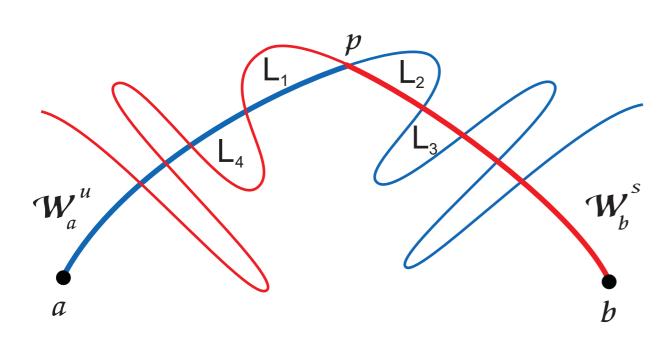
## CAGD Methods for Invariant Manifold Computations

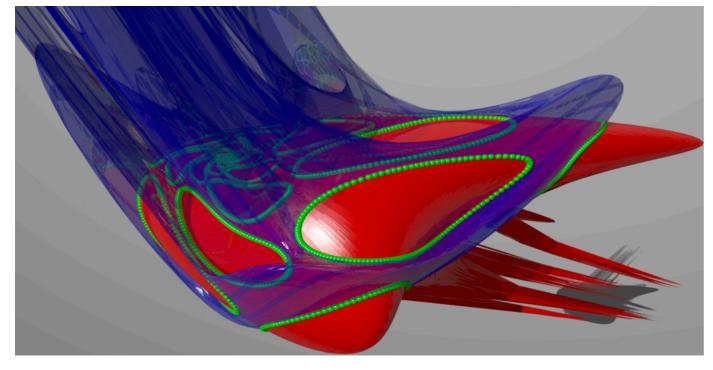
Roy Goodman and Jacek Wróbel New Jersey Institute of Technology



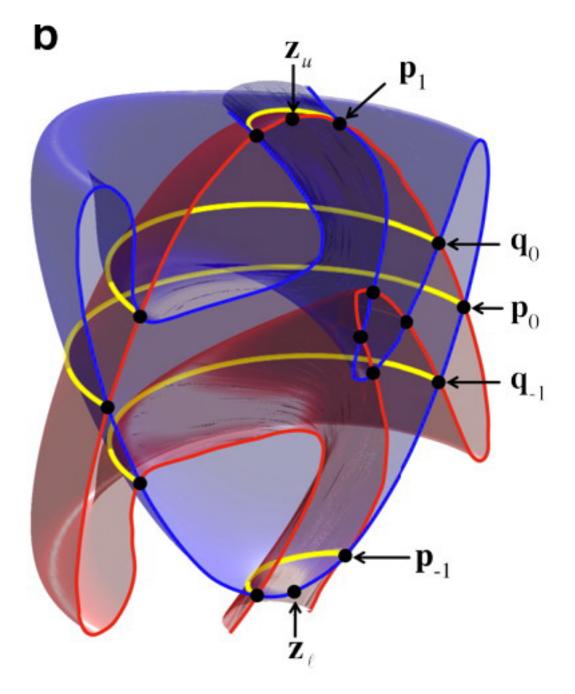


# Invariant Manifolds are important in understanding dynamics





#### Mireles James/Capinski 2017



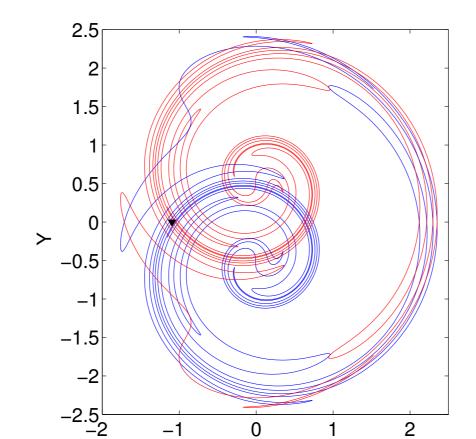
Smith et al 2017

## Setup

Consider a diffeomorphic mapping  $\mathbf{x}' = f(\mathbf{x}), \mathbf{x} \in \mathbb{R}^2$ with a hyperbolic fixed point  $\mathbf{x}^*$ i.e. such that  $Df(\mathbf{x}^*)$  has eigenvalues  $0 < |\lambda_s| < 1 < |\lambda_u|$ 

Define the stable and unstable manifolds

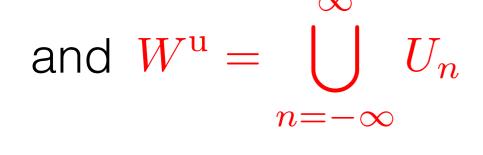
$$W^{s}(\mathbf{x}^{*}) = \{ \mathbf{x} \in \mathbb{R}^{2} : f^{k}(\mathbf{x}) \to \mathbf{x}^{*} \text{ as } k \to \infty \}$$
$$W^{u}(\mathbf{x}^{*}) = \{ \mathbf{x} \in \mathbb{R}^{2} : f^{-k}(\mathbf{x}) \to \mathbf{x}^{*} \text{ as } k \to \infty \},$$

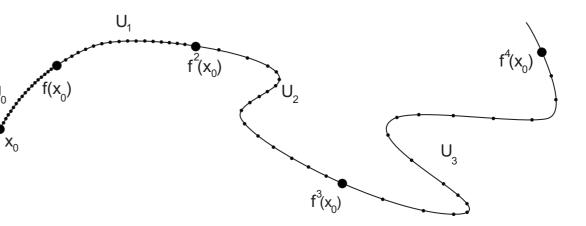


## Fundamental segments

Pick a point  $x_0$  near  $x^*$  and inductively define  $x_{n+1}=f(x_n)$ . Then the  $n^{th}$  fundamental segment is defined as

 $U_n = W^{\mathbf{u}}[x_n, x_{n+1}]$ 

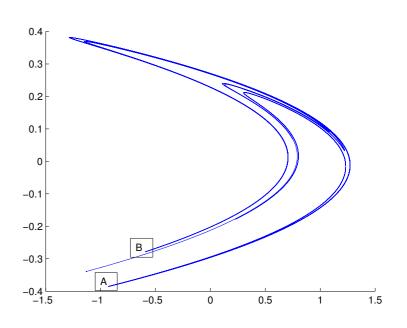




#### Issues:

Not many points required to resolve  $U_0$  but dynamic stretching and folding will require more points to resolve later segments.

Curvature can vary by orders of magnitude after just a few iterates.



## Existing Methods of Computation

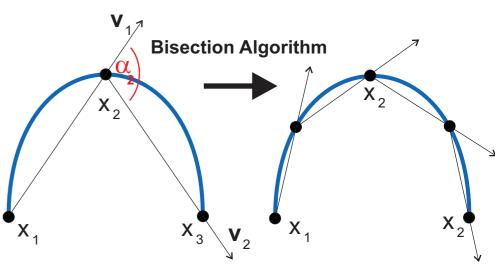
- Iteration of fundamental segments
- Marching methods: given a manifold computed up to a given point, extending manifold by a given amount, see esp.
  Krauskopf & Osinga
- Parameterization methods: seek functional representation for  $W^{u}$  (generally only useful locally)  $(r(t)) \xrightarrow{\infty} (a_{k})$

$$\binom{x(t)}{y(t)} = \sum_{k=0}^{\infty} \binom{a_k}{b_k} t^k$$

(and many others)

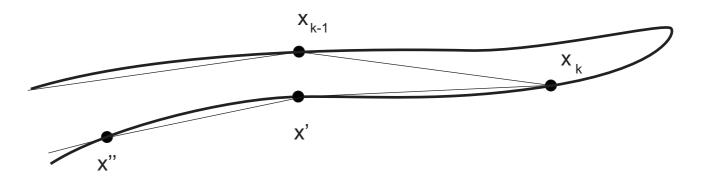
### Existing Methods: Linear Interpolation

Consider adaptively drawing a parametric curve. Basis for Carter's adaptive (bisection) algorithm. Bisect if



 $\alpha_k > \operatorname{tol}_1 \text{ or } l_k \alpha_k > \operatorname{tol}_2$ 

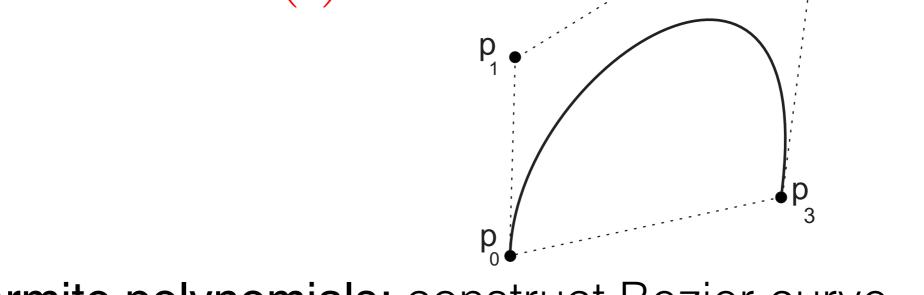
Marching algorithm (Hobson): Similar. Add one point to previously computed curve. Requires finding the right pre-image at each point, throws away many points. Occasionally cuts corners



## Tools from CAGD

 $\boldsymbol{n}$ 

**Bézier curves:** Form a convex combination  $\beta(t) = \sum_{k=0}^{n} B_k^n(t) \mathbf{p}_k$ of (n+1) *control points* using Bernstein Polynomials  $B_k^n(t) = {n \choose k} t^k (1-t)^{n-k}$ 



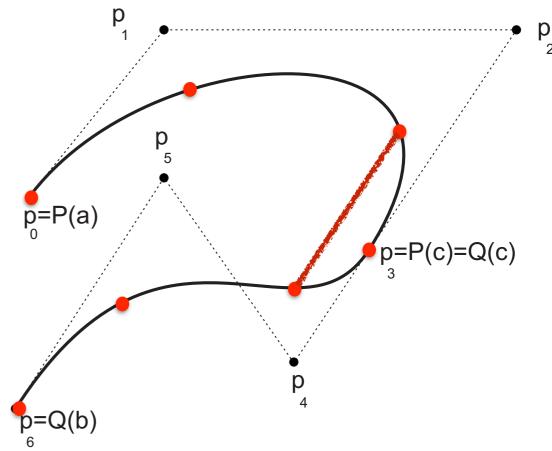
Cubic Hermite polynomials: construct Bezier curve interpolating points  $x_0$  and  $x_1$  with tangent vectors  $v_0$  and  $v_1$  by letting

$$\mathbf{p}_0 = \mathbf{x}_1, \mathbf{p}_1 = \mathbf{x}_1 + \vec{\mathbf{v}}_1/3, \mathbf{p}_2 = \mathbf{x}_2 - \vec{\mathbf{v}}_2/3, \mathbf{p}_3 = \mathbf{x}_2,$$

## Catmull-Rom splines

Partial interpolation using composite cubic Bézier functions.

First and last control point on each segment chosen to interpolate data.



Second and third control points on each segment chosen to approximate tangent vector at endpoints using centered differences.

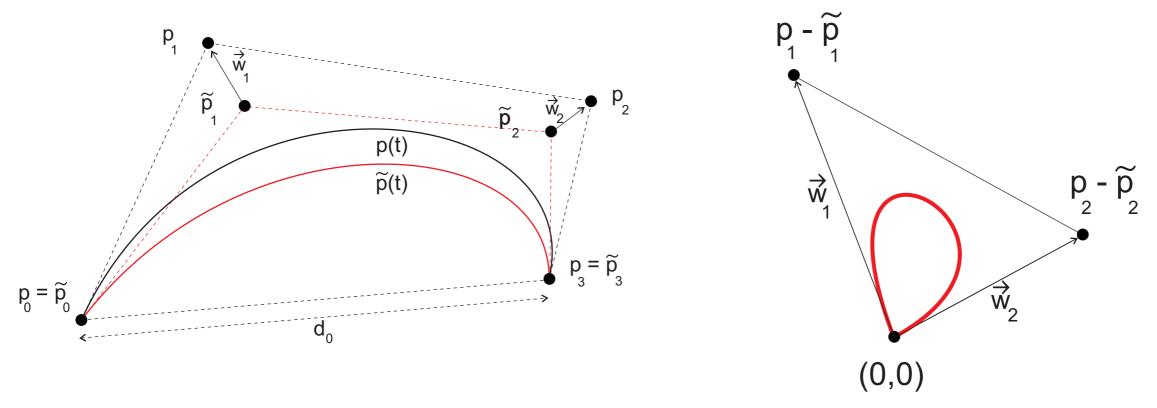
Allows for local refinement (as opposed to more familiar cubic splines).

Adaptive Catmull-Rom 1: Flatness conditions

- 1.  $\max\{d_1, d_2\}$
- 2.  $(|\mathbf{p}_0\mathbf{p}_1| + |\mathbf{p}_1\mathbf{p}_2| + |\mathbf{p}_2\mathbf{p}_3| |\mathbf{p}_0\mathbf{p}_3|),$
- 3.  $\max\{d_1/d_0, d_2/d_0\},\$
- 4. the angle between  $\vec{\mathbf{v}}_1$  and  $\vec{\mathbf{v}}_2$ ,
- 5.  $(|\mathbf{p}_0\mathbf{p}_1| + |\mathbf{p}_1\mathbf{p}_2| + |\mathbf{p}_2\mathbf{p}_3| |\mathbf{p}_0\mathbf{p}_3|)/|\mathbf{p}_0\mathbf{p}_3|.$

Adaptive Catmull-Rom 2: Error refinement conditions

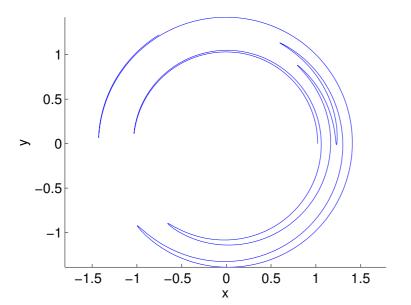
Compute two approximations, subtract and obtain the error polygon

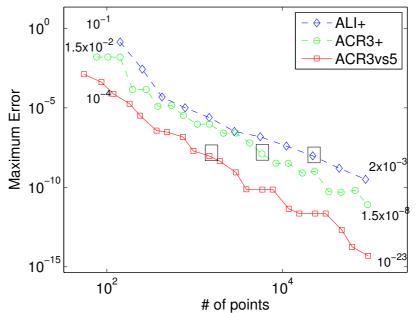


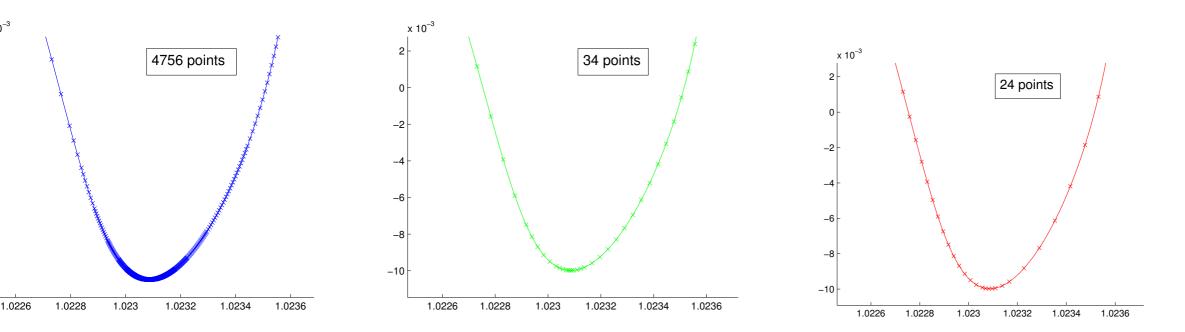
1.  $\max\{|\vec{\mathbf{w}}_1|, |\vec{\mathbf{w}}_2|\},\$ 

2. max 
$$\left\{\frac{|\vec{\mathbf{w}}_1|}{d_0}, \frac{|\vec{\mathbf{w}}_2|}{d_0|}\right\}$$

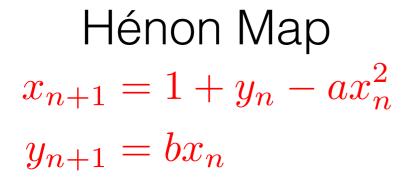
## Numerical Results: model problem







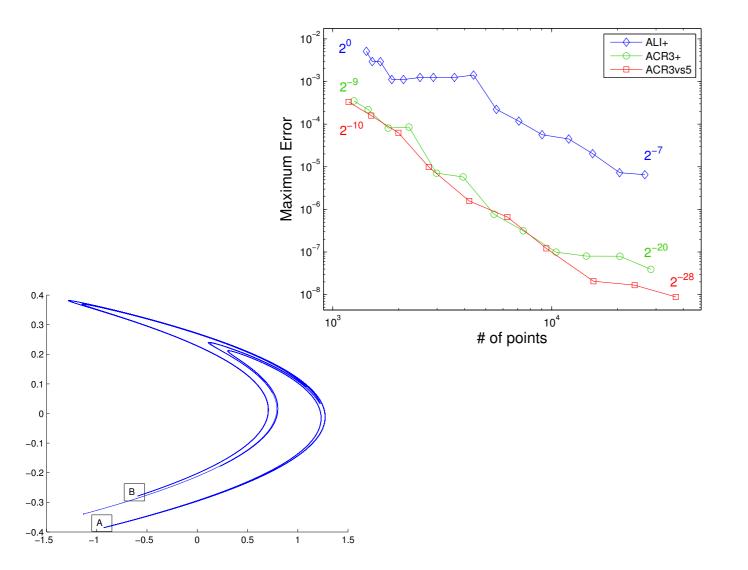
### Numerical Results: Real Maps

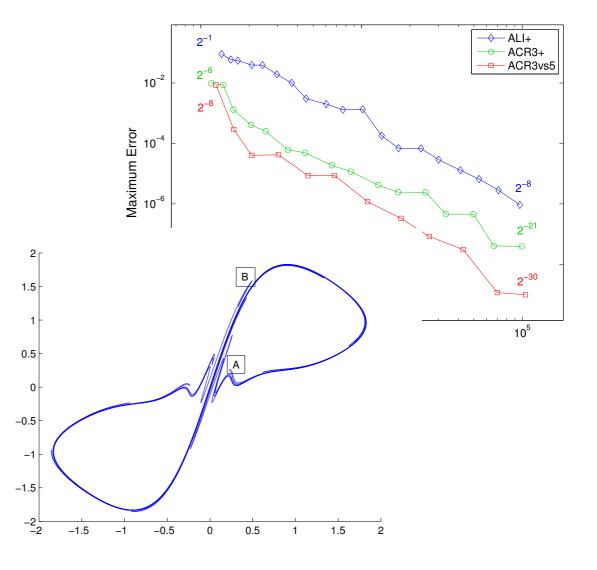


McMillan Map

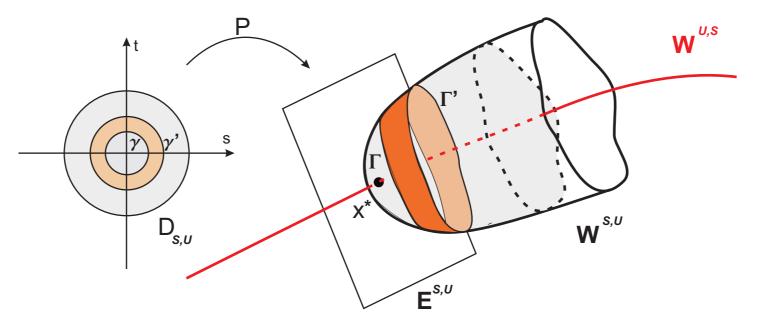
 $x_{n+1} = y_n,$ 

$$y_{n+1} = -x_n + 2y_n \left(\frac{\mu}{1+y_n^2} + \varepsilon\right)$$





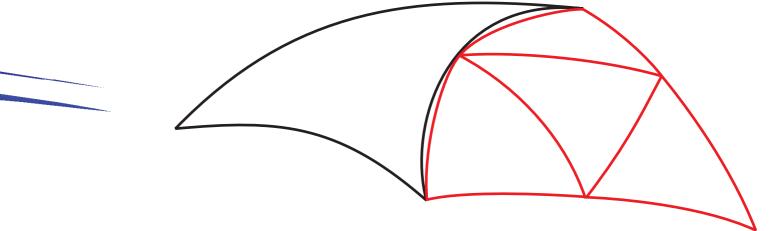
### 2D Unstable Manifolds for 3D Maps



#### Significant new challenges

## Dynamics: Exponentially anisotropic Growth

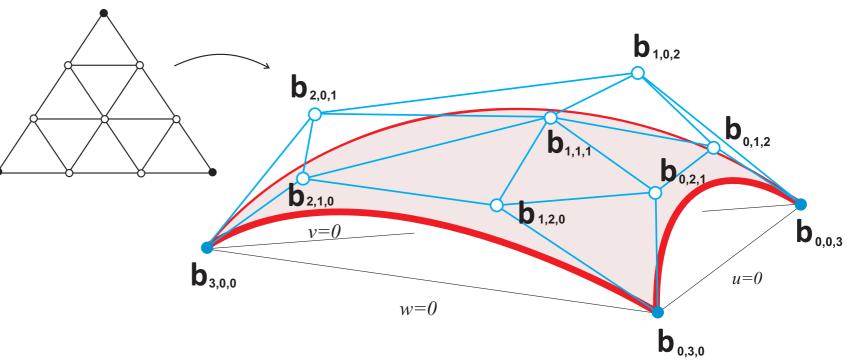
Computational/Geometric

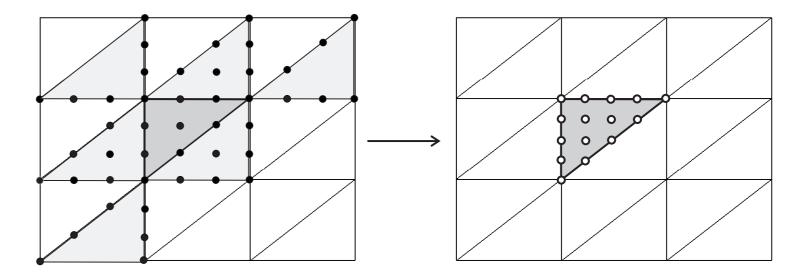


## CAGD Toolbox

Bézier triangular patches

Quasi-interpolation using quartic 2D Bernstein polynomials: 10 data points/triangle, +46 points from neighboring triangles, giving 15 control points/patch





Quasi-interpolation: choose coeffs such that polynomials of given degree represented exactly

## Adaptive quasi-interpolating quartic Bezier patches

Sorokina/Zeilfelder 2008, Hering-Bertram et al 2009

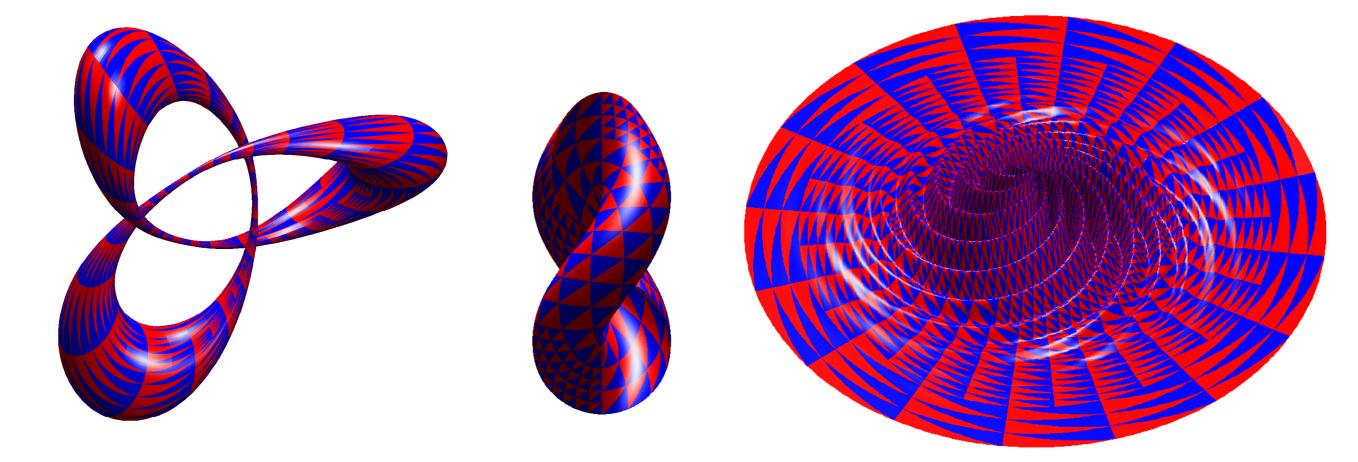
A Band-aid approach

Identify triangles on which need refining, bisect into four half-length triangles  $\bigwedge$ 

Interpolate the difference between the data and the current interpolant on the refined grid.

Overlay the higher resolution patch on the previous computation

## Applied to model problems



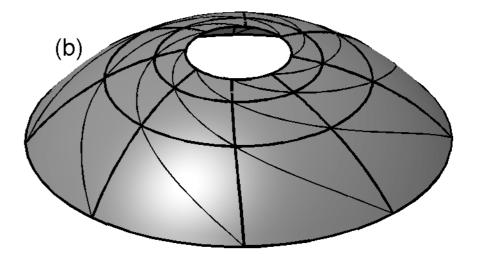
## Application to Unstable Manifolds

Fundamental Segments→Fundamental Annuli

**Proper loop:** A simple closed curve on  $W^u$  with the fixed point on its interior and which does not intersect its image under the map.

Fundamental annulus: Region of  $W^u$  contained between a proper loop  $\gamma$  and its image  $F(\gamma)$ .

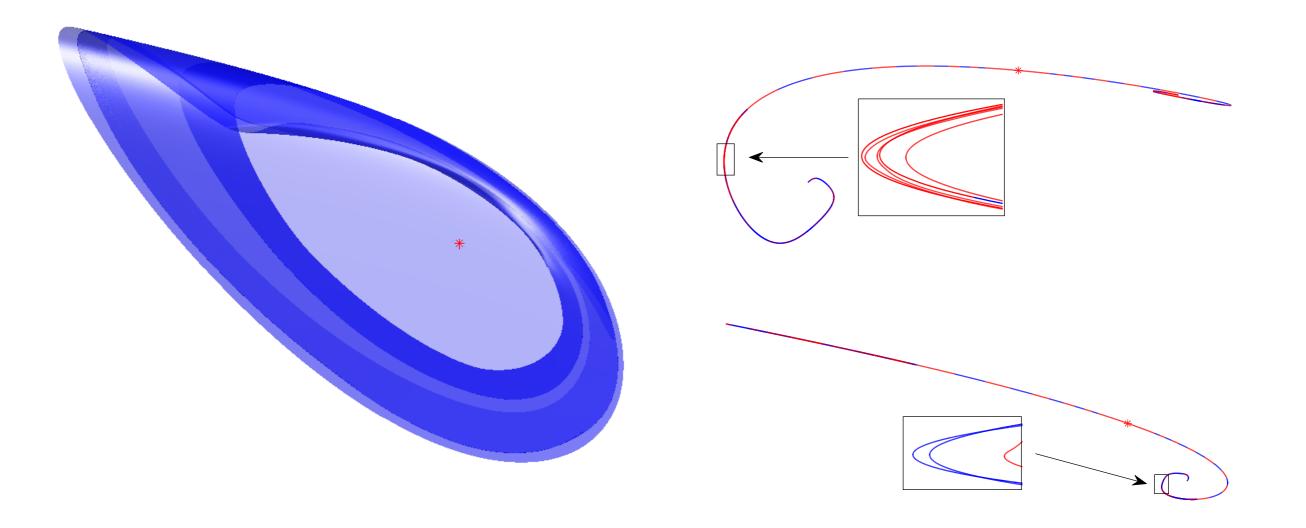
Parameterization method used for initial annulus



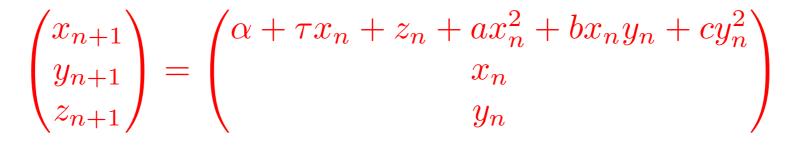
## Arneodo-Coullet-Tresser map

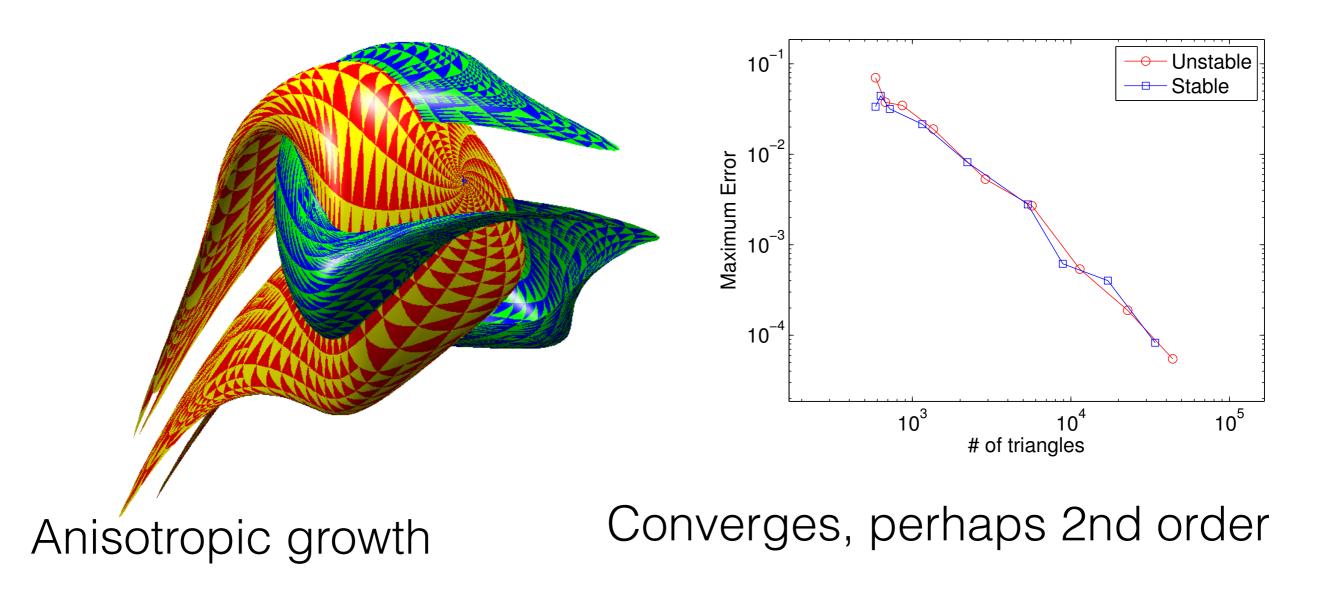
A discrete map whose attractor resembles the Rössler system's attractor

$$\begin{pmatrix} x_{n+1} \\ y_{n+1} \\ z_{n+1} \end{pmatrix} = \begin{pmatrix} ax_n - \omega b(y_n - z_n) \\ \frac{b}{\omega} x_n + a(y_n - z_n) \\ cx_n - dx_n^k + ez_n \end{pmatrix}$$



## Volume-preserving Hénon Map

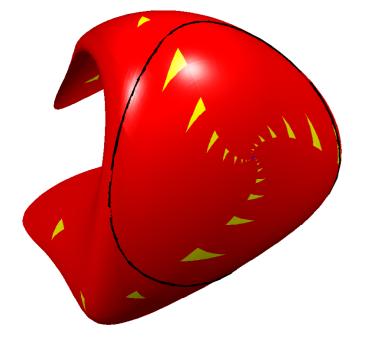


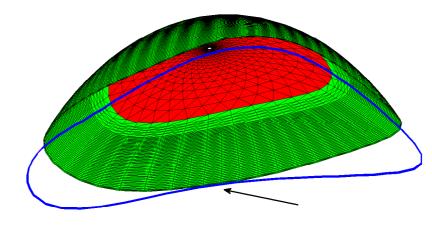


Can Geodesic-Level-Set-Method save the day?

Emphatically, no.

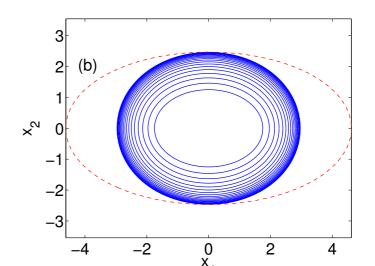
If computational boundary not a proper loop, can't find pre-image of needed next points





Simplified model problem  $\mathbf{x}_{n+1} = \begin{pmatrix} 0 & -AB & 0 \\ \frac{A}{B} & 0 & 0 \\ 0 & 0 & \frac{1}{2} \end{pmatrix} \mathbf{x}_n, \quad B > A > 1$ 

#### Level sets converge



### That leaves parameterization

Let's look at it in 2 space dimensions: Goal: Construct functions  $\mathbf{p}(t)$  and  $\Lambda(t)$  such that

 $\mathbf{p}(t) = \begin{pmatrix} x(t) \\ y(t) \end{pmatrix}$  parameterizes the unstable manifold, requiring:

- Invariance under the map  $\mathbf{f}(\mathbf{p}(\mathbf{t})) = \mathbf{p}(\Lambda(t))$
- Curve passes through fixed point  $\mathbf{p}(0) = \mathbf{x}^*$
- Curve tangent to unstable subspace at fixed point  $\frac{d\mathbf{p}(\mathbf{t})}{dt}\Big|_{t=0} = c\mathbf{v}_{\text{unstable}}$

## How parameterization works

In practice, defined by a power series  $\mathbf{p}(t) = \sum_{k=0}^{\infty} {a_k \choose b_k} t^k$ and  $\Lambda(t) = \lambda_{\text{unstable}} t$ 

Conditions 
$$\mathbf{p}(0) = \mathbf{x}^*$$
 and  $\left. \frac{d\mathbf{p}(\mathbf{t})}{dt} \right|_{t=0} = c\mathbf{v}_{\text{unstable}}$ 

used to determine leading-order terms.

Invariance condition  $\mathbf{f}(\mathbf{p}(\mathbf{t})) = \mathbf{p}(\Lambda(t))$  satisfied by expanding both sides in power series and matching coefficients

Methods based on automatic differentiation for expanding functions of power series on LHS

# In practice only useful for generating small portion of manifolds

#### Standard Map $x_{n+1} = x_n + \epsilon \sin \theta_n$ $\theta_{n+1} = x_n + \theta_n + \epsilon \sin \theta_n$ Unstable manifold of (0,0) showing catastrophic failure around t = 33 $\int_{0}^{1} \frac{1}{1 - \log \log \log d (0, 1/2)} d \theta d (0, 1/2) d \theta d (0, 1/2)$

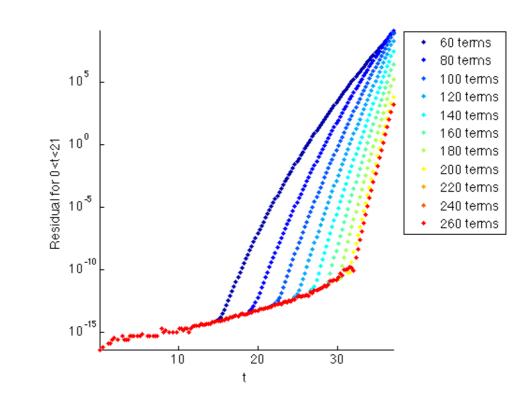
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3

2



Residual  $|\mathbf{f}(\mathbf{p}(\mathbf{t})) - \mathbf{p}(\Lambda(t))|$ 

How can we generalize the method to give more global information?