

Introduction to Nonlinear Dynamics

Santa Fe Institute
Complex Systems Summer School
June 2018

© 2018
Elizabeth Bradley

Liz Bradley
lizb@cs.colorado.edu

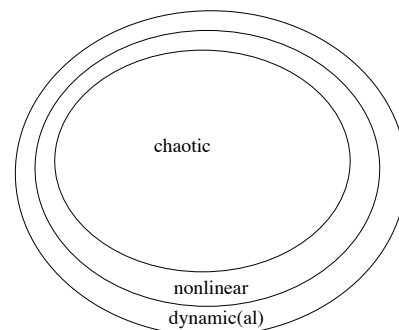


<http://ayresriverblog.com>

Chaos

Complex behavior, arising in a deterministic nonlinear dynamic system, which exhibits two special properties:

- sensitive dependence on initial conditions
- characteristic structure...



Chaos

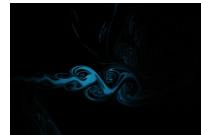
Complex behavior, arising in a deterministic nonlinear dynamic system, which exhibits two special properties:

- sensitive dependence on initial conditions
- characteristic structure...

Systems that exhibit chaos are ubiquitous; many of them are also simple, well-known, and “well-understood”

Where nonlinear dynamics turns up

- Flows (of fluids, heat, ...)
- Eddy in creek
- Weather
- Vortices around marine invertebrates
- Air/fuel flow in combustion chambers



Where nonlinear dynamics turns up

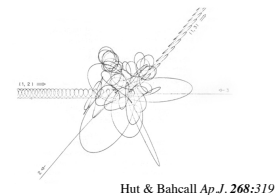
- Driven nonlinear oscillators
- Pendula
- Hearts
- Fireflies



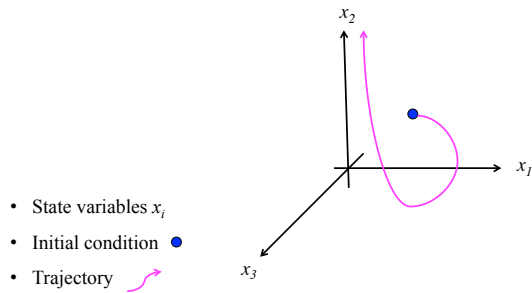
- and lots of other electronic, chemical, & biological systems

Where nonlinear dynamics turns up

- Classical mechanics
- three-body problem
- paired black holes
- pulsar emission
-
- Protein folding
- Population biology
- And many, many other fields (including yours)



The basic representation in nonlinear dynamics: the state space



The damped pendulum



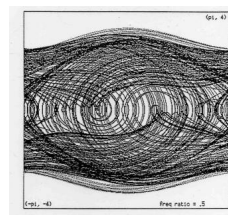
- State variables?
- Initial condition?
- Trajectory?

Fixed points

- Stable: perturbations shrink
- Unstable: perturbations grow

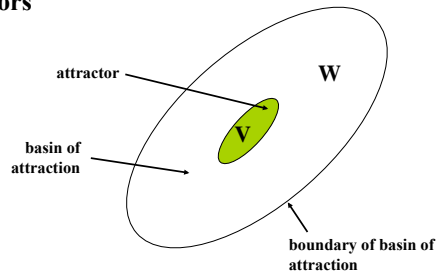


The *driven* damped pendulum...



...can be chaotic (for some drive parameters)

Attractors

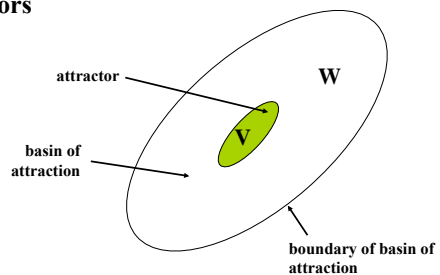


A useful metaphor:



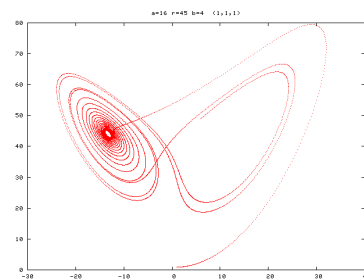
(image from wikipedia)

Attractors



- Attractors exist only in dissipative systems!
- Dissipation \iff contraction of state space under the influence of the dynamics
- Can still have chaos if no dissipation...just not chaotic *attractors*

The archetype of chaos: Lorenz



Deterministic Nonperiodic Flow¹

EDWARD N. LORENZ

Massachusetts Institute of Technology

(Manuscript received 18 November 1962, in revised form 7 January 1963)

ABSTRACT

Finite systems of deterministic ordinary nonlinear differential equations may be designed to represent forced dissipative hydrodynamic flow. Solutions of these equations can be identified with trajectories in phase space. For those systems with bounded solutions, it is found that nonperiodic solutions are ordinarily unstable with respect to small modifications, so that slightly differing initial states can evolve into considerably different states. Systems with bounded solutions are shown to possess bounded numerical solutions. A simple system representing cellular convection is solved numerically. All of the solutions are found to be unstable, and almost all of them are nonperiodic.

The feasibility of very-long-range weather prediction is examined in the light of these results.

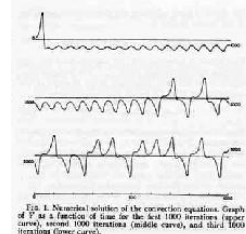


Fig. 1. Numerical solution of the convection equations. Graph of x as a function of time for the first 100 iterations (upper curve), second 100 iterations (middle curve), and third 100 iterations (lower curve).

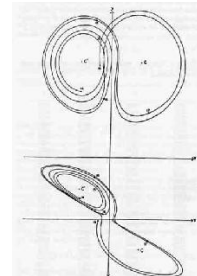


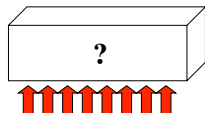
Fig. 2. Numerical solution of the convection equations. Trajectory in the x, y, z phase space for the first 100 iterations of the trajectory starting at the origin and evolving for 100 iterations. The axes are labeled x, y, z . The axes are labeled x, y, z . The axes are labeled x, y, z .

- Equations:

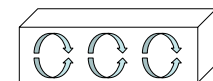
$$x' = a(y - x)$$

$$y' = rx - y - xz$$

$$z' = xy - bz$$



(first three terms of a Fourier expansion of the Navier-Stokes eqns)




- State variables:

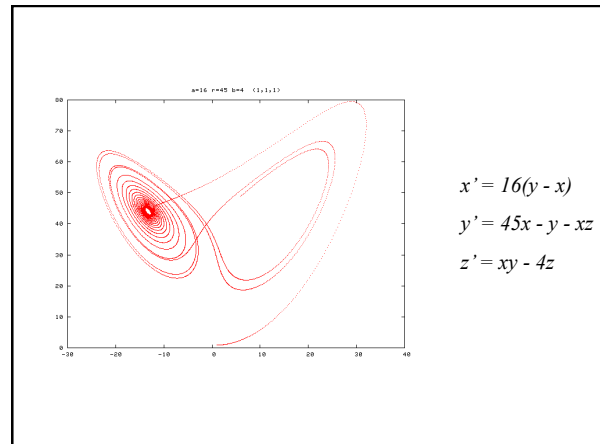
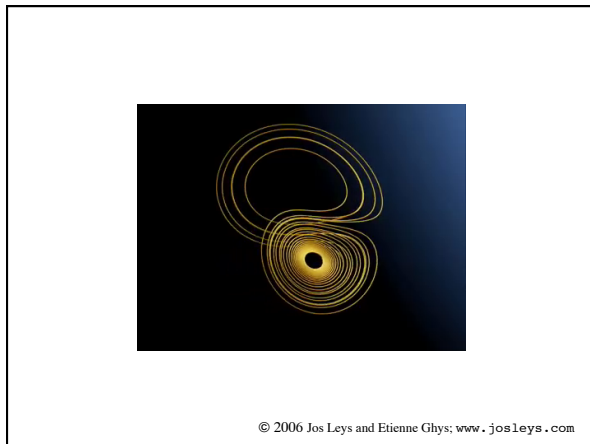
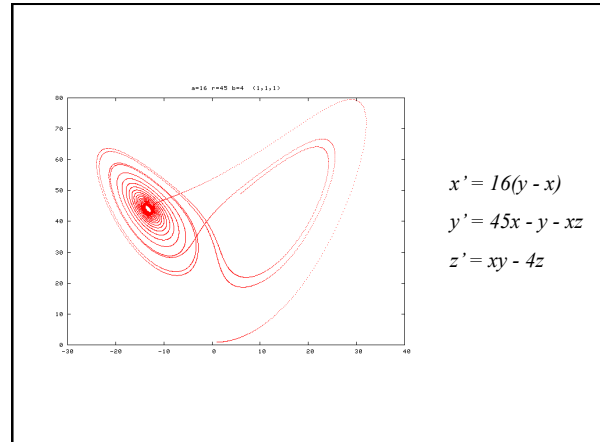
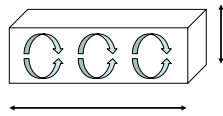
- x convective intensity
- y temperature
- z deviation from linearity in the vertical convection profile

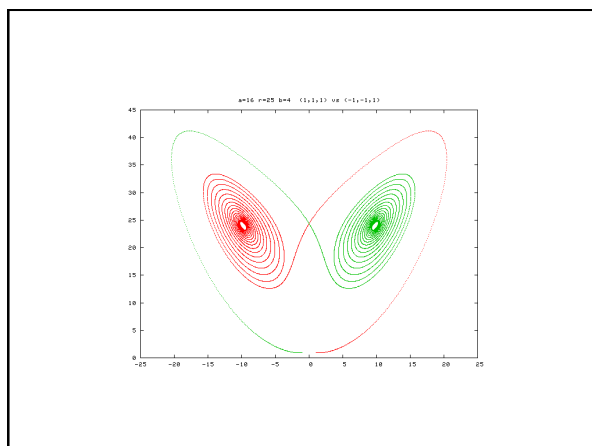
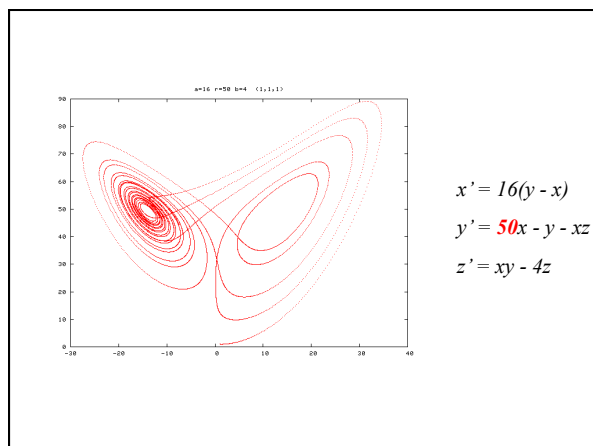
- Parameters:

- a Prandtl number - fluids property

- r Rayleigh number - related to ΔT 

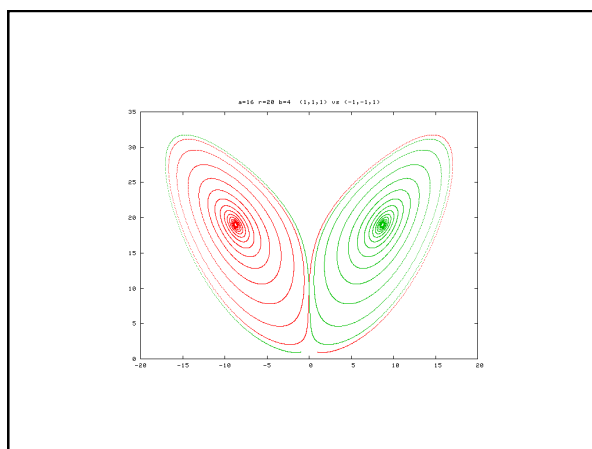
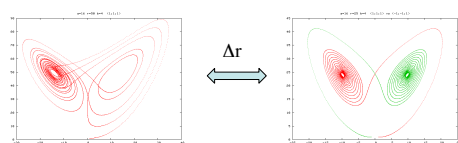
- b aspect ratio of the fluid sheet

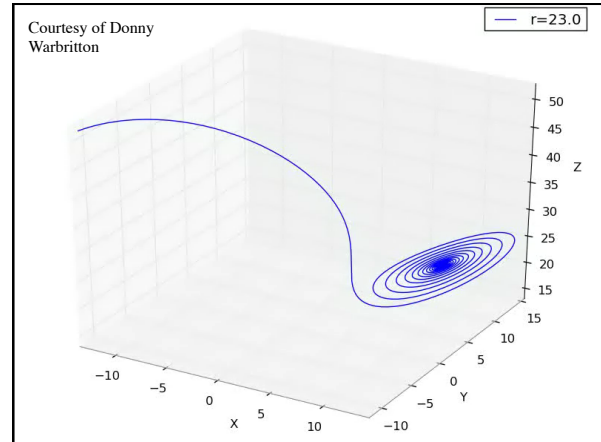
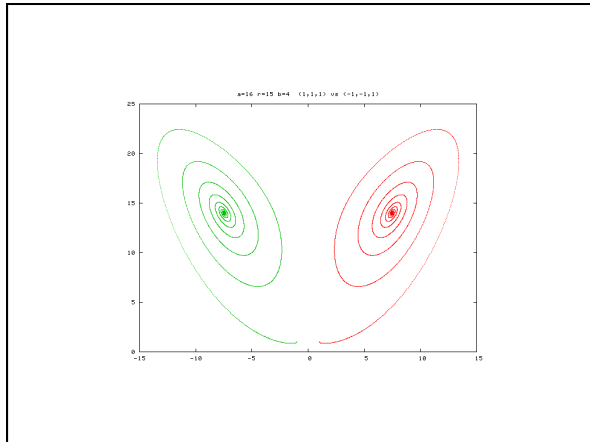




Recall: bifurcations

Qualitative changes in the dynamics—i.e., topological changes in the attractor—caused by changes in parameters:





Before we leave Lorenz...

Deterministic Nonperiodic Flow¹

EDWARD N. LORENZ

Massachusetts Institute of Technology

(Manuscript received 18 November 1962, in revised form 7 January 1963)

ABSTRACT

Finite systems of deterministic ordinary nonlinear differential equations may be designed to represent forced dissipative hydrodynamic flow. Solutions of these equations can be identified with trajectories in phase space. For these systems with bounded solutions, it is found that nonperiodic solutions are ordinarily unstable with respect to small modifications, so that slightly differing initial states can evolve into considerably different states. Systems with bounded solutions are shown to possess bounded numerical solutions. A simple system representing cellular convection is solved numerically. All of the solutions are found to be unstable, and almost all of them are nonperiodic. The feasibility of very-long-range weather prediction is examined in the light of these results.

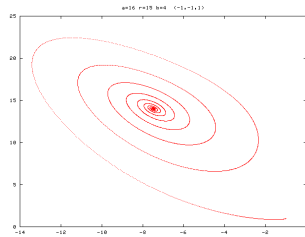
Attractors

Four types:

- fixed points
- limit cycles (*aka* periodic orbits)
- quasiperiodic orbits
- chaotic attractors

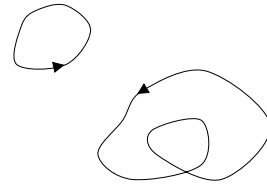
Attractors

- Fixed point



Attractors

- Limit cycle

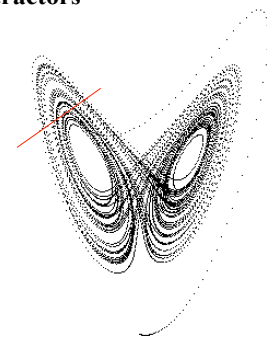


Attractors

- Quasi-periodic orbit...

"Strange" or chaotic attractors

- *often* fractal
- covered densely by trajectories
- exponential divergence of neighboring trajectories...



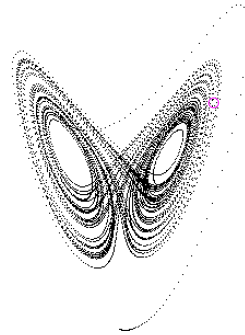
Fractals and chaos

The connection: *many (most)* chaotic systems have fractal state-space structure.

But **not** “all.”

“Strange” or chaotic attractors

- *often* fractal
- covered densely by trajectories
- exponential divergence of neighboring trajectories...

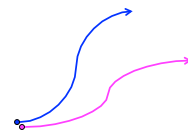


Courtesy of Mike Neuder



Lyapunov exponents and chaos

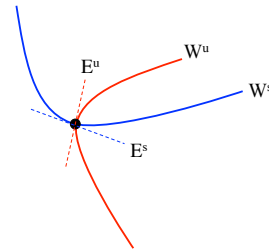
- distance between forward images of two nearby points grows as $e^{\lambda t}$ in the limit, as $t \rightarrow \infty$



Lyapunov exponents: some details

- negative λ_i compress state space; positive λ_i stretch it
- there are as many λ_i as there are state-space dimensions
- long-term average in definition; biggest one (λ_1) dominates as $t \rightarrow \infty$
- λ_i are same for all ICs in one basin
- nonlinear analogs of eigenvalues: n λ in an n -dimensional system
- they parametrize growth/shrinkage along the unstable and stable manifolds W^u and W^s
- positive λ_1 is a signature of chaos

λ_i and the un/stable manifolds (W^u and W^s)



Attractors

Four types:

- fixed points
- limit cycles (*aka* periodic orbits)
- quasiperiodic orbits
- chaotic attractors

A nonlinear system can have any number of attractors, of all types, sprinkled around its state space

Their basins of attraction (plus the basin boundaries) *partition* the state space

And there's no way, *a priori*, to know where they are, how many there are, what types, etc. (which is **not** the case in linear systems!)



(image from wikipedia)

Concepts: review

- State variable
- State space
- Initial condition
- Trajectory
- Attractor
- Basin of attraction
- Transient
- Fixed point (un/stable)
- Bifurcation
- Parameter
- Lyapunov exponent

Conditions for chaos**(in continuous-time systems)****Necessary:**

- Nonlinear
- At least three state-space dimensions

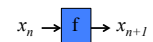
Necessary and sufficient:

- Cannot be solved in closed form (“nonintegrable,” in Hamiltonian parlance)

- discrete time systems:
 - time proceeds in clicks
 - “maps”
 - modeling tool: *difference* equation
- continuous time systems:
 - time proceeds smoothly
 - “flows”
 - modeling tool: *differential* equations

What do *those beasts* look like and how do we deal with them?Difference equations:

- e.g., $x_{n+1} = \cos(x_n)$



- given state x at time n , tells you state at time $n+1$
- solve by iterating

A canonical difference equation:

The logistic map: $x_{n+1} = R x_n (1 - x_n)$

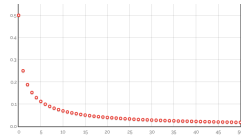
If $R=1$ and $x_0=0.5$, $x_1=1(0.5)(1-0.5)=0.25$

$x_2=1(0.25)(1-0.25)=0.1875$

...

Eventually, x settles down at 0:

Much more on
this in Joshua
Garland's lecture
this afternoon



What do **those beasts** look like and how do we deal with them?

Difference equations:

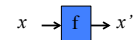
- e.g., $x_{n+1} = R x_n (1 - x_n)$



- given state x at time n , tells you state at time $n+1$
- solve by iterating

Differential equations:

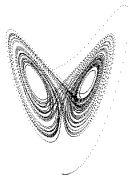
- e.g., $d^2x(t)/dt^2 = -x(t)$



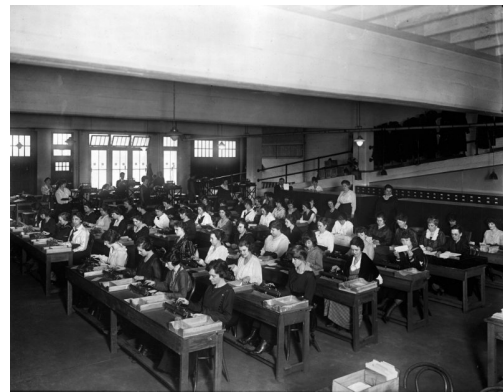
- given state x at time t , tells you *the direction in which that state will evolve*
- solve with an ODE solver (see Liz's notes)

The basic idea behind (one family of) ODE solvers:

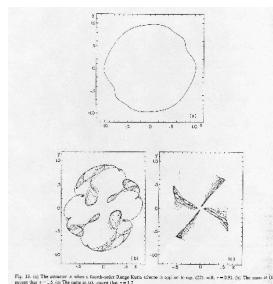
- Follow the slope that the ODE gives you
- Simplest: Euler
- More creative: legion...e.g., `ode45`, `ode34`



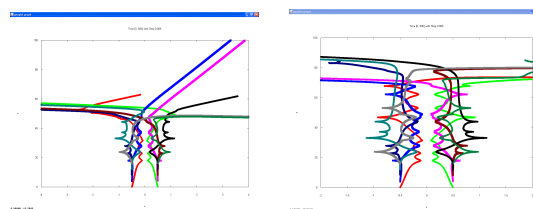
All very well if you have a nice modern computer...



www.computerhistory.org

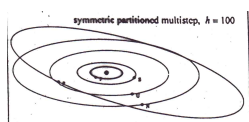


Different timestep

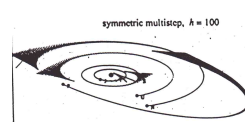
Lorenz, *Physica D* 35:229

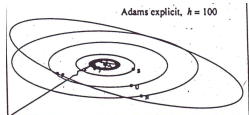
Different arithmetic

N. Ross Ph.D. thesis, Ucolorado, 2008



Different solver algorithm...





Moral: numerical methods can run amok in “interesting” ways...

- can cause distortions, bifurcations, etc.
- and these look a lot like *real, physical* dynamics...
- source: algorithms, arithmetic system, timestep, etc.
- Q: what could you do to diagnose whether your results included spurious numerical dynamics?

Moral: numerical methods can run amok in “interesting” ways...

- can cause distortions, bifurcations, etc.
- and these look a lot like *real, physical* dynamics...
- source: algorithms, arithmetic system, timestep, etc.
- Q: what could you do to diagnose whether your results included spurious numerical dynamics?

• *change the timestep*

• *change the method*

• *change the arithmetic*

But beware
machine ϵ ...

Another important issue

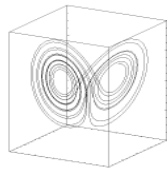
Many solvers, such as Matlab's `ode45`, are *adaptive*: they change the timestep and/or the method itself, on the fly, in order to correctly simulate the dynamics.

(The algorithms for this are interesting; we can talk about them offline.)

That means that the points that are output by tools like `ode45` are *not evenly spaced in time*. That can matter, depending on how you're using that solution...

So ODE solvers make mistakes.

...and chaotic systems are sensitively dependent on initial conditions....



...??!

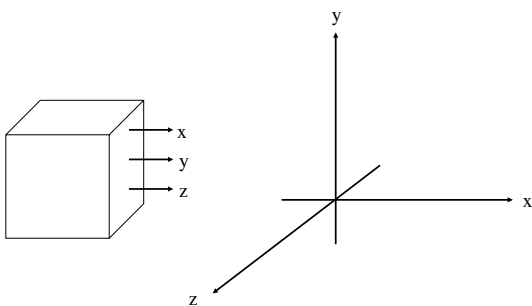
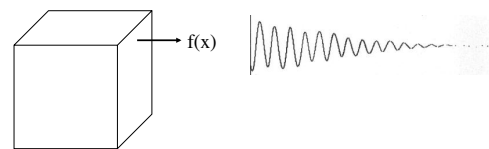
Shadowing lemma

Every* noise-added trajectory on a chaotic attractor is *shadowed* by a true trajectory.

Important: this is for *state* noise, not *parameter* noise.

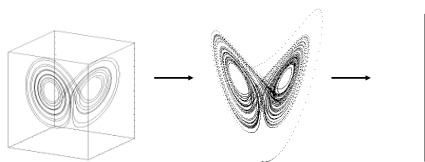
(*) Caveat: not if the noise bumps the trajectory out of the basin

That state-space stuff is all very well, but it's a bit utopian.

**Reality:**

- Rarely do you even *know* what the state variables are.
- Even if you did, you might not be able to *measure* all of them.
- And even if you could, doing so might *change the dynamics*...

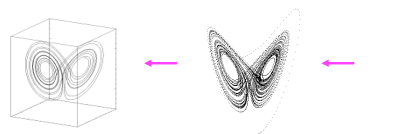
What we're really asking for when we do time-series analysis on scalar data...



Undoing a projection = gack =

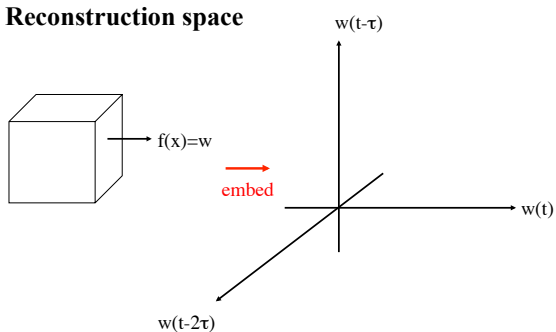
Delay-coordinate embedding

“reinflate” that squashed data to get a *topologically identical* copy of the original thing.

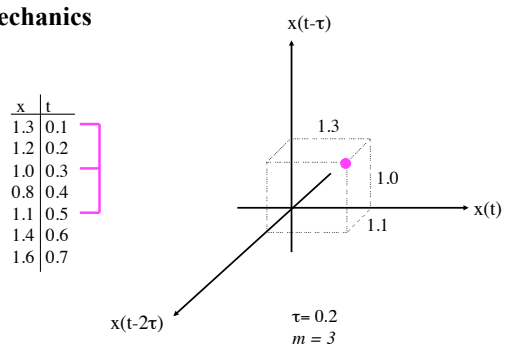


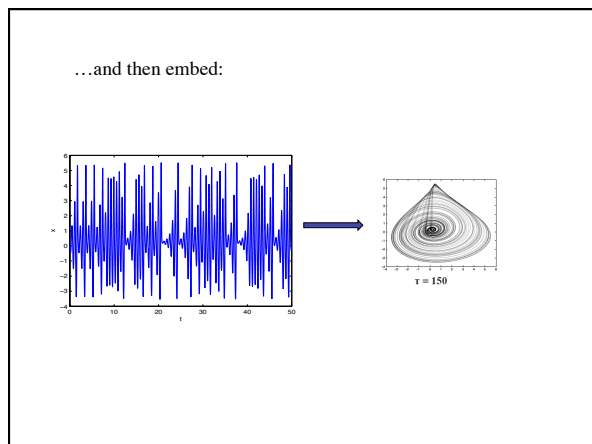
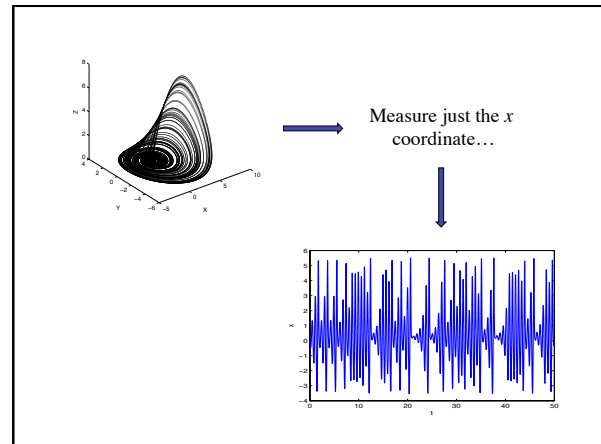
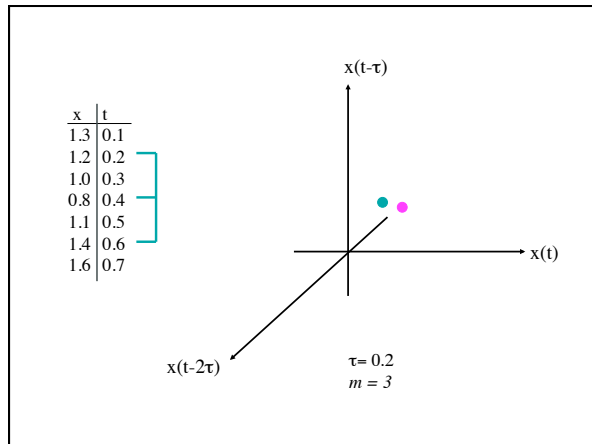
(not quite, but almost...)

Reconstruction space



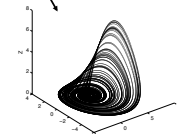
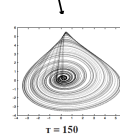
Mechanics





Takens* theorem

For the right τ and enough dimensions, the embedded dynamics are diffeomorphic to (and thus have same topology as) the original state-space dynamics.



* Whitney, Mane, ...

Note: the measured quantity must be a smooth, generic function of at least one state variable, and must be uniformly sampled in time.

Diffeomorphic: mapping from the one to the other is differentiable and has a differentiable inverse.

What that means:

- *qualitatively* the same shape (topology)



- i.e., can deform one into the other...



www.shapeways.com/shops/henryseg

Diffeomorphic: mapping from the one to the other is differentiable and has a differentiable inverse.

What that means:

- *qualitatively* the same shape (topology)
- i.e., can deform one into the other
- have same dynamical invariants (e.g., λ)



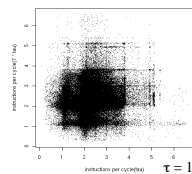
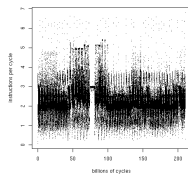
Calculating λ (& other invariants) from data

- The bible: H. Kantz & T. Schreiber, *Nonlinear Time Series Analysis*
- Associated software: TISEAN
www.mpi-pks-dresden.mpg.de/~tisean
- A recent review article: EB & H. Kantz, "Nonlinear Time Series Analysis Revisited," *CHAOS* **25**:097610 (2015)

Much more on this in Joshua Garland's lecture tomorrow

NLTSA* of computer performance dynamics

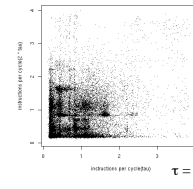
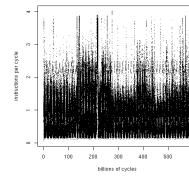
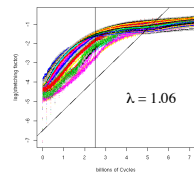
* nonlinear time-series analysis



$\tau = 194, m = 10$

bzip2 dynamics on an Intel Core2

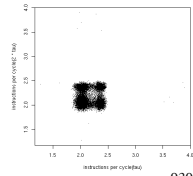
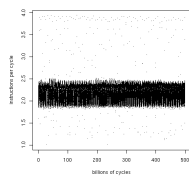
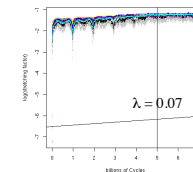
Mytkowicz et al., *Chaos* 19:033124



$\tau = 973, m = 12$

bzip2 dynamics on an Intel Pentium 4

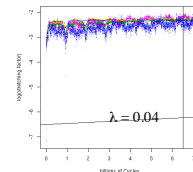
Mytkowicz et al., *Chaos* 19:033124



$\tau = 930, m = 8$

povray dynamics on an Intel Core2

Mytkowicz et al., *Chaos* 19:033124



Caveat: need enough data...

If Δt is not uniform

~~Theorem (Takens): for $\tau > 0$ and $m > 2d$, reconstructed trajectory is diffeomorphic to the true trajectory~~

~~Conditions: evenly sampled in time, smooth generic measurement function~~

Interspike interval embedding

idea: lots of systems generate spikes — hearts, nerves, etc.

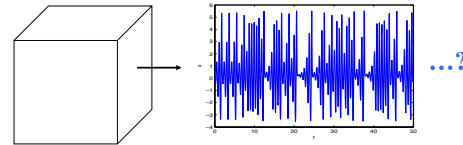
if you assume that the spikes are the result of an integrate-and-fire system, then the Δt has a one-to-one correspondence to some state variable's *integrated* value...

in which case the embedding theorems still hold.

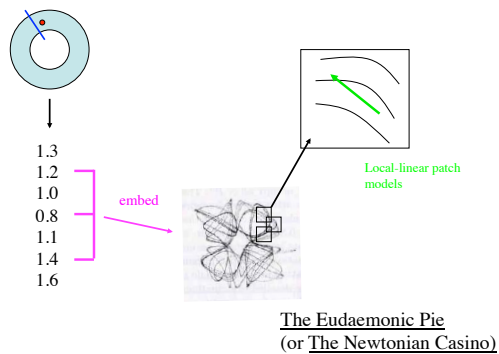
(with the Δt s as state variables)

Sauer *Chaos* 5:127

Prediction

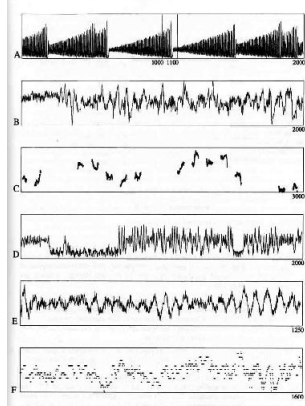


Predicting the path of a roulette ball...



The Santa Fe competition

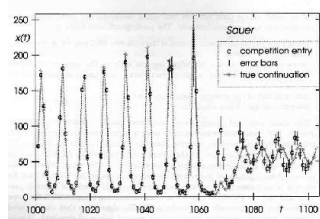
- Weigend & Gershenfeld, 1992
- put a bunch of data sets up on an ftp server
- and invited all comers to predict their future
- chronicled in *Time Series Prediction: Forecasting the Future and Understanding the Past*, Santa Fe Institute, 1993 (from which the images on the following half-dozen slides were reproduced)



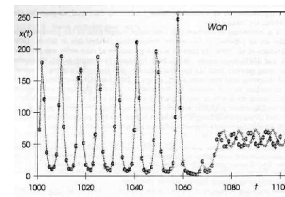
The Santa Fe competition: data

- Laboratory laser
- Medical data (sleep apnea)
- Currency rate exchange
- RK4 on some chaotic ODE
- Intensity of some star
- A Bach fugue

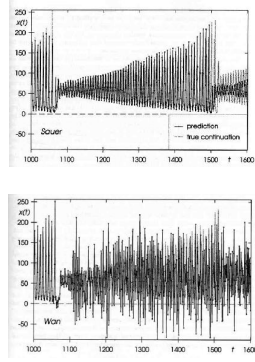
Embedding + patch models: (Sauer)



Neural net: (Wan)



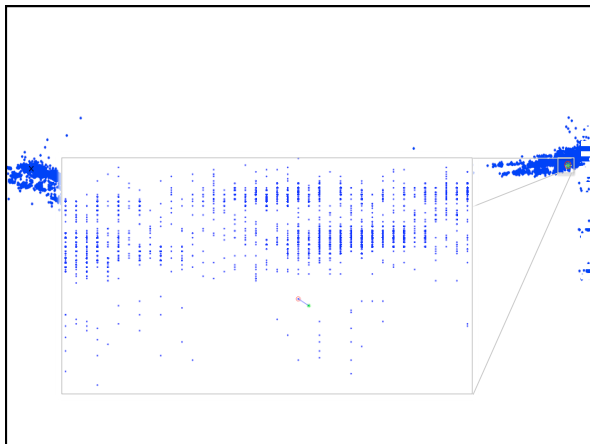
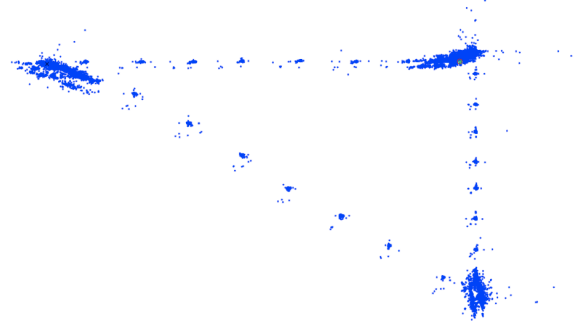
Further out:



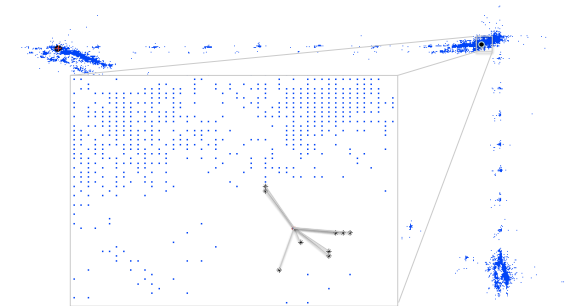
Sauer

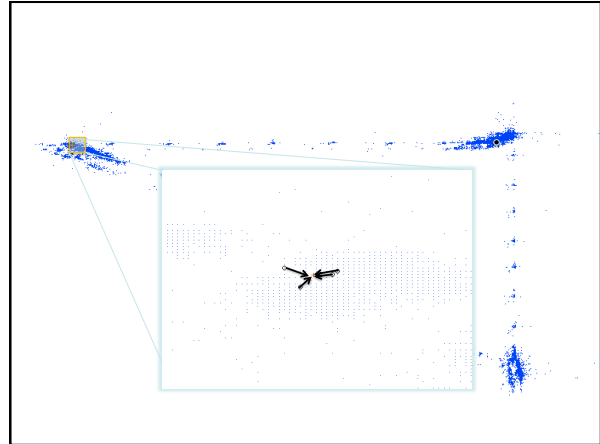
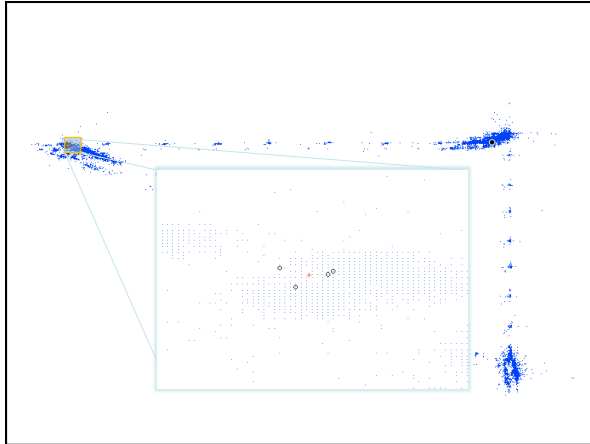
Wan

**An even simpler prediction method:
Lorenz's method of analogues**

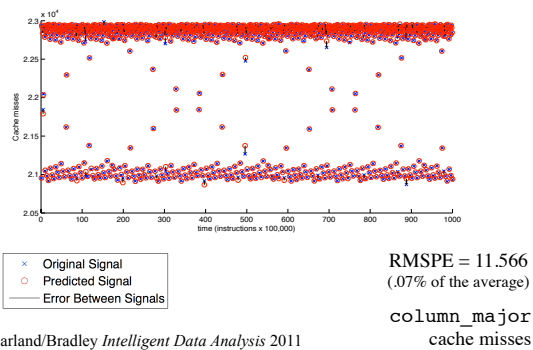


A k -nearest neighbor modification of LMA





Using k LMA to predict computer dynamics



Garland/Bradley *Intelligent Data Analysis* 2011

Noise...

Linear filtering: a very very bad idea if the system is chaotic

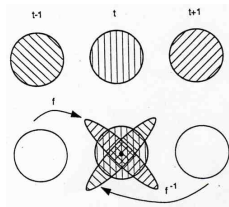
Don't bleach chaotic data

Chaos 3, 771 (1995), <https://doi.org/10.1063/1.1659356>
James Theiler
• Center for Nonlinear Studies and Theoretical Division, Los Alamos National Laboratory, Los Alamos, New Mexico 87545,
• Santa Fe Institute, 1600 Old Mexico Trail, Santa Fe, New Mexico 87501

- Frequency is a bad discriminator of signal and noise in chaotic signals
- The math behind linear filters relies on superposition, which doesn't hold in nonlinear systems

Nonlinear alternatives:

- use the stable and unstable manifold structure on a chaotic attractor...

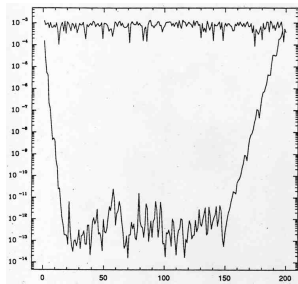


Farmer & Sidorowich, in *Evolution, Learning and Cognition*, World Scientific, 1983

Idea:

- If you have a model of the system, you can simulate what happens to each point in forward *and backward* time
- If your system has transverse stable and unstable manifolds, that does useful things to the noise balls
- Since all three versions of that data should be identical at the middle time, can average them
- ➡ noise reduction!
- Works best if manifolds are perpendicular, but requires only transversality

Results:



Farmer & Sidorowich, in *Evolution, Learning and Cognition*, World Scientific, 1983

Noise...

Linear filtering: a very very bad idea if the system is chaotic

Nonlinear alternatives:

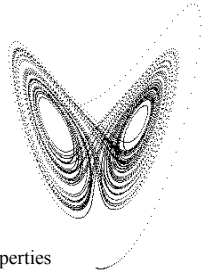
- use the stable and unstable manifold geometry on a chaotic attractor
- what about using the *topology* of the attractor?

Topology-based signal separation

Chaos 14, 305 (2004), <https://doi.org/10.1063/1.1705852>

V. Robins
• Department of Applied Mathematics, Research School of Physical Sciences and Engineering, The Australian National University,
N. Rooney and E. Bradley

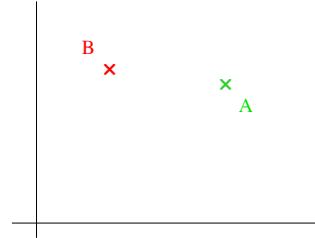
Chaos and control



Can we use some of those cool properties
and turn them to advantage?
e.g., dense attractor coverage

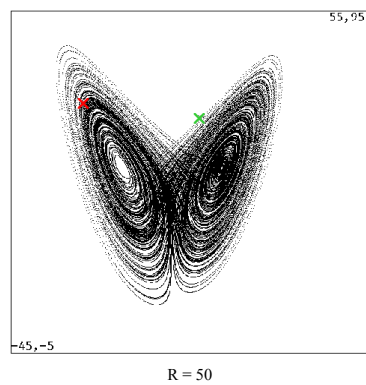
Control:

getting from A to
B, minimizing
some cost
functional

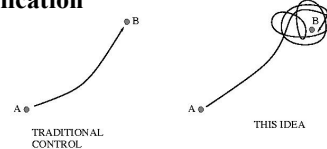


Lorenz System:

denseness,
reachability, and
control



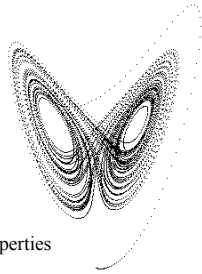
Denseness & reachability in a real engineering application



- can control position/volume/density of attractor — *within limits*
- possibly not reachable any other way
- not for time-critical applications (that “eventually”)

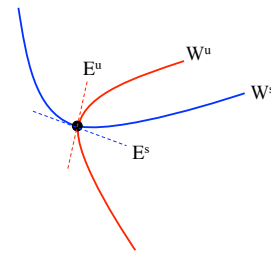
Using Chaos to Broaden the Capture
Range of a Phase-Locked Loop
Elizabeth Bradley, Member, IEEE

Chaos and control



Can we use some of those cool properties
and turn them to advantage?
e.g., dense attractor coverage
or the manifold structure?

Remember those λ_i & un/stable manifolds?
They play a critical role here...

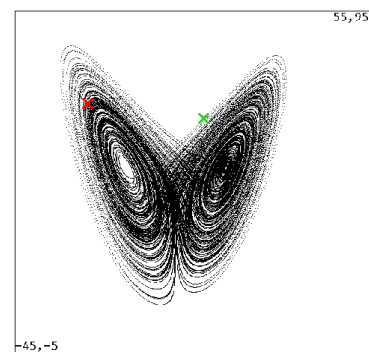


OGY control

- dense attractor coverage \rightarrow reachability
- un/stable manifold structure + local-linear control \rightarrow controllability

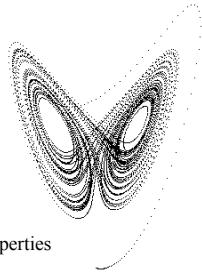
Ott et al., PRL 64:1196

Use local-linear control, designed using the eigenvalues and eigenvectors at that point \times to balance a chaotic system on a UPO passing through that point.



But you're relying on denseness to get you into the controllable region, and that may take a while...

Chaos and control



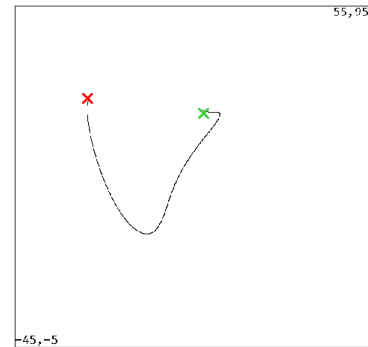
Can we use some of those cool properties and turn them to advantage?

e.g., dense attractor coverage

Or the manifold structure?

Or the sensitive dependence on ICs?

Lorenz System: SDOIC-based targeting



Four R switches; 240X faster

Bradley, *Cybernetics & Systems* 26:299

Program in
Applied
Mathematics



Erik Bollt

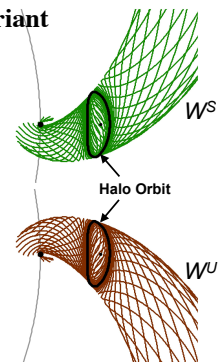
University of Colorado at Boulder
Boulder CO 80309-0526
(303) 492-4068

Other cool ways to use invariant manifolds

Want to get a spacecraft onto a "halo orbit," which is a UPO of the dynamics.

Unstable Periodic Orbits (UPOs) have invariant manifolds:

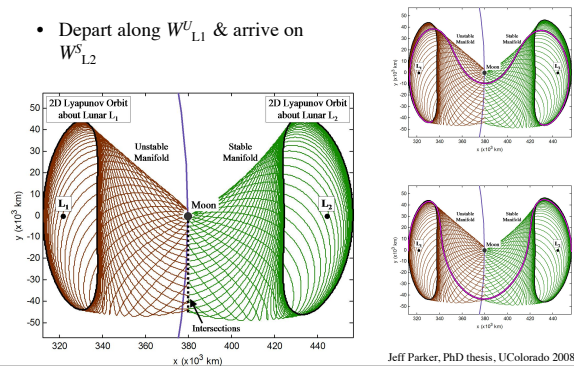
- Stable Invariant Manifold (W^s)
 - The set of all trajectories a particle could use to arrive onto the UPO.
- Unstable Invariant Manifold (W^u)
 - The set of all trajectories a particle could take after a small perturbation from the UPO.



Jeff Parker, PhD thesis, UColorado 2008

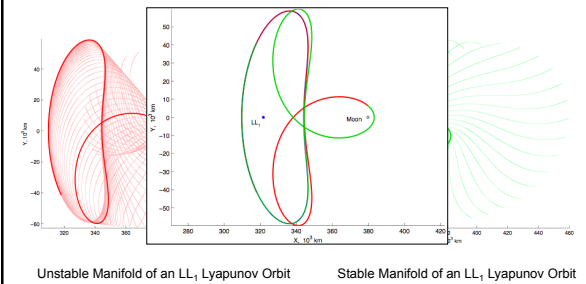
Low-energy (cheap) orbit transfers

- Depart along $W_{L_1}^U$ & arrive on $W_{L_2}^S$



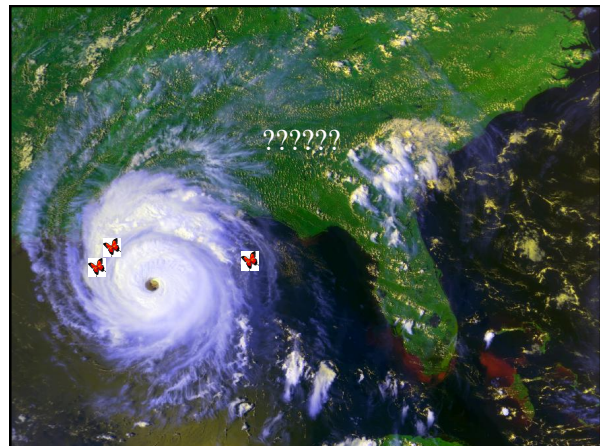
Homoclinic orbits - The best case

- If a trajectory in Stable and Unstable intersect ("homoclinic connection")

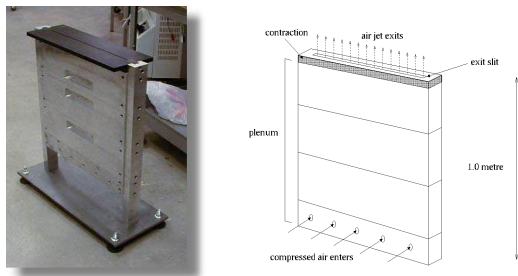


Can we do any of that in spatially extended systems?

(i.e. harness the butterfly effect, exploit un/stable manifold geometry?)

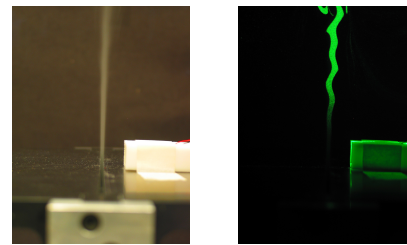


A 2D jet



Peacock *et al.*, *Exp. Fluids* 37:22

End view

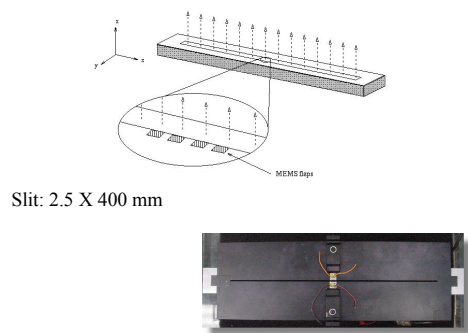


room lighting

stop-action laser "slice"

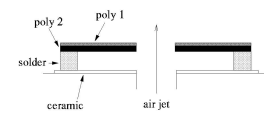
aerosolized canola oil

Forcing the jet flow



Slit: 2.5 X 400 mm

MEMS actuators



Video : overhead view at 2Hz, 10V

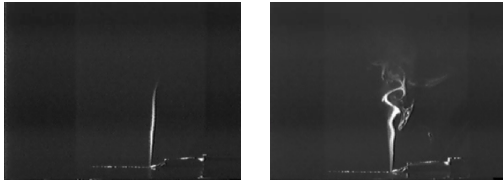
Area of individual flap is 1.0 x 0.25mm

Ma *et al.*, *IEEE Trans. Adv. Packaging* 26:268

The Butterfly effect in action...

no forcing

6Hz forcing

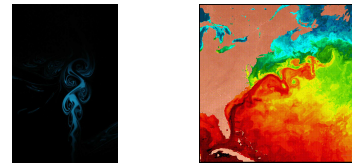


MEMS flap

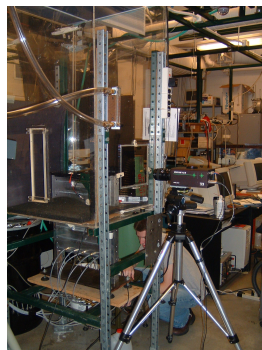
Forcing generates coherent structures that enhance entrainment and mixing

Peacock et al., Exp. Fluids 37:22

Does this have anything to do with reality?



Measurement & isolation:

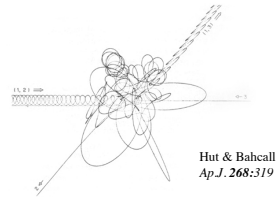


Another interesting application: chaos in the solar system

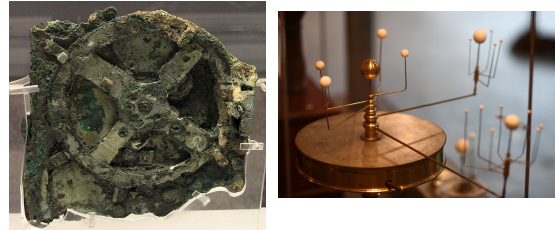
- orbits of Pluto, Mars
- Kirkwood gaps
- rotation of Hyperion & other satellites
- ...

Solar system stability:

- recall: two-body problem not chaotic
- but three (or more) can be...



Exploring that issue before the digital computer age...

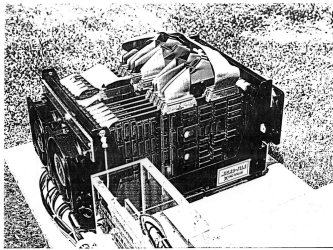


An *orrery*, which is a *mechanical computer* whose gear ratios and circular platters simulate the orbits of the planets

Exploring that issue, circa 1980:

- write the n -body equations for the solar system
- solve them using symplectic ODE solvers on a special-purpose computer

The *digital orrery*
(Wisdom & Sussman)



Numerical Evidence That the Motion of Pluto Is Chaotic

GERALD JAY SUSSMAN AND JACK WISDOM

The Digital Orrery has been used to perform an integration of the motion of the outer planets for 845 million years. This integration indicates that the long-term motion of the planet Pluto is chaotic. Nearby trajectories diverge exponentially with an e-folding time of only about 20 million years.

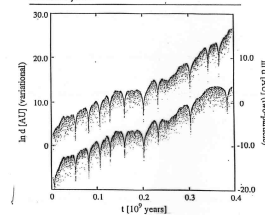


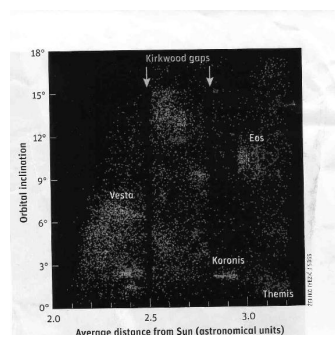
Figure 3: The exponential divergence of nearby trajectories is indicated by the average linear growth of the logarithm of the distance between two trajectories. In the upper panel we see the growth of the vertical distance around a reference trajectory. In the lower panel we see how two trajectories diverge with time. The distance between two trajectories that are initially very close to each other diverges exponentially. The vertical method of studying neighboring trajectories does not have the problem of singularities. Note that the two methods are in excellent agreement until the two-trajectory method has nearly saturated.

Science 241:433

Should we worry?

- No.

Kirkwood gaps:



From *Sky & Telescope*

Chaos and the Kirkwood gaps

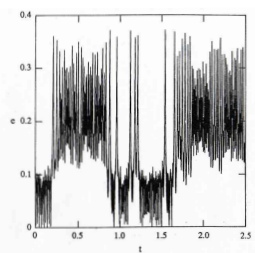


FIGURE 5. Eccentricity of a typical chaotic trajectory over a longer time interval. the time is now measured in millions of years. Bursts of high eccentricity behavior are interspersed with intervals of irregular low eccentricity behavior, broken by occasional spikes.

Wisdom, *Nuclear Phys. B* 2:391

Evidence in favor of the conjecture:

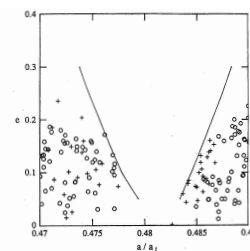
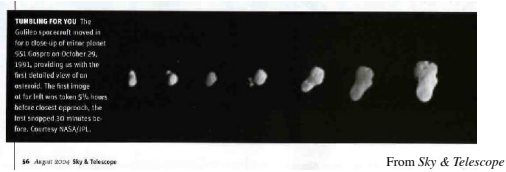


FIGURE 9. Comparison of the actual distribution of asteroids with the outer boundaries of the chaotic zone. There is both a chaotic region and quasi-periodic region in the gap, but trajectories of both types are planet crossing.

Wisdom, *Nuclear Phys. B* 2:391

Chaotic tumbling of satellites:

Voyager and Galileo **saw** this...



Ap. J. **97**:570
Ap. J. **98**:1855

...so did Cassini:



www.nasa.gov/mission_pages/cassini/multimedia/pia06243.html

Chaotic tumbling of satellites:



This happens for **all** satellites at some point in their history, unless they are perfectly spherical and in perfectly circular orbits (pf: KAM theorem; see Wisdom paper on syllabus)

Some of them are still tumbling chaotically because of their geometry, but most (like the earth and its moon) have settled down into tidal equilibria

More chaos in the solar system:

- obliquity of Mars (Touma & Wisdom, *Science* **259**:1294)



www.solarviews.com

- etc.

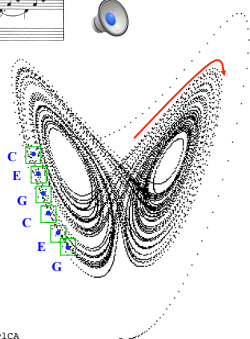
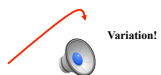
Musical Variations from a Chaotic Mapping

Dabby Chaos 6:95



Pitch sequence:
C, E, G, C, E, G, C, E...

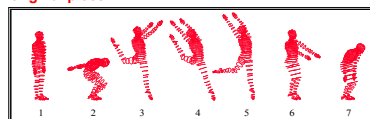
C symbol dynamics



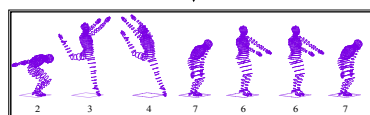
Also fun: <http://www.youtube.com/watch?v=B2XLE9TyICA>

Chaotic variations on movement sequences

original piece

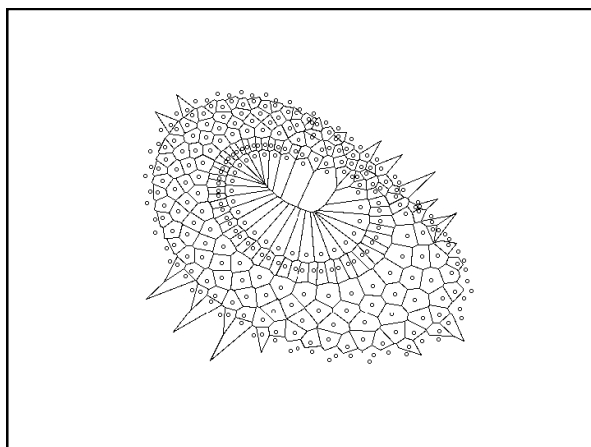
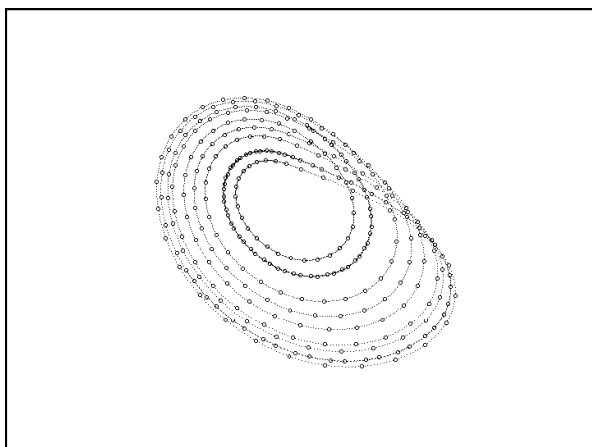


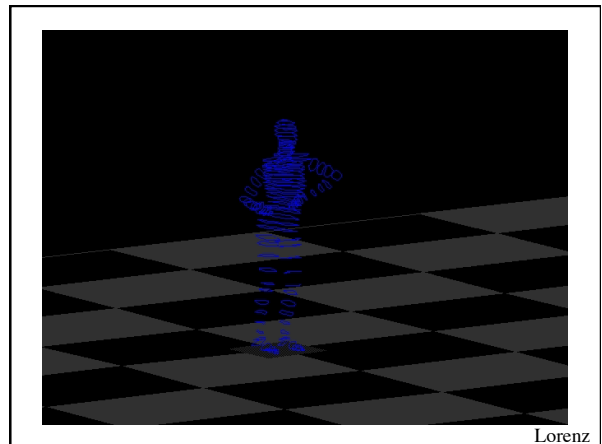
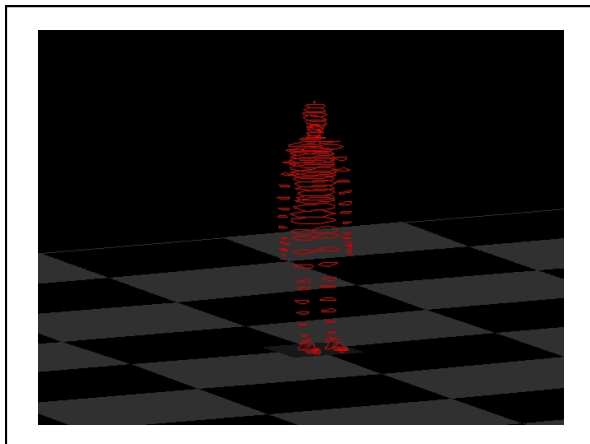
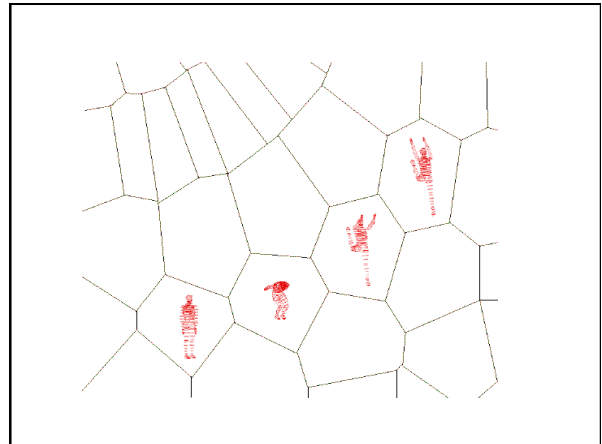
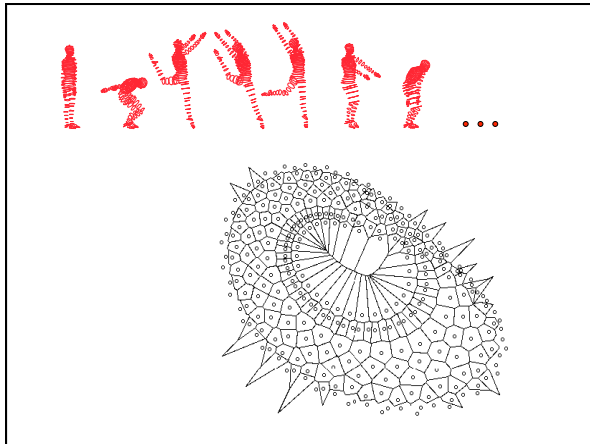
chaotic mapping



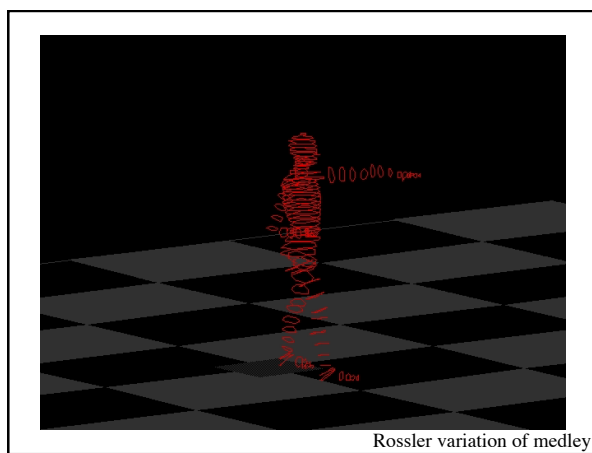
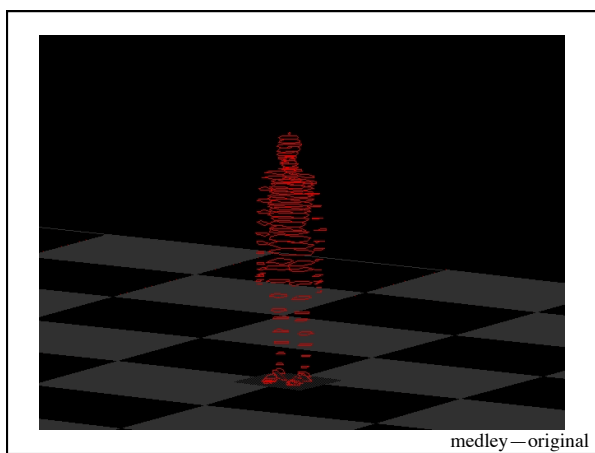
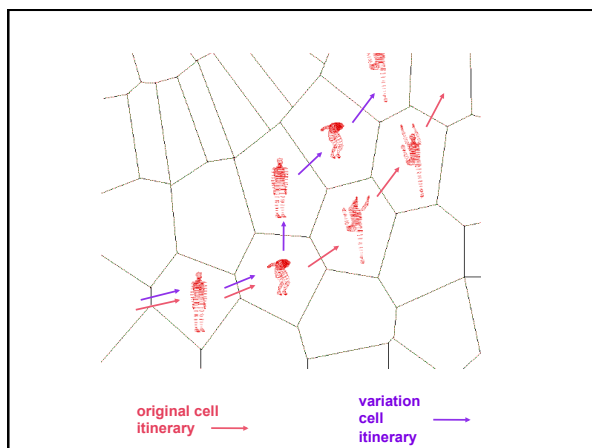
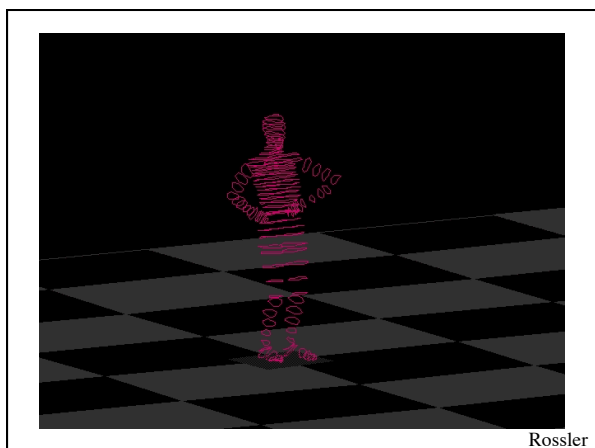
chaotic variation

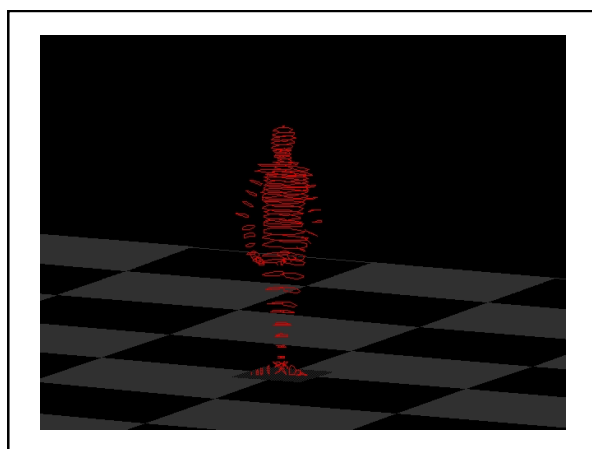
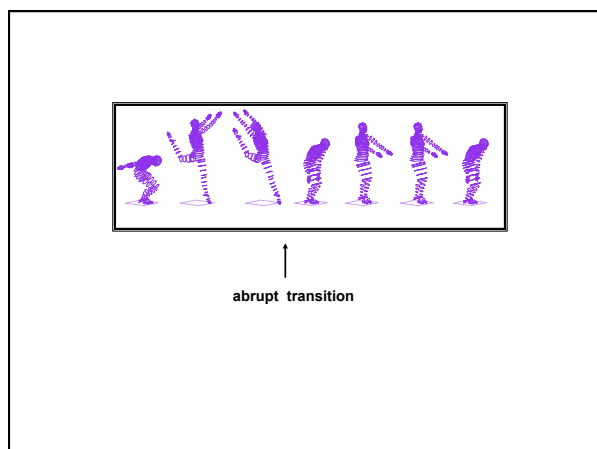
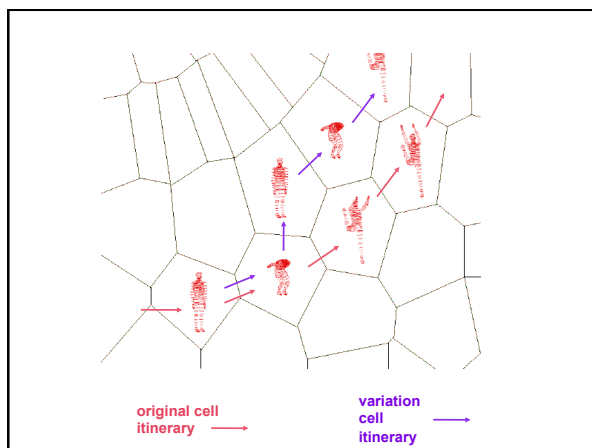
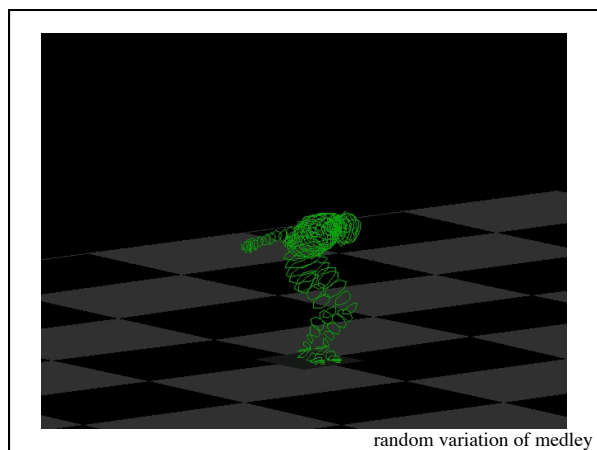
Bradley & Stuart, *Chaos* 8:800

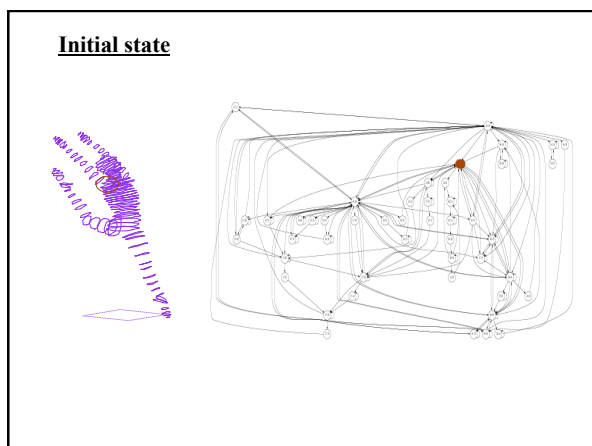
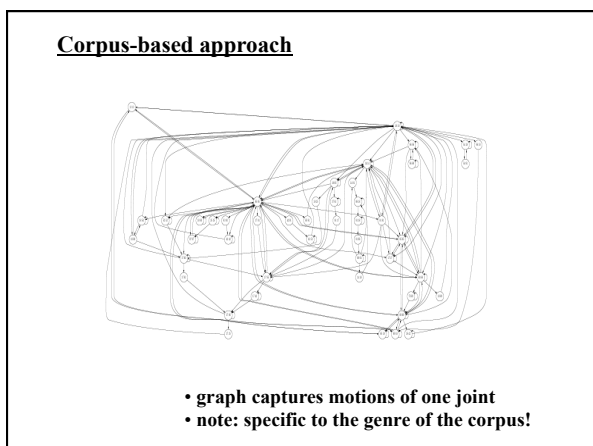
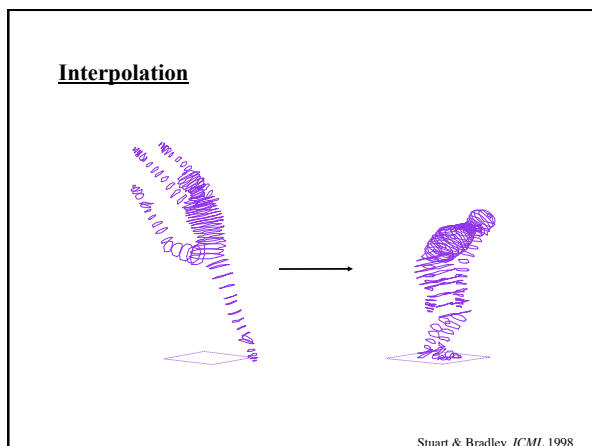
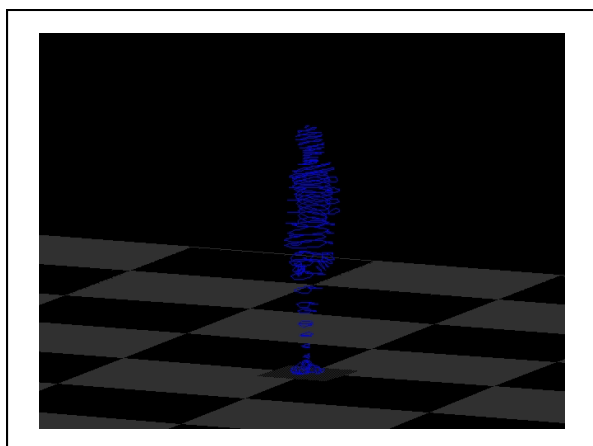


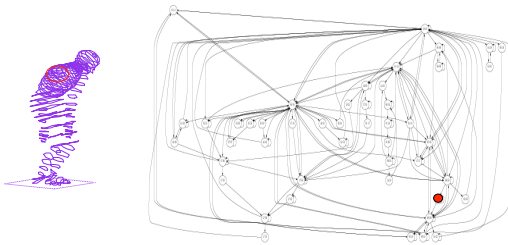
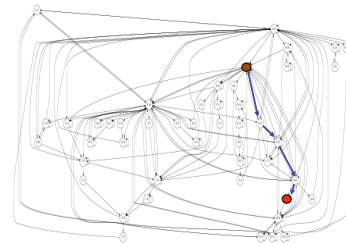


Lorenz

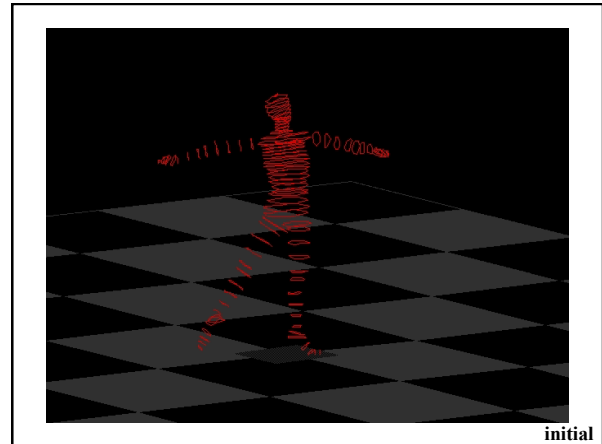
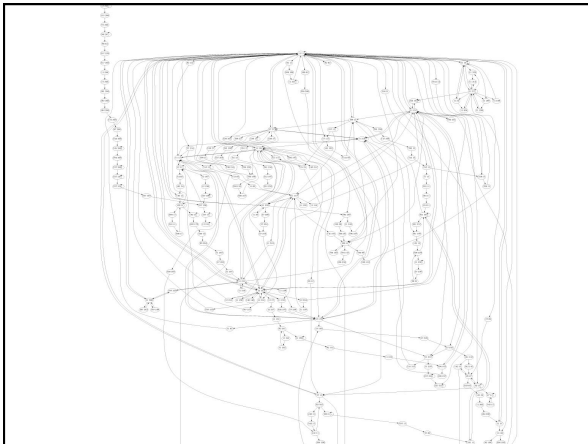


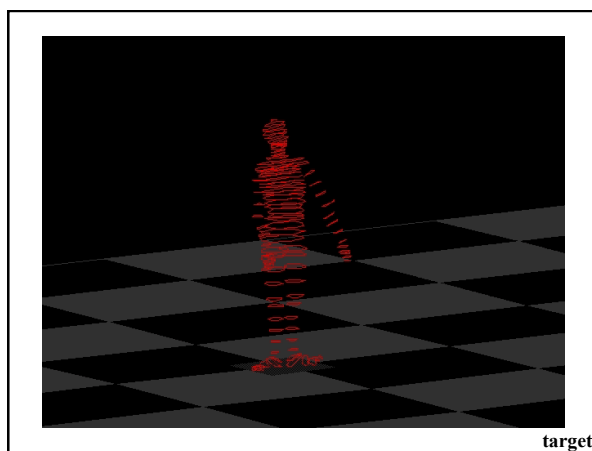
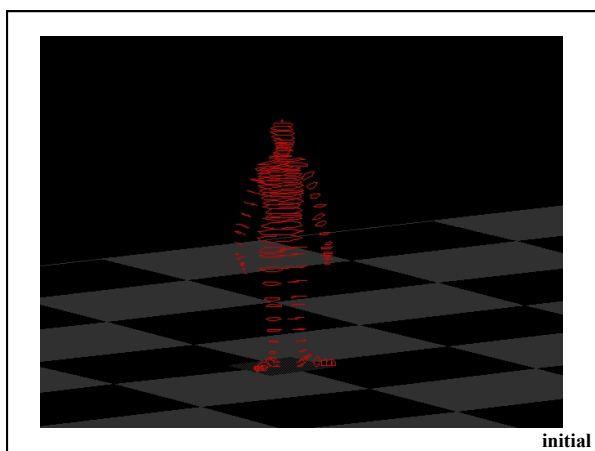
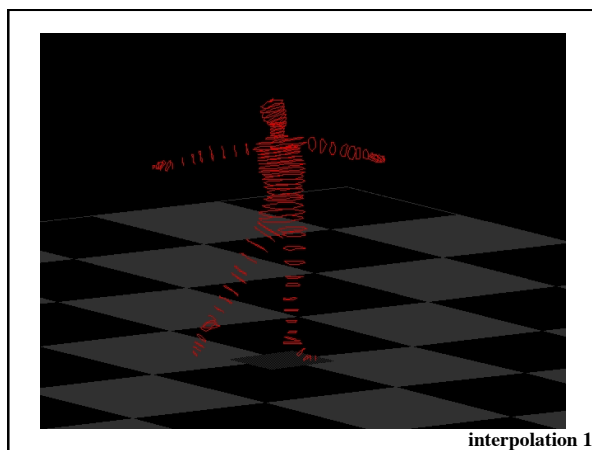
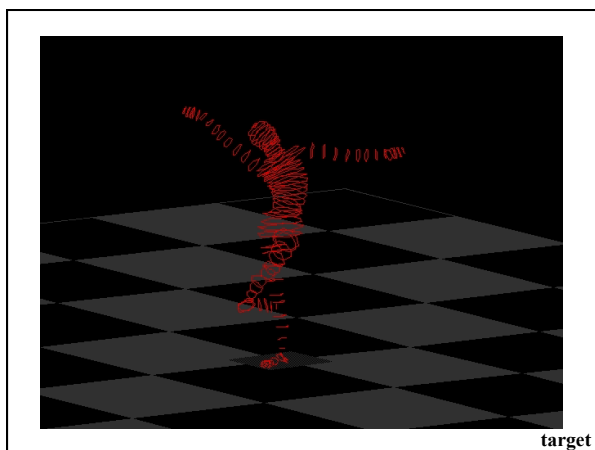


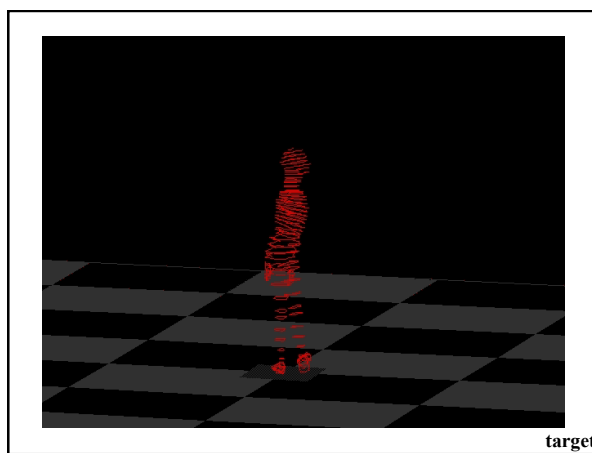
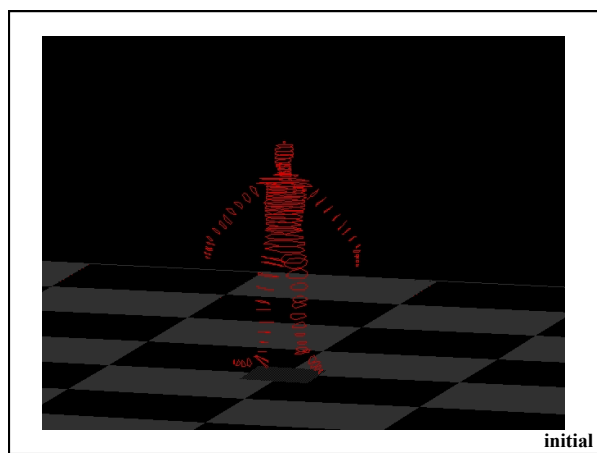
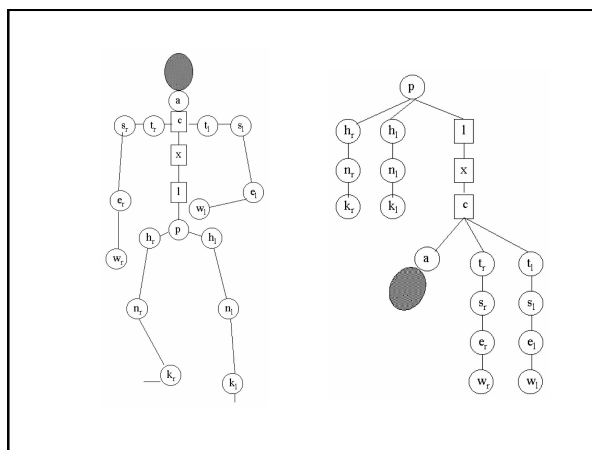
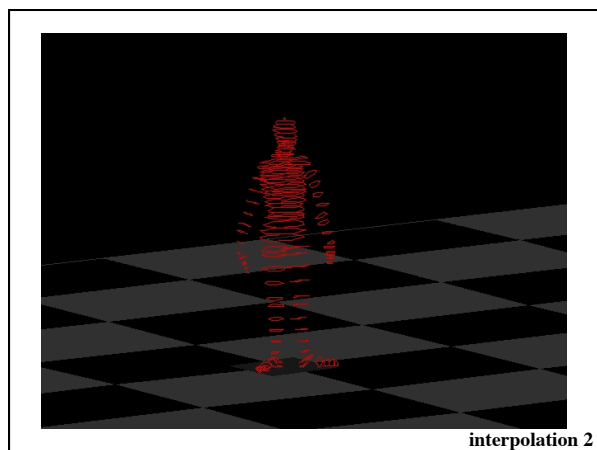


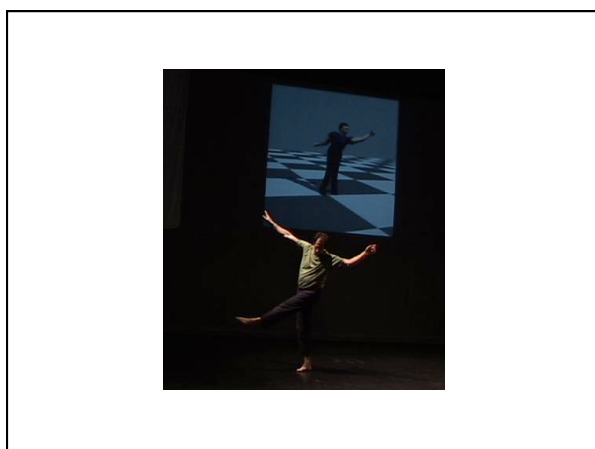
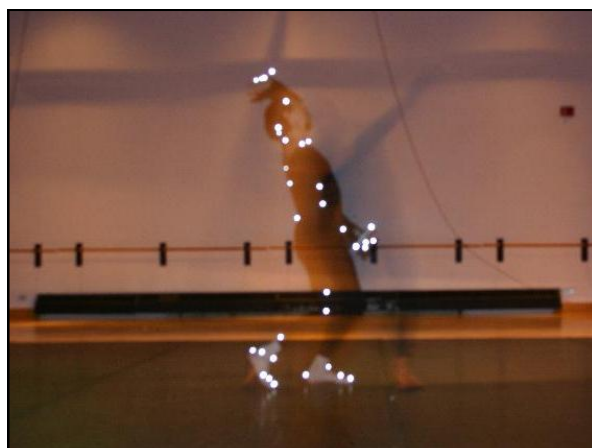
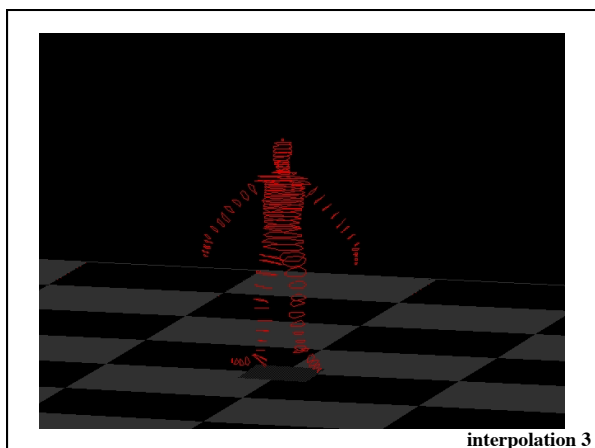
Target state**Graph search**

...for 44 joints in parallel!









Con/cantation: (chaotic variations)

A computer-assisted theme and variations performance project

Radcliffe Institute for Advanced Study

Created by David Capps and Liz Bradley
Video and layout: Angelika von Chamier

Ideas and algorithms: Josh Stuart
Motion capture and animation: Carnegie Mellon Graphics Laboratory
(Professor Jessica Hodgins, leader: Justin Macey, motion-capture technician: Mo Mahler, animation and character design)
Code: David Trowbridge and Evan Sheehan
Inspiration: Diana Ebbby

Made possible with support from the Radcliffe Institute for Advanced Study, the National Science Foundation (05-0326322), the David and Lucile Packard Foundation, and the Graduate Council on Arts and Humanities at the University of Colorado.

Tuesday, April 17th
5pm
Radcliffe Gym

Radcliffe Yard
10 Garden Street
Cambridge, MA 02138

Free Admission

Chaos vs. complexity??

