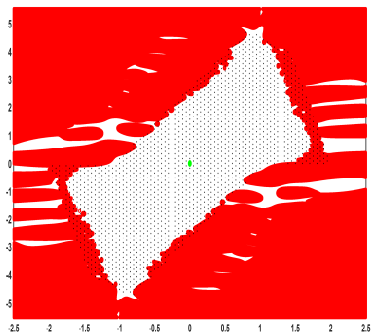
# Examples: Van der Pol (time-reversed, equilibrium)

$$\dot{x} = -y$$

$$\dot{y} = x - 3(1 - x^2)y$$



Black: 1926 collocation points  
Blue:  $M(\mathbf{x})$  not positive definite



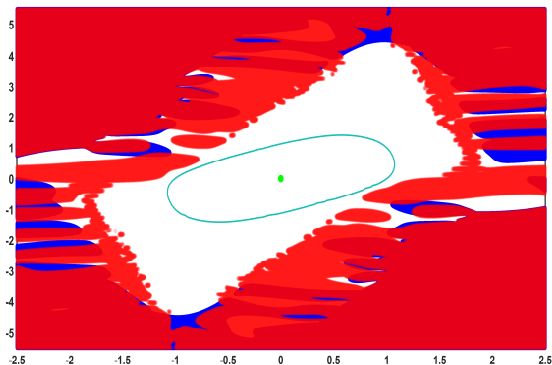
Green: equilibrium  
Red:  $LM(\mathbf{x})$  not negative definite



# Example: Van der Pol (time-reversed, equilibrium)

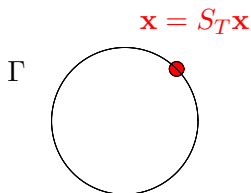
$$\dot{x} = -y$$

$$\dot{y} = x - 3(1 - x^2)y$$



Dark green: positively invariant set (using Lyapunov-like function)

# Contraction metric for periodic orbit



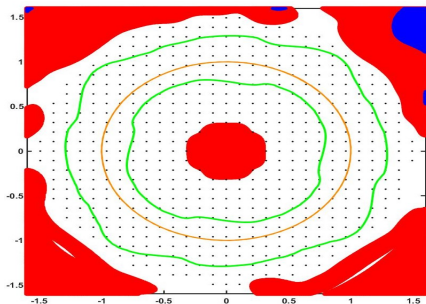
- **periodic orbit**  $\Gamma = \{S_t \mathbf{x} \mid t \in [0, T)\}$  with  $\mathbf{x} = S_T \mathbf{x}$
- **basin of attraction**  
 $A(\Gamma) = \{\boldsymbol{\xi} \in \mathbb{R}^n \mid \text{dist}(S_t \boldsymbol{\xi}, \Gamma) \xrightarrow{t \rightarrow \infty} 0\}$
- similar method for periodic orbits: contraction only in  $(n - 1)$ -dimensional hyperplane perpendicular to  $\mathbf{f}(\mathbf{x})$

## Example: unit circle (periodic orbit)

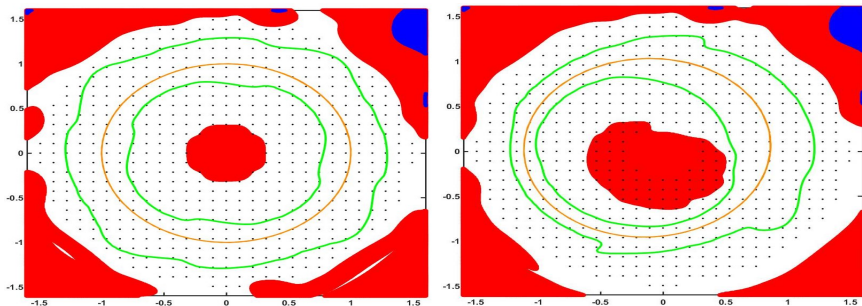
$$\dot{x} = (x + \varepsilon)(1 - x^2 - y^2) - (y + \varepsilon)$$

$$\dot{y} = (y + \varepsilon)(1 - x^2 - y^2) + (x + \varepsilon)$$

$\varepsilon = 0$



$\varepsilon = 0.2$  (same metric)



## Review

- P. Giesl, S. Hafstein & C. Kawan, *Review on contraction analysis and computation of contraction metrics*. J. Comp. Dyn. accepted, arXiv:2203.01367

## Existence of contraction metrics

- P. Giesl, *Converse theorems on contraction metrics for an equilibrium*. J. Math. Anal. Appl. **424** (2015), 1380-1403.
- P. Giesl, *On a matrix-valued PDE characterizing a contraction metric for a periodic orbit*. Discrete Contin. Dyn. Syst. Ser. B **26** (2021), 4839-4865.

## Computation

- P. Giesl & H. Wendland, *Kernel-based Discretisation for Solving Matrix-Valued PDEs*. SIAM J. Numer. Anal. **56** No. 6 (2018), 3386-3406.
- P. Giesl, *Computation of a contraction metric for a periodic orbit*. SIAM J. Appl. Dyn. Syst. **18** (2019), 1536-1564.

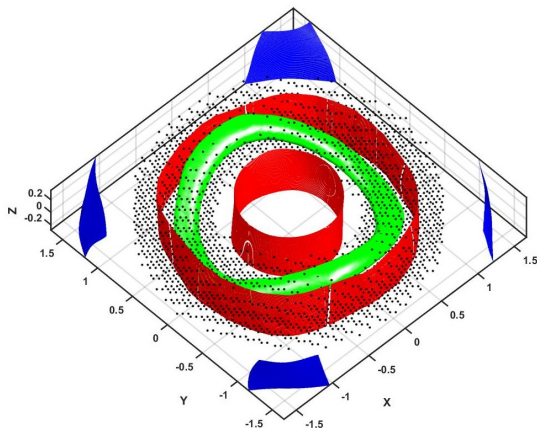
## CPA verification

- P. Giesl, S. Hafstein & I. Mehrabinezhad, *Computation and Verification of Contraction Metrics for Equilibria*. J. Comput. Appl. Math. **390** (2021), 113332.
- P. Giesl, S. Hafstein & I. Mehrabinezhad, *Computation and verification of contraction metrics for periodic orbits*. J. Math. Anal. Appl. **503** (2021), Article 125309.

- Analytical tools:
  - (complete) Lyapunov function  $V: \mathbb{R}^n \rightarrow \mathbb{R}$
  - contraction metric  $M: \mathbb{R}^n \rightarrow \mathbb{S}^{n \times n}$ ,  
robust with respect to perturbations, no information about equilibrium/periodic orbit required
- Numerical methods:
  - RBF (Radial Basis Functions) – meshless collocation (solve system of linear equations or quadratic optimisation for differential inequalities)
  - CPA (continuous piecewise affine) – linear optimisation (triangulation of compact phase space, verification)

- Discrete systems  $\mathbf{x}_{n+1} = \mathbf{f}(\mathbf{x}_n)$
- Periodic time  $\dot{\mathbf{x}} = \mathbf{f}(t, \mathbf{x}), \mathbf{f}(t + T, \mathbf{x}) = \mathbf{f}(t, \mathbf{x})$
- Finite time  $\dot{\mathbf{x}} = \mathbf{f}(t, \mathbf{x}), t \in [0, T]$
- Non-smooth systems
- Stochastic systems
- Dimension of attractors, entropy

# QUESTIONS?



Webpage: <http://users.sussex.ac.uk/~pag20/>