# Dynamics Days 2010 Schedule

**January 4 – 7, 2010**

**Organizing Committee:**
Adilson E. Motter (Chair), William L. Kath & Edward Ott

**Hilton Garden Inn**
Evanston, IL

<table>
<thead>
<tr>
<th>Sunday, January 3rd</th>
<th>Welcoming Reception</th>
</tr>
</thead>
<tbody>
<tr>
<td>7:00 – 8:30PM</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Monday, January 4th</th>
<th>Materials Pick-up</th>
</tr>
</thead>
<tbody>
<tr>
<td>8:20 – 9:40AM</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>9:40 – 10:00</th>
<th>Coffee Break</th>
</tr>
</thead>
</table>
| 10:00 – 10:40        | Robert Ecke (Los Alamos National Laboratory)  
Fragile Jamming and Hysteresis in 2D Granular Packing |
| 10:40 – 11:20        | Fred MacKintosh (Vrije University)  
Non-Equilibrium Fluctuations and Mechanics of Active Gels and Living Cells |
| 11:20 – 11:40        | Pinaki Chakraborty (University of Illinois at Urbana-Champaign)  
Rotating Volcanic Plumes: Lobate Umbrellas, Tomatoes, and Lightning Sheaths |
| 11:40 – 12:00        | Laura E. Schmidt (University of Twente)  
Role of Bubbles on Heat Transfer and Turbulence in Rayleigh-Benard Convection |

<table>
<thead>
<tr>
<th>12:00 – 1:50</th>
<th>Lunch (on your own)</th>
</tr>
</thead>
</table>
| 1:50 – 2:30          | Julio Ottino (Northwestern University)  
The Evolution of Mixing: From Stretching and Folding to Cutting and Shuffling |
| 2:30 – 2:50          | Alexey Snezhko (Argonne National Laboratory)  
Dynamic Self-Propelled Structures in Nonequilibrium Magnetic Layers |
| 2:50 – 3:30          | Predrag Cvitanovic (Georgia Institute of Technology)  
Geometry of Turbulence: A Stroll Through 61,506 Dimensions |

<table>
<thead>
<tr>
<th>3:30 – 4:00</th>
<th>Coffee Break</th>
</tr>
</thead>
</table>
| 4:00 – 4:20          | Louis Pecora (Naval Research Laboratory)  
Regeneration of Tunneling Rates with Quantum Chaos |
| 4:20 – 4:40          | Ned J. Corron (U. S. Army RDECOM)  
Matched Filter for Chaos |
| 4:40 – 5:20          | Mary Silber (Northwestern University)  
Quasipatterns by Design |
| 5:20 – 6:00          | Raymond Goldstein (University of Cambridge)  
Synchronization of Eukaryotic Flagella |

<table>
<thead>
<tr>
<th>6:30 – 9:00</th>
<th>Conference Dinner</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time</td>
<td>Speaker</td>
</tr>
<tr>
<td>------------</td>
<td>----------------------------------------------</td>
</tr>
<tr>
<td>8:20-9:00</td>
<td>Harry Swinney (University of Texas at Austin)</td>
</tr>
<tr>
<td>9:00-9:20</td>
<td>Wolfgang Losert (University of Maryland at College Park)</td>
</tr>
<tr>
<td>9:20-9:40</td>
<td>Heather Hardway (Boston University)</td>
</tr>
<tr>
<td>9:40-10:00</td>
<td>Coffee Break</td>
</tr>
<tr>
<td>10:00-10:40</td>
<td>Jonathan Widom (Northwestern University)</td>
</tr>
<tr>
<td>10:40-11:20</td>
<td>José N. Onuchic (University of California at San Diego)</td>
</tr>
<tr>
<td>11:20-11:40</td>
<td>Luis Mier-y-Teran (Northwestern University)</td>
</tr>
<tr>
<td>11:40-12:00</td>
<td>Chris Fall (University of Illinois at Chicago, Kellogg School of Management)</td>
</tr>
<tr>
<td>12:00-1:30</td>
<td>Lunch (on your own)</td>
</tr>
<tr>
<td>1:50-2:30</td>
<td>Jean-Pierre Eckmann (University of Geneva)</td>
</tr>
<tr>
<td>2:30-2:50</td>
<td>Ralph V. Chamberlin (Arizona State University)</td>
</tr>
<tr>
<td>2:50-3:30</td>
<td>David Campbell (Boston University)</td>
</tr>
<tr>
<td>3:30-4:00</td>
<td>Coffee Break</td>
</tr>
<tr>
<td>4:00-4:20</td>
<td>James Yorke (University of Maryland at College Park)</td>
</tr>
<tr>
<td>4:20-4:40</td>
<td>Thomas L. Carroll (Naval Research Laboratory)</td>
</tr>
<tr>
<td>4:40-5:20</td>
<td>Juan M.R. Parrondo (Complutense University of Madrid)</td>
</tr>
<tr>
<td>5:20-5:40</td>
<td>Zachary Nicolaou (Northwestern University)</td>
</tr>
<tr>
<td>5:40-6:00</td>
<td>Sean Cornelius (Northwestern University)</td>
</tr>
<tr>
<td>7:00-9:00</td>
<td>Poster Session I &amp; Reception</td>
</tr>
</tbody>
</table>
## Dynamics Days 2010 Schedule

### Wednesday, January 6th

<table>
<thead>
<tr>
<th>Time</th>
<th>Speaker(s)</th>
<th>Topic</th>
</tr>
</thead>
<tbody>
<tr>
<td>8:20 - 9:00</td>
<td>Steven Strogatz (Cornell University)</td>
<td>Spiral Wave Chimerae</td>
</tr>
<tr>
<td>9:00 - 9:20</td>
<td>Hiroshi Kori (Ochanomizu University)</td>
<td>Response of Oscillator Networks: A Centrality Measure Quantifying the Relative Importance of a Node</td>
</tr>
<tr>
<td>9:20 - 9:40</td>
<td>Takashi Nishikawa (Clarkson University)</td>
<td>Visual Analytics for Discovering Group Structures in Networks</td>
</tr>
<tr>
<td>9:40 - 10:00</td>
<td>Coffee Break</td>
<td></td>
</tr>
<tr>
<td>10:00 - 10:40</td>
<td>Hans Harrmann (Swiss Federal Institute of Technology – Zurich)</td>
<td>The Apollonian World</td>
</tr>
<tr>
<td>10:40 - 11:20</td>
<td>Peter Grassberger (University of Calgary)</td>
<td>Clustering Phase Transitions in Complex Networks</td>
</tr>
<tr>
<td>11:20 - 11:40</td>
<td>Hiroya Nakao (Kyoto University)</td>
<td>Self-Organization of Non-Uniform Dynamical Patterns in Complex Networks of Diffusively Coupled Oscillators</td>
</tr>
<tr>
<td>11:40 - 12:00</td>
<td>Mason Porter (University of Oxford)</td>
<td>Communities in Networks</td>
</tr>
<tr>
<td>12:00 - 1:50</td>
<td>Lunch (on your own)</td>
<td></td>
</tr>
<tr>
<td>1:50 - 2:30</td>
<td>Daniel Gauthier (Duke University)</td>
<td>Observation of Boolean Chaos</td>
</tr>
<tr>
<td>2:30 - 2:50</td>
<td>Joern Davidsen (University of Calgary)</td>
<td>Filament Turbulence &amp; Cardiac Fibrillation</td>
</tr>
<tr>
<td>2:50 - 3:30</td>
<td>Andreas Trabesinger (Nature Physics)</td>
<td>Publishing in Nature Physics</td>
</tr>
<tr>
<td>3:30 -</td>
<td>Coffee Break</td>
<td></td>
</tr>
<tr>
<td>3:30 - 8:30</td>
<td>[Hellborn Symposium* at Northwestern (Buses leave for Northwestern at 3:30)]</td>
<td></td>
</tr>
<tr>
<td>3:30 - 4:00</td>
<td>Refreshments</td>
<td></td>
</tr>
<tr>
<td>4:00 - 5:00</td>
<td>James Yorke (University of Maryland at College Park)</td>
<td>Chaos</td>
</tr>
<tr>
<td>5:00 - 6:30</td>
<td>Wine &amp; Cheese</td>
<td>*Also available via live broadcast to the conference site.</td>
</tr>
<tr>
<td>6:00 - 6:30</td>
<td>Buses leave for Conference</td>
<td></td>
</tr>
<tr>
<td>7:00 - 9:00</td>
<td>Poster Session II &amp; Reception</td>
<td></td>
</tr>
</tbody>
</table>
### Dynamics Days 2010 Schedule

**Thursday, January 7th**

<table>
<thead>
<tr>
<th>Time</th>
<th>Event</th>
</tr>
</thead>
<tbody>
<tr>
<td>8:20 – 9:00</td>
<td>Dirk Helbing (Swiss Federal Institute of Technology – Zurich)</td>
</tr>
<tr>
<td></td>
<td>Cooperation, Norms, and Conflict: Towards Simulating the Foundations of</td>
</tr>
<tr>
<td></td>
<td>Society</td>
</tr>
<tr>
<td>9:00 – 9:20</td>
<td>Elizabeth Leicht (University of California at Davis)</td>
</tr>
<tr>
<td></td>
<td>Doing More with Less: Emergence of Large-Scale Connectivity in Networks</td>
</tr>
<tr>
<td></td>
<td>with Design</td>
</tr>
<tr>
<td>9:20 – 9:40</td>
<td>Jan Nagler (Max Planck Institute for Dynamics and Self-Organization)</td>
</tr>
<tr>
<td></td>
<td>Discontinuous Phase Transitions in Random Network Percolation</td>
</tr>
<tr>
<td>9:40 – 10:00</td>
<td>Coffee Break</td>
</tr>
<tr>
<td>10:00 – 10:40</td>
<td>Theo Geisel (Max Planck Institute for Dynamics and Self-Organization)</td>
</tr>
<tr>
<td></td>
<td>Phase Transitions Towards Self-Organized Criticality in Neuronal Systems</td>
</tr>
<tr>
<td>10:40 – 11:20</td>
<td>Sera Solla (Northwestern University)</td>
</tr>
<tr>
<td></td>
<td>Decoding Neural Signals for the Control of Movement</td>
</tr>
<tr>
<td>11:20 – 11:40</td>
<td>Wai Shing Lee (University of Maryland at College Park)</td>
</tr>
<tr>
<td></td>
<td>Dynamics of Spatially Distributed Large Coupled Oscillator Systems</td>
</tr>
<tr>
<td>11:40 – 12:00</td>
<td>Erik Boltt (Clarkson University)</td>
</tr>
<tr>
<td></td>
<td>How Can I Say that a &quot;Toy&quot; Model Reminds Me of Observations?</td>
</tr>
<tr>
<td></td>
<td>A Dynamical Systems Perspective of Comparing Non-Conjugate Systems</td>
</tr>
<tr>
<td>12:00 – 1:50</td>
<td>Lunch (on your own)</td>
</tr>
<tr>
<td>1:50 – 2:30</td>
<td>Ulrike Feudel (University of Oldenburg)</td>
</tr>
<tr>
<td></td>
<td>Coagulation and Fragmentation of Inertial Particles in Chaotic Advection and Random Flows</td>
</tr>
<tr>
<td>2:30 – 2:50</td>
<td>Jens C. Zahnov (Carl von Ossietzky University)</td>
</tr>
<tr>
<td></td>
<td>Fragmentation and Size Distributions of Fractal Aggregates in Fluid Flows</td>
</tr>
<tr>
<td>2:50 – 3:30</td>
<td>Jeffrey Rogers (DARPA)</td>
</tr>
<tr>
<td></td>
<td>Research Funding: A Perspective from the Other Side</td>
</tr>
<tr>
<td>3:30 – 3:30</td>
<td>Coffee Break</td>
</tr>
<tr>
<td></td>
<td>End of Conference Talks at Hotel</td>
</tr>
<tr>
<td>3:30 – 6:30</td>
<td>Heilborn Symposium at Northwestern (Buses leave for Northwestern at 3:30)</td>
</tr>
<tr>
<td>3:30 – 4:00</td>
<td>Refreshments</td>
</tr>
<tr>
<td>4:00 – 5:00</td>
<td>Jacques Laskar (CNRS Paris Observatory)</td>
</tr>
<tr>
<td></td>
<td>Is the Solar System Stable?</td>
</tr>
<tr>
<td>5:00 – 6:30</td>
<td>Wine &amp; Cheese</td>
</tr>
<tr>
<td>6:00 – 6:30</td>
<td>Buses leave for the Conference Hotel</td>
</tr>
</tbody>
</table>
## Dynamics Days 2010 Schedule

### Friday, January 8th

<table>
<thead>
<tr>
<th>Time</th>
<th>Event</th>
</tr>
</thead>
<tbody>
<tr>
<td>3:30 - 6:30</td>
<td>Hellborn Symposium at Northwestern</td>
</tr>
<tr>
<td>3:30 - 4:00</td>
<td>Refreshments</td>
</tr>
<tr>
<td>4:00 - 5:00</td>
<td>Murray Gell-Mann (Santa Fe Institute &amp; Caltech) Simplicity and Complexity</td>
</tr>
<tr>
<td>5:00 - 6:30</td>
<td>Wine &amp; Cheese</td>
</tr>
</tbody>
</table>

### Session Chairs

- **January 4, Morning**: Adilson E. Motter
- **January 4, Afternoon**: Jerry Gollub
- **January 5, Morning**: Takashi Nishikawa
- **January 5, Afternoon**: Wolfgang Losert
- **January 6, Morning**: Edward Ott
- **January 6, Afternoon**: Charles Finney
- **January 7, Morning**: William L. Keith
- **January 7, Afternoon**: Ned Corron

### Poster Committee

- Ned Corron
- Joern Davidson
- Charles Finney
- Juan G. Restrepo

**Hotel Wireless Internet Code: 2145**
Dynamics Days 2010
International Conference on Chaos and Nonlinear Dynamics
January 4 - 7, 2010

Northwestern Institute on Complex Systems
Dynamics Days 2010

Organizing Committee

Adilson E. Motter (Chair)
Northwestern University

William K. Kath
Northwestern University

Edward Ott
University of Maryland
College Park

Advisory Board

Igor Aranson
Argonne National Laboratory

Robert Bebringer
Duke University

Dirk Brockmann
Northwestern University

Ned Carron
U.S. Army

Jim Crutchfield
University of California, Davis

Charles Finney
Oak Ridge National Laboratory

Herbert Levine
University of California, San Diego

Wolfgang Losert
University of Maryland, College Park

Annie Wilkinson
Northwestern University

Wendy Zhang
University of Chicago
Filtering Coherent Atomic Beams: The Peierls-Nabarro Energy Landscape of the Nonlinear Trimer

Atomic Bose-Einstein condensates (BECs) trapped in optical lattices (OLs) have been the subject of great recent experimental and theoretical interest, both in their own right and as analog models of certain solid-state systems. Recent studies of the leakage of a BEC trapped in an OL have shown that localized nonlinear excitations known as “Discrete Breathers” (DBs) can prevent atoms from reaching the leaking boundaries, thereby slowing the decay of the condensate.

To understand the mechanism by which these DBs enhance the trapping, we study the case of atom transport—“tunneling”—through a DB on a nonlinear trimer. We show that this transport is related to the destabilization and subsequent motion of DB and that there exists a threshold in the total energy on the trimer that controls this destabilization. We find that this threshold and the resultant tunneling can be described analytically by defining a two-dimensional “Peierls-Nabarro” energy landscape which restricts the dynamics of the trimer to a limited region of phase space. We further establish that the value of the threshold is related to the Peierls-Nabarro barrier of a single DB. Our results suggest a possible means for controlling the transmission of coherent atomic beams in interferometry and other processes.

This work has been carried out in collaboration with Holger Herrig and Jerome Darrigo.

Geometry of Turbulence: A Stroll Through 61,506 Dimensions

In the world of moderate Reynolds number, everyday turbulence of fluids flowing across planes and down pipes a velvet revolution is taking place. Experiments are almost as detailed as the numerical simulations, DNS is yielding exact numerical solutions that one dared not dream about a decade ago, and dynamical systems visualization of turbulent fluid's state space geometry is unexpectedly elegant.

We shall take you on a guided tour (ChaosBook.org/tutorials) of this newly breached, hitherto inaccessible territory. Mastery of fluid mechanics is no prerequisite, and perhaps a hindrance: the talk is aimed at anyone who has ever wondered why - if no cloud is ever seen twice - we know a cloud when we see one? And how do we turn that into mathematics?
**Robert Ecke** Los Alamos National Laboratory

*Fragile Jamming and Hysteresis in 2D Granular Packing*

The assembly and compaction of a network of rigid contacts among compressible discrete objects such as colloidal particles, the cells formed by foams, and granular materials is at heart of important questions in disordered systems.

Theoretical ideas including a universal jamming transition, rigidity percolation, and undulation/growth of loose/close packing have helped guide a range of interesting experiments on physical systems. Here, an experiment on axially compressed photoelastic disks is used to explore some of the theoretical concepts noted above and to contrast with the real impact of stick-slip friction in real physical granular materials. As disks are initially compressed and gradually form a packed or jammed state by progressing through a 'fragile' state where the compaction process, the displacement field and the stress chain distribution all exhibit a smooth exponential increase with increasing packing fraction. Further, upon successive compression/decompression, the system packing fraction slowly increases, followed logarithmically, although the irreversible energy dissipated per compression/decompression cycle remains approximately constant.

**Jean-Pierre Eckmann** University of Geneva

*Non-Equilibrium Particle Systems*

I will try to review (mostly) rigorous results on extended 1-dimensional systems well out of equilibrium and in which particles interact with scatterers. This, in line with the spirit of "Dynamics Days", the rules of the game are completely deterministic, with only randomness coming from the coupling of the system to (grand-canonical) heat baths. Astonishingly, most "evident" questions still await an answer: Is there a unique steady state? Can the system "freeze"? I will try to summarize our present state of knowledge in this context.

**Ulrike Feudel** University of Oldenburg

*Coagulation and Fragmentation of Inertial Particles: Chaotic Advection and Random Flows*

Inertial particles in fluid flows are of increasing interest in different disciplines such as dynamical systems theory, atmospheric and marine science as well as others. (continued)
Dynamics Days 2010 Invited Speakers

Coagulation and Fragmentation of Inertial Particles in Chaotic Advection and Random Flows (continued)

In many cases particles are not only transported passively by advection but exhibit a dynamics of their own as they can form larger particles upon collision or can break up. Examples of particle dynamics are raindrop formation in clouds, sedimentation of particles in lakes and the ocean or flocculation of marine aggregates and cells.

We present a coupled model for advection, coagulation and fragmentation that is based on the dynamics of individual, spherical inertial particles in two-dimensional flows. The basic equations describing the dynamics of these particles are the Maxey-Riley equations. We consider idealised flows like periodic flows leading to chaotic advection of the particles as well as random flows. Due to the particle inertia advection leads to the accumulation of the particles on attractors in the flow. The collision of the particles leads to coagulation and larger coagulates are formed. These can in turn fragment due to shear forces in the flow. Two different mechanisms of fragmentation are taken into account. On the one hand coagulates can fragment if their size exceeds a predefined maximum size. On the other hand fragmentation can take place when the shear forces in the flow become larger than the binding forces of the coagulate. We find that the combination of coagulation and fragmentation leads to an asymptotic steady state for the size distribution of the coagulates which depends crucially on the considered mechanism of fragmentation. We discuss the dependence of the final size distributions on the properties of the coagulates as well as of the flow.

This work done in collaboration with Jan C. Zabza, Tanaka Tel, and Rafael D. Viela.

Daniel Gauthier Duke University

Observation of Boolean Chaos

I will describe the recent observation of deterministic chaos in a simple network of electronic logic gates that are updated asynchronously. The resulting power spectrum is ultrawide band, extending to beyond 2 GHz. The observed behavior is reproduced qualitatively using Boolean delay equations that take into account signal propagation times that depend on the recent history of the gates and filtering of pulses of short duration. I will discuss possible applications of Boolean chaos as an ultrawide-band source of radio waves and as a random number generator.


Figure: Hugo L. D. de S. Cavalcante, Daniel J. Gauthier, Joshua E. S. Soder and Rui Zhang
Dynamics Days 2010 Invited Speakers

**Theo Geisel** Max Planck Institute for Dynamics and Self-Organization

*Phase Transitions Towards Self-Organized Criticality in Neuronal Systems*

In recent work we have demonstrated the existence of genuine self-organized criticality (SOC) in neuronal networks [1] caused by depressing dynamical synapses, i.e., where the synaptic coupling exhibits fatigue under repeated presynaptic firing. This adaptation mechanism drives the network into a self-organized critical regime by adjusting the average coupling strengths to a critical value. The size distribution of critical avalanches exhibits an inverse power law, which has been observed in the same form experimentally in neuronal cultures as well as in awake monkeys.

We have now generalized this study to include facilitating besides depressing synaptic dynamics as found in biological systems. We show analytically that the generalized model attains SOC in an extended region of parameter space that is reached through phase transitions. The critical region of the connectivity parameter is sandwiched between a sub- and a supercritical regime which also can be reached experimentally by a manipulation of the synaptic strengths. The system exhibits a rich dynamical behavior including a hysteresis between critical and noncritical dynamics, switching of the dynamics in dependence of external inputs, and first- and second-order phase transitions that form a cusp bifurcation [2]. This is the first observation of a complex classical bifurcation scenario combined with a SOC phase.


---

**Raymond Goldstein** University of Cambridge

*Synchronization of Eukaryotic Flagella*

It has long been conjectured that hydrodynamic interactions between beating eukaryotic flagella underlie their ubiquitous forms of synchronization, yet there has been no experimental test of this connection. The biflagellated alga *Chlamydomonas* is a simple model for such studies, as its two flagella are representative of those most commonly found in eukaryotes. Using micromanipulation and high-speed imaging we show that the flagella of a *C. reinhardtii* cell present periods of synchronization interrupted by phase slips. The dynamics of slips and the statistics of phase-locked intervals are consistent with a low-dimensional stochastic model of hydrodynamically coupled oscillators, with a noise amplitude set by the intrinsic fluctuations of single flagellar beats.

(continued)
Dynamics Days 2010 Invited Speakers

Synchronization of Eukaryotic Flagella (continued)

Moreover, in the dark, a single cell stochastically switches between periods of synchrony with slips and periods of asynchrony ("drifts") in which the two flagella beat at significantly different frequencies. We show by means of extensive three-dimensional tracking of swimming trajectories that drifts are associated with sharp turns, resulting in a eukaryotic version of the run-and-tumble locomotion found in bacteria. Finally, the dynamics of phototaxis in simple eukaryotes is considered from the perspective of evolutionary transitions to multicellularity. The unicellular algae *Chlamydomonas* swims in helical trajectories whose geometric properties are modulated by signals received from a photosensor that sweeps the surroundings as the cell rotates. Its large spherical multicellular descendant *Volvox* is composed of thousands of *Chlamydomonas*-like cells, and spins about a body-fixed axis as it swims. Using micromanipulation and particle-imaging velocimetry of flagella-driven flows, we show that the frequency response of *Volvox meridii* to periodic light signals is tuned to match the natural rotational frequency of the colony. A hydrodynamic model of phototactic steering shows that colony rotation is necessary to achieve accurate phototaxis.

Peter Grassberger University of Calgary

Clustering Phase Transitions in Complex Networks

Ensembles of networks are used as null models in many applications. However, simple null models often show much less clustering than their real-world counterparts. In this paper, we study a model where clustering is enhanced by means of a fugacity term as in the Strauss (or "triangle") model, but where the degree sequence is strictly preserved—thus maintaining the quenched heterogeneity of nodes found in the original degree sequence. For regular graphs (identical degrees for all nodes) with degree $k=2$ we find a first order transition. For all non-regular networks that we studied (including Erdős-Rényi and scale-free networks) we find multiple jumps resembling Bakkshen jumps together with strong hysteresis. The latter transitions are driven by the sudden emergence of "cluster cores": groups of highly interconnected nodes with higher than average degrees. To study these cluster cores visually, we introduce $q$-clique adjacency plots. We find that these cluster cores constitute distinct communities which emerge spontaneously from the triangle generating process. Finally, we point out that cluster cores produce pitfalls when using the present (and similar) models as null models for strongly clustered networks, due to the very strong hysteresis which effectively leads to broken ergodicity on realistic time scales.

Work done in collaboration with David Foster, Jacob Foster, and Maya Paczuski.
**Dynamics Days 2010 Invited Speakers**

**Dirk Helbing**  
Swiss Federal Institute of Technology - Zurich  

**Cooperation, Norms, and Conflict: Towards Simulating the Foundations of Society**

In order to understand social systems, it is essential to identify the circumstances under which individuals spontaneously start cooperating or developing shared behaviors, norms, and culture. In this connection, it is important to study the role of social mechanisms such as repeated interactions, group selection, network formation, costly punishment and group pressure, and how they allow to transform social dilemmas into interactive situations that promote the social system. Furthermore, it is interesting to study the role that social inequality, the protection of private property, or the ongoing globalization play for the resulting "character" of a social system (cooperative or not). It is well-known that social cooperation can suddenly break down, giving rise to poverty or conflict. The decline of high cultures and the outbreak of civil wars or revolutions are well-known examples. The more surprising is it that one can develop an integrated game-theoretical description of phenomena as different as the outbreak and breakdown of cooperation, the formation of norms or subcultures, and the occurrence of conflicts.

**Hans Herrmann**  
Swiss Federal Institute of Technology - Zurich  

**The Apollonian World**

2200 years ago Apollonius of Perga introduced the first space-filling tiling of discs or spheres. The underlying topology bears an astonishing richness of properties. I will show that the contact network is scale-free and small world. It allows to describe some basic properties of porous media and neural networks. It is robust against random attacks and can be optimized very well against malicious attacks. The Paris model shows unique anomalies when studied on Apollonian networks and car traffic models show an abrupt gridlock. A large family of related topologies allows for slipless rotations between touching discs. I will discuss their construction and their fractal dimensions. These configurations fulfill Kolmogorov scaling and display Richardson's diffusion law in the limit of small Stokes numbers and constitute therefore an interesting toy model for turbulence. The synchronization of rotations occurs in avalanches following a broad size distribution.
Fred MacKintosh Vrije University

Non-Equilibrium Fluctuations and Mechanics of Active Gels and Living Cells

Much like the bones in our bodies, the cytoskeleton consisting of filamentous proteins largely determines the mechanical resilience and stability of cells. Such important cellular processes as locomotion, cell division, and mechanosensing are largely governed by complex networks of cytoskeletal biopolymers and the associated proteins that cross-link these and/or generate forces within the network. In addition to their important role in cell mechanics, cytoskeletal biopolymers have also provided new insights and challenges for polymer physics and rheology. Biopolymer networks, for instance, exhibit strongly nonlinear rheology—in many cases stiffening by orders of magnitude when subject to shear strains of less than unity. In the cell, these polymer networks or gels are far from equilibrium in a way unique to biology; they are subject to active, non-thermal internal forces generated by molecular motors. We describe recent theoretical and experimental results on active networks in vitro that demonstrate significant non-equilibrium fluctuations due to motor activity [1,2]. Furthermore, such gels hold out the promise of active materials, whose stiffness can be controlled by enzymatic activity. We also show how fluctuations and dynamics of individual cytoskeletal filaments can be used to probe both mechanical properties and non-equilibrium activity in living cells [3,4].


José Onuchic University of California at San Diego

The Energy Landscape for Folding and Molecular Motors — The Kinesin Story

Fueled by ATP, conventional kinesins take unidirectional steps along the single postfillament of microtubules by alternating binding of two motor domains to the binding sites. The structural changes of kinesin motors are closely coupled to the ATP binding and its subsequent hydrolysis. Although several experimental efforts have elucidated the physical principle of kinesin dynamics, schematically summarized in a mechanosensitive cycle, limitations in the spatial and temporal resolution of current experiments have prevented a straightforward understanding of kinesin dynamics based on its microscopic structure. By exploiting a structure-based model of kinesin motors, we develop the energy landscape for this molecular motor and address a few selected issues on the kinesin dynamics. Finally, the equilibrium ensemble of kinesin structures, whose both heads are bound to the microtubule binding site, show that the internal tension (f = 10-15 pN) built along the neck-linker exclusively disrupts the ATP binding pocket of the leading head from its native-like environment. This result clarifies the origin of kinesin's high processivity, supporting the inherent strain-induced regulation mechanism between the two motor domains. Secondly, we address the controversial issue of step formation during the stepping motion. By solving the potential of mean forces experienced
Dynamics Days 2010 Invited Speakers

The Energy Landscape for Folding and Molecular Motors – The Kinesin Story (continued)

by kinesin's tethered head relative to the microtubule surface and performing Brownian dynamics simulations, the stepping dynamics of kinesin motors is shown as a complex process that hinges on the interplay between the dynamics of necklinker zipping, diffusion, and geometry of microtubule surface. A transient trapping of kinesin head to the tubulin binding site in the adjacent protodimer can produce a substep in the averaged time trace. We estimate \( \tau \approx 20 \mu s \) as the lower limit of necklinker zipping time to observe the substep. Lastly, we show that partial unfolding of kinesin structure facilitates the binding kinetics of kinesin to the microtubule.

Julio Ottino Northwestern University

The Evolution of Mixing: From Stretching and Folding to Cutting and Shuffling

The fingerprint of mixing is stretching and folding. Mathematically this entails forming homoclinic or heteroclinic points or the formation of a horseshoe map and has practical consequences such as exponential stretching of material lines. Heuristically this can be traced back to streamline crossing. Strictly speaking, horseshoes are measure zero, and the effect of this measure zero set on a full neighborhood of trajectories has to be determined with the help of numerics. There are two branches in the previous there. The first has to do with analytical prediction. Linked Twist Maps embody the notion of "streamline crossing" in a rigorous mathematical sense and constitute one class of systems where mathematical prediction of chaos on a set of full measure (i.e., positive area) is possible without resorting to computations. The second with a new mechanism of mixing, one that does not involve stretching and folding but rather cutting and shuffling, a mechanism that can be put on a firm theoretical foundation using an emerging area of dynamical systems theory called piecewise isometries. An isometry is a map that preserves distances (for example, a rigid rotation). Piecewise means that two (different) isometries are joined along a curve separating the domains of the two isometries. A single isometry cannot be chaotic in the sense of having exponential separation of points as the map is iterated, since the distance between points remains constant during iteration. However, when two or more isometries are combined the resulting dynamics can exhibit great complexity.

Juan Parrondo Complutense University of Madrid

Cooling Classical Particles with a Microcanonical Szilard Engine

We show that it is possible to extract energy from a single isolated system if its initial energy is known. We construct an explicit example based on the celebrated Szilard engine. Our microcanonical version of the engine allows extraction of energy without the need of any measurement. The extraction possible by a cyclic protocol which reduces the energy of a single particle by increasing the uncertainty of its energy, a mechanism that could be in principle extended to systems with several degrees of freedom.
Jeffrey Rogers DARPA

Research Funding: A Perspective from the Other Side

Securing research funding is often time-consuming and, can be, a difficult task. This talk will provide a perspective on attracting and maintaining support from a scientist who joined the Defense Advanced Research Projects Agency (DARPA) to fund research involving nonlinear sciences. Funding opportunities through early career awards, advanced studies, and projects will be touched on in the context of the speaker’s current interests in exploiting dynamics of NEMS and microphotonics architectures, managing laser instabilities, design and verification of multiscale electronic systems, and early detection of traumatic brain injury.

Mary Silber Northwestern University

Quasipatterns by Design

I will describe the controlled generation of quasipatterns via a symmetry-breaking parametric instability in a model PDE. Two mechanisms for quasipattern and superlattice pattern formation will be reviewed, and the special challenges associated with using bifurcation theory to understand quasipatterns will be highlighted. My presentation describes some work done with Alastair Rucklidge.

Sara Solla Northwestern University

Decoding Neural Signals for the Control of Movement

The activity of neurons in an area of the brain referred to as primary motor cortex provides the signals that control the ability to execute movements. One of the crucial questions, still unresolved, is that of identifying the code used by this neural ensemble. We address this question through the analysis of data obtained for an awake behaving monkey. An implanted multielectrode array records the activity of about one hundred neurons in primary motor cortex during the execution of a sequence of straight reaches to nearby targets. A natural representation for the ensemble activity is provided by a high-dimensional space in which each axis represents the activity of a single neuron as an independent degree of freedom.

(Continued)
Dynamics Days 2010 Invited Speakers

Decoding Neural Signals for the Control of Movement (Continued)

However, the observed correlations among neurons whose activity is decorably modulated by the task suggest that the population defines a low-dimensional space within the high-dimensional space of independent firing activities. We have used linear and nonlinear methods for dimensionality reduction to find the low-dimensional structure that captures the underlying relationship between population neural activity and behavioral task. The use of multidimensional scaling in conjunction with an empirical measure of geodesic distances yields a low-dimensional manifold whose intrinsic coordinates capture the geometry of the task in the external physical space. Although the dimensionality of this manifold follows from a linear model that considers neurons as independently modulated by each direction, its curvature is a consequence of neural interactions.

Steven Strogatz
Cornell University

Spiral Wave Chimeras

Chimera states are remarkable spatiotemporal patterns discovered recently in nonlocally coupled systems of limit-cycle oscillators. Their defining feature is that the system splits into synchronized and desynchronized subpopulations, even though all the oscillators are identical and symmetrically coupled. This talk will summarize what has been learned — and what remains unknown — about chimeras in 1-D arrays, 2-D arrays, and interacting populations. In particular, 2-D chimeras take the form of a new kind of spiral wave: In place of a phase singularity with zero-amplitude oscillators at the center of the spiral, here the core consists of desynchronized oscillators running at full amplitude. Simulations and analysis of this “spiral wave chimera” will be presented.

Figure: E.A. Martens, C.R. Laing, and S.H. Strogatz

Harry Swinney
The Univeristy of Texas at Austin

Lethal Protein Produced in Response to Competition Between Bacterial Colonies

We have conducted experiments on neighboring colonies of \( P. \) aeruginosa bacteria grown on an agar gel by inoculation from the same culture (i.e., the colonies are siblings). The colonies are found to mutually inhibit growth through secretions that become lethal if the level exceeds a well-defined threshold [1]. Analysis of the secretions reveals the presence of subtilisin (a protease) and a 12 kDa protein, which we have named SIF (sibling lethal factor) [2]. Subtilisin promotes the growth of the colonies, while SIF is lethal. SIF is found to be encoded by a gene belonging to a large family of bacterial genes of previously unknown function. The experimental results are used to develop a model (six coupled PDEs), which predicts that once subtilisin exceeds a threshold, as occurs at the interface between competing colonies, then SIF is secreted into the medium and rapidly kills cells. Laboratory tests yield results for the dynamical behavior that is in accord with the predictions of the model. The existence of many (Continued)
Dynamics Days 2010 Invited Speakers


toxin Protein Produced in Response to Competition Between Bacterial Colonies (continued)

bacteria of genes encoding homologs of the gene that encodes SII suggests that the mechanism we observe for self-regulation of
colony growth may well occur in other bacteria.


Andreas Trabesinger Nature Physics

Publishing in Nature Physics

Following a general overview of the Nature physical-sciences titles, this talk discusses what happens to papers submitted to Nature Physics, providing insight into the editorial process and the editors' checkpoints.

Jonathan Widom Northwestern University

The Genomic Code for Nucleosome Positioning

Eukaryotic genomes are packaged into nucleosome particles that occlude the DNA from interacting with most DNA binding proteins. We have discovered that genomes care where their nucleosomes are located on average, and that genomes manifest this care by encoding an additional layer of genetic information, superimposed on top of other kinds of regulatory and coding information that were previously recognized. We have developed a partial ability to read this nucleosome positioning code and predict the in vivo locations of nucleosomes. Most recently, we showed that the distribution of nucleosomes reconstituted on yeast genomic DNA in a purified in vitro system closely resembles that in vivo, implying that much of the in vivo nucleosome organization is explicitly encoded in the genomic DNA sequence itself, through the nucleosome DNA sequence preferences. A statistical model based only on the in vitro nucleosome DNA sequence data is significantly predictive of the detailed distribution of nucleosome locations in yeast, C. elegans, and humans, suggesting that there may exist a universal genomic code for nucleosome positioning. Our results suggest that genomes utilize the nucleosome positioning code to facilitate specific chromosome functions, including to delineate functional versus nonfunctional binding sites for key gene regulatory proteins, and to define the next higher level of chromosome structure. The physical basis of the nucleosome DNA sequence preferences lies in the sequence-dependent mechanics of DNA itself.

Figure: E. Segal and J. Widom.
Dynamics Days 2010 Contributed Talks

**Erik Boltt** Clarkson University

*How Can I Say that a “Toy” Model Reminds Me of Observations? A Dynamical Systems Perspective of Comparing Non-Conjugate Systems*

We address a fundamental modeling issue in science as related to the field of dynamical systems: when is a model of a physical system a “good” representation? Conjugacy provides a means to define if two systems are dynamically equivalent; it is the central equivalence relationship in the field of dynamical systems. However, it cannot cope with systems which are not dynamically identical. What then to do with the common scientific practice of modeling, whereby we build heuristic and phenomenological models which “remind” us of the true system? We develop mathematical technology to decide when dynamics of a toy model are like dynamics of the physical system. When applied to non-conjugate dynamical systems, we show that a fixed point iteration scheme yields a limit point, that is a function we call a “commuter” — a non-homeomorphic change of coordinates translating between deterministic systems. This translation is true to the concepts of dynamical systems in that it matches systems within the language of their orbit structures. We introduce methods to compare nonequivalent systems by quantifying a defect of the commuter function’s failure to be a homeomorphism — an approach that better respects the dynamics than any traditional comparisons based on normed linear spaces. Our discussion addresses a fundamental issue: how does one make principled statements of the degree to which a “toy model” might be representative of a more complicated system. We highlight our methods with a lower-ordered models of more complicated systems.

**Thomas L. Carroll** Naval Research Laboratory

*Detecting Recursive and Non Recursive Filters Using Chaos*

Filtering a chaotic signal through a recursive (or IIR) filter has been shown to increase the dimension of the chaos under certain conditions. Filtering with a non-recursive (or FIR) filter should not increase dimension, but it has been shown that if the FIR filter has a long tail, measurements of actual signals may appear to show a dimension increase. I simulate IIR and FIR filters that correspond to naturally occurring resonant objects, and I show that using dimension measurements, I can distinguish the filter type. These measurements could be used to detect resonances using radar, sonar or radar signals, or to determine if a resonance is due to an IIR or an FIR filter.

**Pinaki Chakraborty** University of Illinois at Urbana-Champaign

*Rotating Volcanic Plumes: Lobate Umbrellas, Tornadoes, and Lightning Sheaths*

A strong volcanic plume consists of a vertical column of hot gases and dust topped with a horizontal umbrella. The column rises buoyed by entrained and heated ambient air, reaches the neutral-buoyancy level, then spreads radially to form the (Continued)
Dynamics Days 2010 Contributed Talks

Rotating Volcanic Plumes: Lobate Umbrellas, Tornadoes, and Lightning Sheaths (continued)

umbrella. In classical models of strong volcanic plumes, the plume is assumed to remain always axisymmetric and nonrotating. In this talk I show that the updraft of the rising column induces a hydrodynamic effect not addressed to date: a "volcanic mesocyclone". This volcanic mesocyclone sets the entire plume rotating about its axis, as confirmed by an unprecedented analysis of satellite images from the 1991 eruption of Mount Pinatubo. The rotation triggers a turbulent Rayleigh-Taylor instability which makes the umbrella lose axial symmetry and become lobate in plan view, in accord with satellite records of recent eruptions on Mount Pinatubo, Marianas, Reventador, Okmok, Chaitén, and Ruang. The volcanic mesocyclone spawns waterpots or dust devils, as seen in numerous eruptions, and grows the electric charges about the plume to form the "lightning sheath" that was so prominent in the recent eruption of Mount Chaitén. The concept of volcanic mesocyclone provides a unified explanation for a disparate set of poorly understood phenomena in strong volcanic plumes. This talk is based on joint work with Gustavo Gibó and Susan Kieffer.

Ralph V. Chamberlin  Arizona State University

Nanothermodynamics and Nonlinear Corrections to Statistical Mechanics

The Boltzmann factor, which comes from the linear change in entropy of an infinite heat bath, does not fully account for nonlinear or inhomogeneous dynamics. Nonlinear terms have been used by Onsager to describe non-equilibrium response, and by Einstein to describe critical fluctuations in a small part of a large system. We apply similar nonlinear terms to the normal fluctuations of individual particles in thermal equilibrium. This "nanothermodynamics" provides a common explanation for the non-exponential relaxation, non-Arrhenius activation, and non-thermal crossover scaling that is often found in complex systems. Theoretical arguments, computer simulations, and experimental data will be presented indicating that it is the local interaction between particles that often yields significant nonlinear corrections to the Boltzmann factor.

Sean Cornelius  Northwestern University

Paradox of Latency in Escherichia coli Metabolic Pathways

Gene-deletion experiments on single-cell organisms have established that expression of most genes is not needed for optimal growth. This problem acquired a new dimension with the recent discovery that environmental and genetic perturbations of the bacterium Escherichia coli are accompanied by the temporary activation of a large number of latent metabolic pathways, which suggests the hypothesis that temporarily activated reactions facilitate adaptation and hence impact growth in the presence of perturbations. We model the dynamics of perturbation and adaptation using a constraint-based approach and find, surprisingly, that the availability of latent pathways consistently offers no adaptive advantage in the short term, and tend in fact to inhibit adaptation after genetic perturbations. This adverse influence rules the possibility that latent pathway activation is a derivative effect of other, potentially suboptimal, adaptive response.
Dynamics Days 2010 Contributed Talks

Ned J. Corron  U. S. Army RDECOM

Matched Filter for Chaos

A chaotic differential equation is shown to admit a simple matched filter for detecting symbolic information in the waveform. The low-dimensional chaotic oscillator yields an exact analytic solution that can be written as a linear convolution of a basis pulse and information sequence. The information symbols form a symbolic dynamics for the chaotic oscillation, completely and uniquely specifying any chaotic trajectory. The matched filter output provides optimal symbol detection in the presence of noise, and an exact expression for the bit-error rate for detecting symbols is derived. The chaotic system and its matched filter are realized using low-frequency electronic circuits containing both analog and digital components. Experimental results confirm the effectiveness of the matched filter for receiving and detecting symbolic content. Scattered to higher-frequency, this realizable system has potential application in Hayes-type chaos communications, where a message signal is encoded in the symbolic dynamics via small perturbations. The discovery of a practical matched filter finally provides a receiver to complement the elegant encoding in such systems.

Joern Davidsen  University of Calgary

Filament Turbulence & Cardiac Fibrillation

How much information do you need to distinguish between different mechanisms for spatiotemporal chaos in three-dimensions? In this talk, I will show that the observation of the dynamics on the surface of a medium can be sufficient. Studying mechanisms for filament turbulence in the context of reaction-diffusion media, we found numerically that two major classes of instabilities have a very different signature on what can be observed on the surface of a three-dimensional medium. These results are of direct relevance in the context of ventricular fibrillation—a turbulent electrical wave activity that destroys the coherent contraction of the ventricular muscle and its main pumping function leading to sudden cardiac death. While it has been proposed that the three-dimensional structure of the heart plays an important role in this type of filament turbulence, only the surface of the heart is currently accessible to experimental observation preventing the study of the full dynamics. Our results suggest that such observations might be sufficient.

Chris Fall  UIC & Kellogg School of Management

Mitochondrial Modulation of Intracellular Ca$^{2+}$ Signaling

Mitochondria have long been known to sequester cytosolic Ca$^{2+}$ and even to shape intracellular patterns of endoplasmic reticulum-based Ca$^{2+}$ signaling. Evidence suggests that the mitochondrial network is an excitable medium which can demonstrate independent Ca$^{2+}$ induced Ca$^{2+}$ release via the mitochondrial permeability transition. The role of this excitability remains unclear, but mitochondrial Ca$^{2+}$ handling appears to be a crucial element in diverse diseases as diabetes, neurodegeneration and cardiac dysfunction that also have bioenergetic components. Here we model a modular computational model for respiration-driven Ca$^{2+}$ handling to include a permeability transition based on a channel-like pore mechanism. We demonstrate both excitability and Ca$^{2+}$ wave propagation accompanied by depolarizations similar to those reported in cell and isolated mitochondria preparations. These waves depend on the energy state of the mitochondria, as well as other elements of mitochondrial physiology. Our results support the concept that mitochondria can transmit state-dependent signals about their function in a spatially extended manner over an excitable medium.
Dynamics Days 2010 Contributed Talks

Heather Hardway  Boston University

Change in Structure and Stability of the Solution Set for an Idealized Gene-Network Model

Using a gene-network model representing the spatio-temporal dynamics of protein gradients in the developing fruit fly embryo, I examine an idealized version, in which a gene is either "on" or "off", representing the classical caricature of a gene. The structure of the steady-state solutions and their stability are examined in the idealized version, viewed as a limiting case for a series of smooth, increasingly steep responses for the gene. Taking the diffusion rate as a bifurcation parameter, an infinite series of simple bifurcations occurs for the smooth response case. However, in the limit, each simple bifurcation point collapses into a single point, resulting in an infinite number of solution branches emanating from a single point. In addition, the linear stability is considered and undergoes a significant change in the limiting case. Results are interpreted in terms of the biological system and possible applications are considered.

Hiroshi Kori  Ochanomizu University

Response of Oscillator Networks: A Centrality Measure Quantifying the Relative Importance of a Node

Some centrality measures are used to determine the relative importance of nodes specifically in directed networks. We analyze a centrality measure called the influence. When we consider an oscillator network, the influence of an oscillator quantifies the magnitude of the collective response to an small input to the oscillator. The influence can also be applied to a strong periodic inputs. For a type of random network, we show that the analytically derived entrainment threshold is approximately equal to the inverse of the influence. We numerically check that this relationship also holds true in a random scale-free network and a neural network.

Wai Shing Lee  University of Maryland, College Park

Dynamics of Spatially Distributed Large Coupled Oscillator Systems

In the past few decades, studies of large systems of coupled oscillators have advanced greatly our understanding of global collective behaviors arise out of interactions among local constituents in complex systems. However, most classical models focus on the dynamics of oscillators assuming no spatial extent, while real physical systems have the oscillators spatially distributed. Our study further the study of large coupled oscillator systems with the oscillators distributed in space. We study the conditions for the occurrence of collective behaviors and characterize the spatially manifested coarsening dynamics arose out of the systems.
Dynamics Days 2010 Contributed Talks

Elizabeth Leicht  University of California at Davis

Doing More with Less: Emergence of Large-Scale Connectivity in Networks with Design

Many biological, social, and technological systems take the form of complex networks. Over the past decade a science of networks has been emerging and providing insights into dynamic aspects of network structure as well as dynamic processes occurring on complex networks. The classic Erdős-Rényi (ER) model of network formation starts from a set of \( n \) unconnected nodes and sequentially adds edges between pairs of nodes uniformly at random. This dynamic process leads to a network with a Poisson degree distribution and a phase transition in network connectivity when the average degree is equal to unity. We present an adaptation of the model for systems possessing heterogeneous nodes. In this model we divide the set of \( n \) nodes into groups and set differing rates for the addition of edges within or between groups. For a range of comparative rates of edge addition within groups and between groups the model can show "cooperative enhancement" with the phase transition marking the onset of large-scale connectivity occurring with fewer edges than were required for the classic ER model. Previous work on altering the ER transition point relied primarily on processes requiring oversight in that a choice between two outcomes must be assessed at each step. Here enhanced connectivity is achieved in an unsupervised manner with a simple modular treatment. The model has implications for systems of interacting networks, single networks with modular or community structure, and networks with node populations. Applications of this work relate to our understanding of disease spreading across geographic regions and how to engineer minimalistic communications networks.

Wolfgang Losert  University of Maryland, College Park

Decision Making and Collective Behavior in Cell Migration

The focus of this work is collective migration, which is crucial e.g. in wound healing, immune response, or the formation of organs. Though the size, shape, and behavior of individual cells when placed by themselves under the microscope varies widely, groups of biological cells that communicate with each other (via biochemical signals and possibly physical interactions) are able to carry out complex tasks very reliably. We will review decision making and group behavior during cell migration in a simple model organism Dictyostelium discoideum. We will assess how information is relayed in space and time on multiple scales from the mm scale where we follow the motion of thousands of individual cells to the micron scale where we have developed a method to follow cell shape dynamics and to monitor cell protrusions. Finally, we will also assess the ability of migrating cells to make more complex decisions such as migration in the presence of obstacles such as cliffs and ridges.
Dynamics Days 2010 Contributed Talks

Luis Mier-y-Teran  Northwestern University

A Time-Delay Model of Protein Synthesis Obtained from Mechanistic Principles and its Application to Gene Networks

The engineering of gene regulatory circuits is one of the main objectives in synthetic and systems biology. Such circuits possess a great number of components with diverse and rich forms of interactions. Mechanistic models of gene networks are difficult to analyze due to the amount of details incorporated. The synthesis of mRNA and protein are carried out via template polymerization processes that possess intrinsic time delays. It has been shown that incorporating time delays in models of gene networks is often essential to capture the whole range of behavior. We present here the development of a time delay model for protein synthesis from a mechanistic model of the process. We use the reduced model to study the behavior of a simple gene network and obtain complex dynamic behavior not observed with commonly used heuristic models and which would be difficult to infer from the original mechanistic model, due to its complexity.

Jan Nagler  Max Planck Institute for Dynamics and Self-Organization

Discontinuous Phase Transitions in Random Network Percolation

The transition to extensive connectedness upon gradual addition of links, known as the percolation phase transition, provides a key prerequisite for understanding networked systems [1]. Until recently, random percolation processes were thought to exhibit continuous transitions in general, but now there is numerical evidence for discontinuities of changes of the order parameter in certain percolation processes [2]. Here we present the concepts of weakly and strongly discontinuous percolation transitions and explain the microscopic mechanisms underlying them. We study both numerically and analytically under which conditions the order parameter may change discontinuously and classify the type of transition in dependence on the dynamics of cluster joining [3].

Work done in collaboration with Anna Levina and Marc Timme.


Zachary Nicolaou  Northwestern University

Network Destabilizations with Inverted Mechanical Responses

A solid material can be regarded as a large mechanical network, with nodes representing the particles composing the material and links between nodes representing interactions between these particles. The network must rearrange itself (continued)
Dynamics Days 2010 Contributed Talks

Network Destabilizations with Inverted Mechanical Responses (continued)

in response to an applied force. The material's response to applied pressures and tensions can then be modeled as a flow of forces through this network. Using this formulation, I will discuss the design of mechanical networks that exhibit properties not found in ordinary materials. I will show, in particular, that we can design a material that counterintuitively expands when pressurized or contracts when tensioned. These results are of potential interest for a wide range of applications.

Hiroya Nakao  Kyoto University

Self-Organization of Non-Uniform Dynamical Patterns in Complex Networks of Diffusively Coupled Oscillators

Complex networks are ubiquitous in a wide variety of real-world systems. To understand their functional roles, it is necessary to explore the dynamics that take place on them. As a simple prototype of network-organized dynamical systems, nonlinear oscillators interacting via complex networks have been extensively studied. In particular, macroscopic synchronization transition exhibited by coupled phase oscillators on complex networks has attracted much attention. However, even more interesting non-uniform dynamical patterns should also be possible on complex networks. Generally, coupled phase oscillators are derived from coupled limit-cycle oscillators by eliminating amplitude degrees of freedom for sufficiently weak coupling. For stronger coupling, such an approximation breaks down and much richer dynamics due to amplitude effects are expected. We demonstrate that diffusively coupled limit-cycle oscillators on complex networks actually exhibit various non-uniform dynamical patterns [1]. Near the supercritical Hopf bifurcation of the constituent limit-cycle oscillators, we can describe the system by a network version of the complex Ginzburg-Landau equation, which is a normal form of general self-oscillatory media. Uniformly oscillating solution of this equation can be linearly unstable with respect to spontaneous phase modulations due to the effect of diffusion, similarly to the Benjamin-Feir instability in spatially extended oscillatory media. Numerical investigations on scale-free networks under this instability condition reveal a wealth of complex non-uniform dynamical patterns, including partial amplitude death, clustering, and chaos. We explain these dynamical patterns by combining periodic mean-field approximation of the network and bifurcation analysis of the constituent oscillators.


Takashi Nishikawa  Clarkson University

Visual Analytics for Discovering Group Structures in Networks

We propose a visual and interactive method for discovering distinct groups of nodes in a network using a user-selected set of node properties computed from the network structure. The user's input on the visual separation of nodes in random 2D projections of a high-dimensional node property space is systematically analyzed to divide the nodes into distinct groups, the number of which is selected by the user interactively. The discovered groups are then examined to reveal their distinguishing characteristics. Our method is capable of discovering communities structures, k-partite structures, or any other structures in which the groups can be distinguished by a combination of node properties. We demonstrate that our method can effectively find and characterize a variety of group structures in model and real-world networks.
Dynamics Days 2010 Contributed Talks

Louis Pecora  Naval Research Laboratory

Regularization of Tunneling Rates with Quantum Chaos

We study tunneling in various shaped, closed, two-dimensional double wells by calculating the energy splitting between symmetric and anti-symmetric state pairs. We use the boundary and finite element methods for the calculations. For shapes that have regular or nearly regular classical behavior (e.g., rectangular or circular wells) the tunneling rates for nearby energy states vary over wide ranges. Rates for energetically close quantum states can differ by several orders of magnitude. This contrasts sharply with the one-dimensional case in which the tunneling rates increase monotonically with energy. As we transition to well shapes that admit more classically chaotic behavior (e.g. the stadium, the Sinai billiard) the range of tunneling rates narrows, often by an order of magnitude or more. For well shapes in which the classical behavior appears to be fully chaotic (as determined from numerical bounce maps) the tunneling rates' range narrows to about a factor of 2 or so between the smallest and largest rates in a wide range of energies. This dramatic narrowing appears to come from destabilization of periodic orbits in the regular wells that produce the largest and smallest tunneling rates. It is in this sense that we say the quantum chaos regularizes the tunneling rates to what appears to be a universal curve. Calculations of Husimi distributions suggest that the rates are strongly dependent on the magnitude of normal momentum and the magnitude of the wave function at the barrier.

Mason Porter  University of Oxford

Communities in Networks

Networks arise pervasively in biology, physics, technology, the social sciences, and a myriad of other areas. They typically exhibit a complicated mixture of random and structured features. Over the past several years, my collaborators and I have conducted several studies of cohesive mesoscopic structures known as "communities," which consist of groups of nodes that are closely related. In this talk, I will discuss some of our results on network community structure in social, political, financial, and biological networks.

Laura E. Schmidt  University of Twente

Role of Bubbles on Heat Transfer and Turbulence in Rayleigh-Bénard Convection

Using direct numerical simulations (DNS) of two-phase Rayleigh-Bénard convection in a cylindrical cell, we investigate how bubbles modify the heat transport and flow properties in the bulk and boundary layers. The dynamics of the system depends on the interaction between many length- and time-scales. The rapid growth of bubbles near the hot bottom plate intensifies the local fluctuations, their buoyancy destabilizes the flow, and the total heat transfer is amplified. These (continued)
Dynamics Days 2010 Contributed Talks

Role of Bubbles on Heat Transfer and Turbulence in Rayleigh-Bénard Convection (continued)

Effects depend strongly on the ratio of sensible heat to the latent heat and the number of bubbles present. However, if the bubbles are artificially forced to maintain a fixed state they stabilize the system by damping temperature gradients, and reduce the Reynolds number of the flow (based on the r.m.s. velocity). To disentangle the interaction of the bubbles with the boundary layers vs. the bulk flow, in separate simulations we introduce bubbles into homogeneous Rayleigh-Bénard convection, where the top and bottom plates have been eliminated.

Alexey Snezhko  Argonne National Laboratory

Dynamic Self-Propelled Structures in Nonequilibrium Magnetic Layers

Magnetic granular layers suspended at the liquid-air or liquid-liquid interface and energized by an alternating magnetic field develop nontrivial dynamic self-assembled structures (magnetic snakes) in a certain range of excitation parameters. These nonequilibrium structures emerge as a result of the competition between magnetic and hydrodynamic forces and have complex magnetic ordering. Strong induced vortex flows on the surface of the liquid finalize the rich hydrodynamic picture of the "magnetic snake". Self-assembled snakes have a complex magnetic ordering. The segments of the snake exhibit long-range antiferromagnetic ordering mediated by the surface waves, while each segment is composed of ferromagnetically aligned chains of microparticles. Above some frequency threshold magnetic snakes spontaneously break the symmetry of self-induced surface flows (symmetry breaking instability) and turn into swimmers. Self-induced surface flows symmetry can be also broken in a controlled fashion by introduction of a large bead to a magnetic snake (bead-snake hybrid), that transforms it into a robust self-locating entity. Observed phenomena have been successfully described by developed phenomenological model.

James Yorke  University of Maryland, College Park

Infinitely Many Cascades Must Exist as Chaos Arises in Dimension 2

Evelyn Sander and I have established a general theory of why period-doubling cascades exist (in N dimensions), including why systems have infinitely many cascades. Feigenbaum's results describe how a cascade's bifurcations scale — if the cascade exists. We show that infinitely many cascades must exist as a system goes from having only finitely many periodic orbits to chaotic dynamics. Our theory is for generic smooth one-parameter maps $F(x)$ where $x$ is $n$-dimensional. Here is one corollary for maps with horseshoes in dimension $2$ such as the time $1$ map of the forced damped pendulum or double well Duffing equation.

The Route to Chaos Theorem. Assume $F(x)$ is smooth and $x$ is two-dimensional. Under additional mild restrictions, if there are parameter values $a_1$ and $a_2$, for which $F(a_1)$ has at most a finite number of periodic orbits, and $F(a_2)$ has chaotic dynamics. Then there are infinitely many period-doubling cascades between $a_1$ and $a_2$. The definition we use for "chaotic dynamics" is satisfied if there are infinitely many saddles whose unstable eigenvalue is $>1$. The above result also holds when $x$ is one dimensional with minor wording changes. In addition we have discovered a new phenomenon in which there are "paired cascades," that is, two cascades that are connected by a path of periodic orbits. The quadratic map $a - x^2$ has no paired cascades but almost all cascades are paired for the forced damped pendulum and for the forced single and double well Duffing equations.
Fragmentation and Size Distributions of Fractal Aggregates in Fluid Flows

Marine aggregates are an important part of the global carbon cycle in the ocean and understanding their formation and dynamics has been a topic of increasing interest in recent years. Typically, such aggregates are created in aggregation and fragmentation processes as large fractal clusters of solid particles. However, the incorporation of this fractal structure of the aggregates as well as the incorporation of finite-size effects such as particle inertia into the usual mean field theory for aggregation and fragmentation is still an unsolved problem. We present results from the numerical simulation of a system formed of inertial particles suspended in a fluid flow, where the particles interact in the form of collisions, aggregation and fragmentation. Upon collision the particles can aggregate and form larger clusters which can break up again due to shear forces in the fluid, resulting in a distribution of aggregates of various sizes. We show how the fractal structure typical of many real aggregates can be included in such a model in form of an effective size and density of the aggregates and discuss consequences for aggregation and fragmentation. In particular, we demonstrate that the time to reach a steady state depends strongly on the fractal dimension of the aggregates. Additionally, we show that the fragmentation of the fractal aggregates is the relevant process that determines the total size distribution of the aggregates. This is of central importance in many natural phenomena such as the formation of clusters of suspended particulate matter in lakes and rivers and marine aggregates in the ocean. While most previous studies emphasize the role of aggregation, our results show that this is more relevant for transient effects. In situations where a steady state is of interest, fragmentation will be the most relevant process.
1. Dynamical approximation of a reprogramming cell culture  
   Bradley Alceo, Michigan State University
2. Sympathetic description of coupled oscillators  
   Gilad Barlev, University of Maryland, College Park
3. Asymptotic of grow-up solutions and global attractors of slowly non-dissipative PDEs  
   Nisan Ben-Gal, Brown University
4. A tour of the traveler's view of a network  
   Christofor Brodka, Northwestern University
5. Stress thickening in dense suspensions  
   Eric Brown, University of Chicago
6. Universality and the lack of it in multiscale human mobility networks  
   Rafsanjan Bruijnoord, Northwestern University
7. Dynamics between time series and network analysis  
   Andrea S. L. O. Campanharo, Northwestern University and National Institute For Space Research (Brazil)
8. Heme-like Boolean chaos in a delayed feedback digital circuit  
   Hugo L. D. de S. Cavalcante, Duke University
9. Evolutionary behavioral aspects of infectious disease: reactions to epidemiological events and hysteria in the media  
   Ahadji Cheff, Arizona State University
10. Chaotic granular mixing in quasi-two-dimensional problems: streamline jumping and piecewise isometries  
    Ivan Christov, Northwestern University
11. Mutation and copy number variation in a genome  
    Brian K. Clark, Illinois State University
12. Dynamics of alternans in one-dimensional cardiac models  
    Shi Dai, Mathematical Biosciences Institute, Ohio State University
13. Spatial scale in human mobility networks - What can we learn from renormalization?  
    Vincent J. David and Dirk Brockmann, Northwestern University
14. The effect of directionality on the synchronizability of networks  
    Elenor Davis, Clarkson University
15. Investigating ten channel dynamics during high-frequency random noise stimulation using Hodgkin-Huxley model  
    Anirban Dutta, Howard Hughes Medical Institute
16. Prediction reproduction and the amount of information stored in the present  
    Christopher J. Ellison, University of Washington at Davis
17. Using synchronization of chaos to identify multiple delay times in Boolean-delay systems  
    Zheng Gao, Duke University
18. Generalized resonant forcing of nonlinear and chaotic dynamics  
    Vadas Gyntauskas, Los Alamos National Laboratory
Dynamics Days 2010 Poster Session

19. The turbulent mean-velocity profile: it is all in the spectrum
Gustavo Giota, University of Illinois at Urbana-Champaign

20. Dynamic control for synchronization of separated cortical areas through ibotenic relay
Leonardo Lyra Gollo, IFISC

21. Dynamics and bifurcations in homogeneous rigid rod suspensions
Arvind Gopinath, Massachusetts Institute of Technology

22. Flow irreversibility in particle suspensions with non-uniform strain
Jeffrey S. Gutin, Haverford College

23. Foams in the phase field crystal equation
Nicholas Guttenberg, University of Chicago

24. Synchronization of uncoupled oscillators by gamma impulses, from phase locking to noise-induced synchronization
Shigemitsu Hata, Kyushu University

25. Gravitationally-unstable premixed flames: the transition to chaos
Elizabeth P. Hicks, University of Chicago

26. MEG study of cognitive functional activities in a human brain: nonlinear dynamical analysis
Sanghyun Im, Korea Advanced Institute of Science and Technology

27. Effects of super-spreaders in epidemic models on dynamic small-world networks
Matthew M. Jones, University of Maine

28. Clustering of brain tumor cells: theory and experiment
Evgeniy Khain, Oakland University

29. Bistability and hysteresis in dense shear granular flow
Evgeniy Khain, Oakland University

30. Macrotscopic kinetic effects of cell-to-cell variation in biochemical reactions
Pan-Jun Kim, University of Illinois

31. Firing patterns in a simple spiking model of neurons
Nayoung Koh and Wook Hee Koh, Hanseo University

32. Modeling and parameter estimation for a spatiotemporal ecological system
Sean Kramer, Clarkson University

33. The application of the transfer entropy to irregularly sampled time series
Christopher Kulp, Lycoming College

34. Diffusive wave dynamics near the break-up of an undersea bubble
Lipeng Lai, University of Chicago

35. Social learning in social networks
P.T. Lamberson, MIT Sloan

36. Role of network topology in the dynamic range of coupled excitable systems
Daniel B. Larremore, University of Colorado at Boulder
37. Critical behavior of the Ising model in annealed scale-free networks
   Sang Hoon Lee, Korea Advanced Institute of Science and Technology

38. Finite-size effects of threshold behavior in the K-satisfiability problem
   Sang Hoon Lee, Korea Advanced Institute of Science and Technology

39. Universality in the one-dimensional chain of phase-coupled oscillators
   Toy Lee, California Institute of Technology

40. Why is Brue paradox rare and synthetic rescue common?
    Joo Sang Lee, Northwestern University

41. How well can one resolve the state space of a chaotic map with noise?
    Domenico Lippolis, Georgia Institute of Technology

42. Information accessibility and cryptic processes
    John R. Mahoney, University of California at Davis

43. Events before droplets splashing on a dry solid surface
    Shreyas Mandre, Harvard University

44. Spontaneous synchronization in fiber laser arrays
    Yumato Matsuoka, Georgia Institute of Technology

45. Chaos and the quantum: how nonlinear classical correlations can overlap with quantum correlations
    Wil C. McHarris, Michigan State University

46. Optimizing mixing in channel flows: kinematic aspects associated with secondary flows in the cross-section
    Kevin Melihany, US Naval Academy

47. Obstacle and predator avoidance in a model for flocking
    Nicholas Mocholik, University of Maryland

48. How to parition a mixed phase space — with applications to atomic inversion
    Kevin Mitchell, University of California at Merced

49. Calculating transition times in a model of language change
    William G. Mitchener, College of Charleston

50. Hybrid steering using physical sensors
    Todd Murphray, Northwestern University

51. Resolving the network synchronization landscape: compensatory structure, quantification, and the positive effect of negative interactions
    Tskadi Nishikawa, Clarkson University

52. Vehicular traffic dynamics: from human to robotic drivers
    Gabor Orosz, University of California at Santa Barbara

53. Evolutionary dynamics of metabolic networks
    Adam R. Pal, Northwestern University

54. Turbulent Taylor-Couette flow between independently rotating cylinders
    Matthew Paolelli, University of Maryland
Dynamics Days 2010 Poster Session

55. Coupling distribution and modeling of stochastically perturbed dynamical systems
Rana Parshad, Clarkson University

56. Points of attraction in nonlinear systems driven with complex signals
Shawn Bethel, U.S. Army Research - Development and Engineering Command

57. Riesz network scaling: anisotropy and scaling crossovers in space and time
Geoffrey M. Pone, University of Illinois at Urbana-Champaign

58. Statistical data assimilation using Monte Carlo evaluation of path integrals
John C. Quinn, University of California at San Diego

59. In vivo characterization of dynamical transitions in mouse cortex across the cell and tissue levels
Jerry Rhee, Northwestern University

60. Multiplexed communications using chaotic systems with multiple delayed feedbacks
Damien Romani, Georgia Institute of Technology

61. Competing synchronous processes
Erminoudas Rossa, Jr., Illinois State University

62. Leaky oscilloscope dynamics
Robert Shaw, ProtoLife, Inc.

63. An adaptive model for the dynamical regulation of conductances in cardiac myocytes
Sebastian Skardal, University of Colorado at Boulder

64. Bifurcation and stability of a system of coupled droplet oscillators with S, symmetry
David Slater, Cornell University

65. Normalized spacings between zeros of Riemann zeta function given by normalized Maxwell-Boltzmann distribution
Stavdal Sornar, Northwestern University

66. Effects of heating on the stability of adaptive synchronization of chaotic systems
Francesco Serroni, Università degli Studi di Napoli Parthenope

67. Critical behavior of epidemic spreading in dynamic small world networks
Thomas E. Stone, University of Maine

68. Dynamics of networks: a computational approach for analyzing time dependent networks
Jie Sun, Clarkson University

69. Multi-scale modeling of coupled oscillator network
Jie Sun, Clarkson University

70. The in-degree-biased voter model
Samarth Swarup, Virginia Polytechnic Institute and State University

71. Dynamics in actuator arrays
Randall Tagg, University of Colorado at Denver

72. Effect of aging on dynamics in small-world networks of Rössler oscillators
Gouhei Tanaka, University of Tokyo
73. Spontaneous synchronization of oscillators with noisy frequency adaption  
    Dane Taylor, University of Colorado

74. Dynamics of vaccination with imperfect knowledge  
    Olivia Woolsey, Northwestern University

75. Propagation of information and estimation of states from data in wave-like spatiotemporal chaos  
    Young-nob Yoon, University of Maryland

76. Relating turbulent friction and energy spectrum in rough-pipe flows  
    Carlo C. Zuniga Zamalloa, University of Illinois at Urbana-Champaign

77. Mostly conjugacy analysis on homeomorphic defect  
    Jianguo Zhen, Clarkson University
The Dynamics Days 2010 is supported by the following organizations:

National Science Foundation
Office of Naval Research
Army Research Office
Weinberg College of Arts and Sciences, Northwestern University
McCormick School of Engineering and Applied Science, Northwestern University
Northwestern Institute on Complex Systems, Northwestern University

NICO

Northwestern Institute on Complex Systems
600 Foster Street, 1st Floor
Evanston, IL 60208

www.northwestern.edu/nico
847.467.1348
nico@northwestern.edu
DYNAMICS DAYS 2010 - MONDAY SESSIONS:
Fragility & Hysteresis in frictional granular jamming. ROBERT ECKE LANL.
GRANULAR jamming in photoelastic discs.

DISORDERED MEDIA \rightarrow glasses, foams, colloids, porous rocks.
2D granular diso & stress chains

LIU/NAGEL, NATURE, 1998 - jamming

\[
\begin{align*}
\text{liquid} & \quad \text{glass} \\
\text{load} & \quad \text{jamming} \\
\text{density} & \quad 1/\phi
\end{align*}
\]

Jamming - stationary w.r.t. small distortions

Point J & frictionless granular packing
\((0 = T_0, 0 = \text{applied stress})\).

\(J = \text{critical packing fraction } \phi_c\)
where \(\phi = \text{volume}\)

\(\phi_c \in \text{finite # grains, sharply defined for increases in } N\).

\(\text{bulk pressure related linearly to modulus, compressibility of individual grains}\).
Majumdar, PRL, 98 (2007)

Near-jammed vs. highly-jammed

Measures global pressure

Role of friction in jamming

Frictionless packing $\gamma_c = 2d$
* packing is static at jamming point
* 4 contacts required

Packing w/ friction $F = F_n + F_t$
* stable to external perturbations for $\gamma_c \neq d + 1$
* 3 contacts required
Assume $F_t \leq \mu F_n$ (Coulomb yield criterion)

EFFECT OF FRICTION ON CONTACTS ($\gamma, \phi_c$

Random close packing = zero friction
Random loose packing = non-zero
Each friction coefficient has own RPI state

Compress uniaxially, measure w/ micrometer

Global pressure measured at A-E

Crumble ball retroceded

Disk positions, contacts, & displacements
Threshold for resolving intensity of force

Quasi-static compression from loose packing
1. Start at random loose configuration
2. \( \exp \Phi \) (factor of 1 in terms of pressure)
3. Compression \( \beta \), \( \Phi \sim \Phi_c \)
4. Also seen inside sensors (little, no anisotropy).
   - Friction allows stability at much lower values of \( \Phi \).

- Rearrangement of particles as pressure applied, stresses propagated throughout system.
- 2nd compression—small-scale movement only (propagation across stress chains).

**STRESS CHAIN NETWORK**

* \((am) \times s^2(au)\) of area domains

PARTICLE DISPLACEMENT

- Count fraction of particles \( N_m / N_p \) moved more than 1% particle diameter.

- \( \Phi_s \) = packing fraction, pressure begins exponential, displacement falls exponentially

- \( \Phi_p \) = pressure stops exponential increase.

- New stress chains formed during \( \Delta \Phi = 3 \times 10^{-4} \)
Stress chain formation spatially correlated with displacement field (and compression).

System size dependence:

3 regimes:
1) $\phi < \phi_1$ - consolidation phase
2) $\phi_1 < \phi < \phi_2$ - fragile phase
3) $\phi > \phi_2$ - jammed (rigid state)

1) Large, frequent displacements
2) Displacements decrease exponentially, so do stress chain domains.
3) No displacements
Hysteresis (repeated cycling).

Friction: set value of $\phi_c$
$\phi_c$ decreases monotonically w/ inc. $\mu$

* Energy dissipation = 0.04 Jukes
* Systems pack more densely w/cycling

Jamming makes sense of disordered systems
* Friction plays role in granular systems
* Friction is hard to control, understand
* Large blocks of coordinated motion

Shear effects - Rheology of jamming (stress vs. strain rate - critical behavior).
Pull a particle through packed medium (local shear is introduced). Breaks up chain stabilization.

**Active Gels & Cytoskeleton - Fred MacKintosh**

- Polymer matrix + mechanical scaffold
- Nonlinear elasticity
- Model active networks
- Active MT mechanics & fluctuations (in vivo, in vitro)
- Nonequilibrium behavior unique to biology (motors exist on topology)

*Alberts, 1994* - microtubule, F-actin in cell

F-actin forms meshwork about microtubule network.

**Actin Cortex Structures**

Linear rheology of biopolymer gels:

- $\kappa 10^3$ Gpa (comparable to gelatin), viscoelastic
- strain stiffening (threshold for loadings above certain strain stiffening)

- **Collagen**
- **Actin**
- **Fibrin**

**Strain**

$G(\text{Pa})$

**ACTIVE, NONEQUILIBRIUM forces in cells → directed motion, active**

1. Active polymerization
2. Molecular motors

(*catalyzed, ATP → ADP, moves a laminsin along MT → conformational changes*)

**PRL, 2004**

**PRL, 1995**

**Nature**

**Actin/Myosin motors - does not work well on its own (many myosins on one actin)**
ACTIN + MYOSIN move actin filament in direction relative to another.


PNAS (2009) Internal stresses on networks, network being granular materials stiffen in ATP-dependent manner.

100-fold stiffening achieved by 1 pN of force. Network exists throughout space & time (motors ubiquitous throughout network).

THERMAL MOTION, equilibrium fluctuations

STOKES–EINSTEIN equ.

FLUCTUATION-DISSIPATION THEOREM

* flux of particles embedded in equilibrium non-equilibrium state.


With motor activity – violation of this (added fluctuations). Active gels.

** LOOK for these effects in living cells (intricate skeleton).

VITAL non-thermal motion, non-directed (Brownian motion). 100-fold stiffening?

FLUX

NO ACTIVITY

10Hz

FREQ
"BRIEF ACCOUNT OF EXISTENCE OF ACTIVE MOLECULES"
Brownian motion, original observation.

PRL 2008, JPC 2009. Molecular motors can hold network in tension; slow buildup, rapid drop

\[ \langle |w|^{2} \rangle \rightarrow \frac{1}{w^{2}} \rightarrow t \]

- Thermal flux \& white noise
- At an elastic limit, response becomes freq. independent (elastico regime).
- (LAU, PRL, 2003) \to viscoelastic liquids, living cells.

\{ DIREC TED MOTION - easy to conclude it is not Brownian \\ UNDIRECTED MOTION - easy to conclude that it is. \}

directed & lateral flux of MTs give rise to athermal bending modes w/ a series of amplitudes.
Mean squared displacement grows linearly in time.
* can be duplicate in vitro w/motors

\[ \text{Var}(a) \]

- THERMAL
- CELL
- WAVEVECTOR \( q \)

* MTs grow, shrink, move; contribute to bent, curved topology.
* Active control of motor properties in biomimetics.
* Fluctuations occur in parallel (finite lifetime for each flux).
* Spontaneous, but enough to hold system in ordered tension.
1D conjugate variables from macro-scale observations

FORCE → FLUCTUATION VARIABLE

Active cytoskeletal control in bronchiome, very little done in area.

ROTATING VOLCANIC PLUMES: LOBATE UMBRELLAS, TORNADOES, LIGHTNING SHEATHS. PINACLI CHAKRABORTY

Fluid mechanics in volcanic eruptions.

PLUME described as a tree structure,
  dominant motion = radial

COLUMN
  dominant motion = upward

Plume rotates counter-clockwise

1 hr  2 hr  3 hr

Lobes of umbrella instability, amplitude greater than wavelength.

ROTATING UMBRELLA -
  translated, expanded, rotated → gives us useful parameters

Look at thunderstorms as an analogy

plume classical motion
  rate mesocyclone (KLEMP, 1987)
Cyclones entrained by updraft, vertical shear from environment.
* Volcanic plume is an order of magnitude greater than thunderstorms (horizontal vortex).

**Rotating Flows: Navier-Stokes Equations**

\[
\frac{\partial u}{\partial t} + \frac{1}{\rho} \nabla p + \mathbf{V}_e \nabla^2 u = 0 \quad \frac{\partial \mathbf{V}}{\partial t} = \frac{\nabla^2 \mathbf{V}}{\rho} - \frac{1}{\rho} \nabla p - \frac{1}{\rho} \mathbf{V}_e \nabla^2 \mathbf{V}
\]

**Coriolis**

**Cylindrical**

\[
\frac{\partial \mathbf{V}}{\partial t} = -\mathbf{V}_e \times \mathbf{V} - \nabla \left( \frac{1}{\rho} \nabla p \right) + \frac{1}{\rho} \mathbf{V}_e \nabla^2 \mathbf{V} - \mathbf{F}_{\text{centripetal}}
\]

**Centrifugal**

\[
\frac{\partial \mathbf{V}}{\partial t} = -\mathbf{V}_e \times \mathbf{V} - \nabla \left( \frac{1}{\rho} \nabla p \right) + \frac{1}{\rho} \mathbf{V}_e \nabla^2 \mathbf{V} - \mathbf{F}_{\text{centripetal}}
\]

**Rossby Number**

\[
\mathcal{F} = \frac{\mathbf{V}_e}{\mathbf{V}} \ll 1
\]

**Analogy:**

Heavier Fluid

\[
\frac{\partial \mathbf{V}}{\partial t} = -\mathbf{V}_e \times \mathbf{V} - \nabla \left( \frac{1}{\rho} \nabla p \right) + \frac{1}{\rho} \mathbf{V}_e \nabla^2 \mathbf{V} - \mathbf{F}_{\text{centripetal}}
\]

Lighter Fluid

\[
\frac{\partial \mathbf{V}}{\partial t} = -\mathbf{V}_e \times \mathbf{V} - \nabla \left( \frac{1}{\rho} \nabla p \right) + \frac{1}{\rho} \mathbf{V}_e \nabla^2 \mathbf{V} - \mathbf{F}_{\text{centripetal}}
\]

\( \lambda, \tau \) (wavelength, timescale) (spiraling plumes)

Mt. Pinatubo = \( \tau = 1.3 \text{ hr}, 1.5 \text{ hr} \) — works for different R values (different volcanic plumes)

Lightning sheath — engulfs entire plume.

Tornadoes — updraft, downdraft, dversonant plumes.

**Centripetal Forces Dominate**

ROLE OF BUBBLES ON HEAT TRANSFER IN RAYLEIGH CONVECTION. LAURA SCHMITT

Rayleigh-Bénard convection - phase change, in thermal convection → whole-fluid behavior

Layer of fluid heated at bottom, cooled at top

KINEMATIC VISCOSITY $\nu = \frac{Pr}{\kappa}$

THERMAL DIFFUSIVITY $\kappa$

INCREASE $\Delta T^2$

$g \beta \Delta T L^3 = Ra$

Changes flow properties.

System response - global quantities

$Nu$ (Nusselt #, heat transfer vs. conduction)

$Re$ (Reynolds #, inertia vs. viscosity).


Bubbles interact mechanically & thermally.

PRE, 80, 026304 (2009). Effects of bubbles on global properties.

Will bubbles enhance heat transfer?

$T_{saturation} = \frac{T_{cold} + T_{hot}}{2}$

LIQUID (EULERIAN)

FORCES (LAGRANGIAN)

BOUSSINESQ ↑ BUBBLES
2-way coupling \rightarrow momentum, thermal
\rightarrow competition between mechanical + thermal FB
\rightarrow Nusselt eqns + FB from bubbles

(\text{drag}, \text{drag}, \text{lift})

Phase change a slow process

\[ \text{Jacobian} \equiv \text{Sensible heat/latent heat} \]

\[ \text{key parameters for phase change.} \]

\[ \text{Jacobian} \geq 0, \text{bubble changes size, transport} \]
\[ \text{dependent on local flow.} \]

\[ \text{Thermal FB - drive convection, stabilize flow.} \]
\[ \text{Mechanical FB - rising motion due to buoyancy,} \]
\[ \text{destabilize flow.} \]

\[ \text{Ja} = 0, \text{velocity } \& T^0 \text{ fields} \]

\[ \text{Bubbles} \]

1) equalize \( T^0 \) field by reducing gradients
2) induce microscale convection via buoyancy
   (pseudo-turbulence)

\[ \text{Re} \left( \langle u_{RMS}, N_b \rangle \right) \]
\[ \text{Ja} = 0 \]
\[ \text{Ja} = 0 \rightarrow \text{Ja} = 0.2 \]

\[ \text{Bubbles can grow/} \]
\[ \text{thermal FB, stabilization shrink at local condition} \]

\[ \text{Ja} = 0.2 \]

\[ \text{Ja} > 0, \text{flow destabilized} \]
\[ \text{turbulence enhanced} \]

\[ \text{Bubbles drive flow by rising motion} \]

\[ \text{N}_{\text{bubbles}} \]
EQUATION OF MIXING: FROM STRETCHING & FOLDING TO CUTTING & SHUFFLING - JULIO OTTINO

LESSON:

MIXING - increase in interfacial area per unit volume ($a_u$) between materials $\dot{a}_u/a_u > 0$

Fluids underlying thinking - FLOW, 1:1 mapping

$x = \phi_t (x)$, $\phi_{t=0} (x)$

$x$ - Eulerian,

$x$ - Lagrangian

$X_n^p \rightarrow X_{n+1}^p$ what elements are same after $n, n+1$?

Hyperbolic, elliptic points, components of manifolds

1) CAUVITY FLOW
   (OTTINO, 1986)
2) ECCENTRIC CYLINDER FLOW
3) BLINKING VORTEX FLOW

Horseshoe maps $\rightarrow$ blinking vortex, tendril-whorl flows (mix well in some regions).

CONTINUUM MECHANICS: STRETCHING $\rightarrow \omega/\theta$

$\lambda, n$ Lyapunov stretching, mixing exponent
Alternate view - 2D flow (streamfunction $\Psi$)
steady $\Psi = \Psi(x,y)$
unsteady $\Psi = \Psi(x,y,t)$ → chaos
streamline crossing necessary for order.

STANDARD PICTURE -
1) increase interfacial area = mixing
2) stretching = mixing
3) horseshoe map = chaos
4) chaos = mixing

Granular mixing by tumbling

\textbf{ROTATION RATE INC.}

different modes/ phases

1) geometry (wedges → wedges)
2) dynamics (mixing/w/wedges)

$J$ = rate of mixing, $X$ = total area being mixed
how does it mix, how good is mixing?

HIERARCHY OF MIXING:

\textbf{ERODIC} - $\Phi^k(A) \cap B \neq \emptyset$

\textbf{WEAK -}
Baker

\textbf{STRONGLY -}
Bermoulli

SMALL HORSESHOE MAP, BAKER TRANSFORMATION
(Beroulli shift - most possible mixing).

A priori prediction of Bermoulli shift, geometric
features NOT mechanism driving flow.
LINKED TWIST MAPS—STURMAN & WIGGINS

- Allow predictions of chaos on set of full measures.
- Application of Ergodic theory.

MIXING GRANULAR MATERIALS—Continuum Model

\[
\begin{bmatrix}
  u_x(x,y) \\
  u_y(x,y) \\
  s(x)
\end{bmatrix}
\]

If flow becomes time-periodic or time-dependent, streamline crossing only in flow layer.

CASE: thickness flowing layer = 0, no streamline crossing.

clf = 0, streamline jumping.
Streamline jumping = chaos.

3D blinking granular flow

CUTTING–SHUFFLING:

\( \frac{\pi}{2} - \frac{\pi}{2} \rightarrow \text{white / black} \)

\( \frac{\pi}{4} - \frac{\pi}{2} \rightarrow \text{glass beads} \rightarrow 10 \text{ interval exchange transformations} \)

\( \frac{1}{\lambda_1} = \frac{1}{\lambda_2} = \frac{1}{\lambda_3} = \frac{1}{\lambda_4} \)

Exhibits nonlinear behavior

Shuffled mapping
PWI protocol \((1/2 - 7/2)\) devise protocol for mixing (bad vs. good).

Mixing at \(t=50\)

\((W_1, W_2)\) can be same/different, different segregation outcomes between B & W).

Symmetry breaking \((11/4 - 7/8)\): development of layers.

- Positive Lyapunov = can lead to bad mixing
- Zero Lyapunov = can lead to good mixing

Underlying assumptions about stretching & folding not necessarily true about chaotic behavior.

*Streamline jumping leads us to cutting & shuffling alternative routes to order?*

*CHAOS beyond the HOESHOE map, mono- & heteroclinic behavior?*

Increase contact area, maximize mixing potential (good mixing).

Dynamic self-propelled structures, ALEXEY SNEZHKO.

Magnetic layers - liquid-air, liquid-liquid interface.

*Collective response of particles in non-equilibrium systems.*

*Self-assembly & control in far-from-equilibrium systems.*
MAGNETIC SNAKES - pattern formation in magnetic driving fields

DC field \textarrow{\textarrow} dipole-dipole repulsion.

Parametric excitation of surface waves by oscillating magnetically-driven particles.

A) $H_{dc} = 2.0 \text{e}$

B) $H_{dc} = 100 \text{e}$ (surface waves move like a snake)

\text{\begin{align*}
A) & \quad \frac{\alpha}{\beta} = \frac{\gamma}{\delta} \\
B) & \quad \frac{\kappa}{\lambda} = \frac{\mu}{\nu} / H_{dc}
\end{align*}}$

LIQUID-AIR approach

PATTERN-ASSISTED SURFACE FLOWS:

Symmetry breaking, onset of self-propulsion

Tails (front - back), breaking spontaneous in both, stronger tail "wind" jet propels structure.

LARGE BEAD (mechanical) "shuts down" one of the tails (engines), controls movement.

PHYS. REV. (E), 102, 118103 (2009), instability occurs at critical parameter value ($\Omega$).

Onset of swimming: $V \approx \sqrt{\frac{\kappa - \gamma}{\nu}}$

PHYS. REV. E, 80, 011310 (2009)
viscosity increased in circle around tail.

**Simplified MD Approach**
- Quasi-2D description of fluid
- Magnetic moments tangential to surface flow
- Magnetic Dipole Hamiltonian
- Random distribution of magnetic moments
- (128 particles) moments become aligned w/ those of their neighbors

**Liquid-Liquid Interface** (signals become smaller)
- 3D hydrodynamics (stars, clams & other structures)
- CLAMS *star & anti-star (magnetic moment dependent)
- STAR LATTICES *symmetry breaking is spontaneous, vortex-dependent
- RICH playground of nontrivial emergent phenomena
- Generic forcing (local flux) -> produces wave, tune-field amplitude & frequency (interplay)
GEOMETRY OF TURBULENCE IN WALL-BOUNDED SHEAR FLOWS, 61,506 DIMENSIONS.

Community of 50 people doing turbulent flows (3D velocity field).

See structures based on geometry, numerical tools also improved.

Unstable structures—need much info about blow behavior.

Turbulence in the engineering sense.

How do we describe structures? Language for this.

INFINITE-D state space, use dynamics for low-dimensional systems.

OBSERVE STRUCTURES $\rightarrow$ recurrent (unstable) structures.

GOAL $\rightarrow$ 1D $\Rightarrow$ map out relationships.

3D plane corvette flow

$u(x,y,z,t) = \begin{cases} 
    u(x,y,z,t) & \text{velocity component} \\
    \text{Episodes of turbulence interspersed by episodes of highly-ordered behavior.}
\end{cases}$
Numerical simulations model experimental observations reasonably well.

- Recognizable recurrent structures (whirls, other patterns in velocity field).

**Exact Solution of Navier-Stokes:**
- laminar equilibrium (static solution).
  - solution is unstable, order fades away & does not return;
- Gibson equilibrium (many new solutions);
- periodic orbits -> equilibrium stationary.

*Turbulence vs. Periodic Solutions* — periodic solutions indistinguishable from turbulent dynamics (highly-ordered regimes interspersed w/turbulent episodes).

- Now there are many exact solutions for N-S; how do we fit them together?
- Unstable toroidal solutions are not robust by comparison w/periodic solutions.

**State-Space Visualization:** global state space basis

- physical structures; three 1/2-cell translates
- project coordinates w/o losing flow information.
- in state-space of fluid, vortices on different dimensions can be very different

\[
e_1 = (1 + T_x + T_z + T_{xz}) u_{nb} \\
e_2 = " " " " \\
e_3 = " " " " \\
e_4 = " " " "
\]

\[4 \text{ selected directions at time } t.\]

**Energy Norm:** \( (u, v) = \frac{1}{V} \int_V u \cdot v \, dx \) (gdot product).
Global portrait not static:

- state space trajectory
  - curve between
  - found stable solutions
  - spiral out into lower-
    dimension space

Heteroclinic Map

- Periodic orbits & transient turbulence
  - all orbits situated between typical orbits
  - close recurrences (revisiting neighborhoods)

3D Vista of Equilibria & Their Manifolds

- Isosurfaces
  - hairpin vortex
  - using low-speed structure-sensitive technique
  - shifting flow structures

- Increasing Reynolds #: get more complex structures

Lagrangian trajectories - each solution by itself is a bad mixer - slicing, recombining different regions might facilitate mixing

Channel Flow, OPL

- Characterizing dimensionality - discretize system, find Lyapunov vectors
Which unstable manifolds cross stable manifolds for stable solutions? Can be used for control.

REGULARIZATION OF TUNNELING RATES W/ QUANTUM CHAOS, LOU PECORA.

Numerical study of tunneling in double wells

\[ \text{Schrödinger's Equation} \]

\[ \frac{\hbar^2}{2m} \frac{d^2 \psi}{dx^2} + (E - V) \psi = 0 \]

Symmetric \[ \psi_s \]

Anti-Symmetric \[ \psi_a \]

TUNNELING RATE \[ \Delta E/\hbar \]

\[ \frac{\Delta E}{\hbar} \text{ increase w/ energy \ (used for Quantum dots)} \]

Energy: Barrier harder & harder.
Tunneling in 2D integrable systems.

Waveguide/resonant cavity mode behavior.

Similar energy tunneling occurs at 2x the rate.

Particle momentum in direction perpendicular to barrier (lower energy) vs. parallel to barrier (higher energy needed).

CIRCULAR WELLS - integrable system, also a broad spectrum of energies.

2D tunneling - non-integrable systems.

* Numerical solution of Schrödinger equation.

Boundary element method (BE).

Elongated stadium

[Diagram]

Collapsed tunneling rates

[Diagram]
SINAI BILLIARD WELLS—same type of collapsing, some compression

BUTTERFLY WELLS—compressed even further (closer to 1D case). Contracted tunneling rates 4-fold (shape of chambers controls tunneling rate), regularization.

CONCAVE WELLS

no structure in map, strongly chaotic → particles come in small directions, barriers become resonant at high E

Poincare' Maps, Classical Dynamics—

MODE MATCHING—can turn 2D tunneling rates into a 1D distribution.

Design of quantum dot experiments—control constraint tunneling spectrum in devices using well shapes?

MATCHED FILTER FOR CHAOS, NEQ CORREL.

OSCILLATOR (chaotic) for communications.

Linear representation w/ fixed pulse.

Hybrid dynamical system—continuous, discrete states
When continuous state $x = 0$, update is sine of waveform.

Oscillator: harmonic oscillator w/ negative dampening.

oscillator can switch output (flip from 0 to 1, 1 to 0)

Find initial condition (setpoint), solve over interval $x$, start over.

Shift map — linear representation.

Analytical solution for continuous, discrete (switching state) solution.

$w(t) = s_n + \frac{1}{2} \sum_{i=0}^{\infty} \sin^2 \frac{\pi}{2}$

Hybrid system

chaotic

setpoints provide freedom to solve

$\{ u_{n+1} = 2u_n - s_n \}$

$\{ s_{n+1} = \text{sgn}(u_{n+1}) \}$

Symbolic dynamics

$u(t) \rightarrow \{ s_n \}^* \rightarrow u(t+1) \rightarrow \{ s_n \}^* \rightarrow n \rightarrow \infty$

Linear synthesis of chaos — solution — linear convolution (communication waveform, basic pulse).
COMMUNICATING WITH CHAOS

Use a linear receiver to detect waveforms.

\[ \text{0110011} \xrightarrow{\text{modulate}} \text{modulate} \xrightarrow{\text{demodulate}} \text{0110011} \]

DRL, 1993 (modulation) \{ literature on this.
No solution for demodulation \}

We can build a matched filter for basis pulse.

\[ \text{BIT-ERROR RATE approximation is reasonable.} \]
(chaotic waveforms do not require a price to pay)

HYBRID ELECTRONIC OSCILLATOR (now works at 10 kHz).

Encode \rightarrow \text{small perturbation control}
Decode \rightarrow \text{matched filter}

QUASI-PATTERNS BY DESIGN, MARY SILBER

KUROKU, 1998-vibrate fluid, standing waves
hexagonal patterns (12-fold rotational symmetry).

PRE 75, 055203 (2007).

Distinct pattern states co-exist in Euclidean invariant patterns \rightarrow symmetry-breaking instabilities.
Observe stable patterns stabilize unstable ones by using "controls" (design principles).

NONLINEAR - existence of patterns
* linear stability problem on top of this

FARADAY WAVES - standing waves created w/ ejecta

PHYSICA D, 1996
PRE, 1996

QUASI-PATTERNS -
* no translational symmetry
* discrete power spectrum (Fourier analysis - rotational symmetry uncovered)
* 8-10-12-fold symmetry

\[
\omega_{\text{wave}} = \frac{\omega_{\text{drive}}}{2}
\]

12-fold quasi-pattern \( (N=11\) quasicrystal \)

SEP. 2007

SPATIALLY - PERIODIC
SOLUTION \( \rightarrow \) space spatial periodicity
* finite # of modes unstable at \( f = f_0 \)
* all other modes, finite dampening
RUCKLIDGE & RUCKLIDGE, 2003 → calculated some quasilattices
* quasi-periodicity up to N=12, beyond this you get irrational numbers.

R GoSS & RUCKLIDGE, 2010 → do quasipatterns exist above N=12 (can't solve PDE)

\[ \frac{\partial U}{\partial t} = MU - (1+\sqrt{2})U - U^3 \]

Existence of quasipatterns not stable.

RESONANT TRIADS: towards stability.
* lowest order nonlinear interactions
* building blocks

* function of angle \( \theta \)

[Diagram of angles and modes]

Population dynamics of waveforms.

FORCING OF FREQUENCY - help along process of pattern formation
(multi-frequency forcing)

PORTER, PRL 2004
TURBULENT CRYSTAL (NEWELL & POMPEAU 1993)
(ZHANG & VINAILIS, 1996)

Make coefficient A large:

\[ B_\Theta = \frac{b_0 + b_{res}}{a} \]
PARAMETRIC FORCING ON MODEL PDE -
* features in common with Faraday wave experiment.

NUMERICAL SCHEME - 4TH ORDER RUNGE-KUTTA (COX & MATTHEWS, 2002).

SELECTING QUASI-PATTERNS -
12-fold patterns 1.003 x critical, 8 3.30 x critical wavelength.
* after 10,000 periods, 12-mode amplitudes differ by 1%.

Domain size 1 fraction approx. of $\sqrt{3}$

APPROXIMATE QUASI-PATTERNS
not universally representative.

approximate order 26th
additional mode (4th)

$\theta$ (degrees) AMPLITUDE

stop simulating at 26th

OPEN PROBLEMS -
* higher-order superlattice patterns.
* closed-loop control.
* higher-order superlattice patterns.

Nonlinear waves $\rightarrow$ complex patterns
(this is also true for quasi-patterns).
Synchronization of Eukaryotic Flagella, R.E. Goldstein, youtube.com/GoldsteinLab
Cilia movement in embryos -> places heart on left side of body -> conserved quantity (cilia/flagella).
Transition from single- to multi-cellular organisms.

Size-Complexity Relation

Bell & Moore (1997)
Bonner (2004)

Cell Types

\[ \text{Total Cell \#} \]

\[ \text{(log)} \]

Volvox - movement using spinning motion, cilia/flagella driven.

Volvox model for biological fluid mechanics.

Hydrodynamic bound state

Volvox in Volvox are active, driven by MT (like spindle in cell division).

Flagellar synchronization in Chlamy
Cell Motility & Cytoskeleton, 7, 87 (1987)

Diffusion vs. Stirring (Peclen #), Chlamy - low Peclen #.

Volvox - high Peclen #.
For different cells:

- Complete = 85%
- Sporadic = 10%
- None = 5%

Quantifying beating:

**STROKES OF FLAGELLA**

Phase slip in flagellapinae,
PRL, 103, 158103 (2009).

\[ y_1, x_2 \]

\[ \Delta \text{ synch} \quad \text{sub drift} \]

\[ t \]

*single cell = all 3 modes!*


\[ \Delta = 5v - 2 \tau \rho \sin(2\pi \Delta) + \varepsilon (t) \]

freq. mismatch coupling strength phase oscillator (kuramoto)
**DIFFUSION -** tilted washboard map.

**SLIPS** = hopping.

**V_{eff}**

**DRIFT** state.

**SCIENCE, 325(487)-2009**

2 years for CHLAMY - low gear (drift), high gear (synchrony).

**SYNCHRONY** state.

**DRIFT** - random walk when CHLAMY wants to turn.

**TIMESCALE ~ 10 sec.**

**FLUX** $\phi$

$\frac{dc}{dx}$ (cm$^{-1}$) (DIFFUSION CONSTANT)

**TRAJECTORY** (not straight) - explores volume - makes sharp turns quite frequently.

**GEOMETRY** of tuning - CHLAMY w/single flagellum. How much does it tumiper beat?

**RUN & TUMBLE** in drift (turn), then synchrony, random walk-like.

**PROB.** (ANGLE)

"RUN & TUMBLE"

**LOCOMOTION**

TURNER ET AL. 2000
What is this good for?

**PHOTOTURN (VOLVOX)** with bottom-heavy ness.

Phototaxis: VOLVOX turns to light source with small delay. Colonial axis is "bottom-heavy" + follows light subject to inertial torque.

VOLVOX is a spherical ECM that contains 1000 CHLAMY (colonial, not multicellular) + coordinated behavior.

**VOLVOX eyespot:**

**DYNAMIC PIV measurements - step response.**

\[
\text{Flow Speed} \quad \begin{array}{c} \text{Adaptation important to} \\ \text{flagellar response.} \\ \text{ANGULAR DEPENDENCE} \\ \text{"North Pole cells do the} \\ \text{t(sec) downregulating.} \\ \text{organism} \\ \text{downregulates} \\ \text{tuning of} \\ \text{flagella.} \\ \text{BAND-PASS frequency-dependent response.} \\ \text{TUNING: peak of frequencies determine} \\ \text{downregulation, dark vs. light sides.} \\ \text{Phototropism of plants (dynamic} \\ \text{phototropism) - homogenous} \\ \text{behavior as it moves toward the light.}
\]
TUESDAY SESSIONS

LETHAL PROTEIN PRODUCED IN RESPONSE TO COMPETITION.
HARRY SWINNEY

FRAC TAL GROWTH PROCESSES

* Electrodeposition (ARGOUD, PRB, 1988).
* Tomoshita (wrinkles in edge), 30-0.08 mm - self-
  similar structure.
* Air-bingingo (PRE - 2005, 2010).
* Fractal growth in bacteria (GEN - JACOB).

BACTERIA (motile) - swim in layer on gel surface.
P. dendritiformis (vary nutrients & substrate).

15h growth of a colony, Flagella have chirality,
symmetry-breaking w/ hardness of surface.

Growth of colony occurs at tips, outer edge of
colony, Sporulation process (higher conc. of
spores as you move towards center).

SIBLING COLONIES - growth initiated as quorum,
local crowding. After 18h, growth is initiated.

growth is linear in direction away from neighbor

growth slows in direction towards neighbor
does not change w.r.t. nutrient conc.

competition of sibling colonies.
MORE THAN INHIBITION -

Subsample of B grows in nutrient-rich broth, but subsample A is dead.

**MODEL**

\[ R_e(t) = V_t - V_{t, \text{mg}} \]

\[ R_p = \alpha R_e(t) \]

6-variable PDE used.

**INHIB. CONC.**

Threshold \( V_t \) inhibitor saturates below threshold.

84h

12h

What is initial inhibitor concentration? (BE'ER, PNAS, 2009).

What is inhibitor? Extract gel from in between colonies, analyze.
FLAGELLIN, SUBTILISIN, ?? → introduce subtilisin
(30kda) (28kda) (12kda) to culture prometastically
growth, later directional sequence ??, which is growth (only get 12kda
an unknown protein, band at high conc. of
SLF - sibling lethal factor, subtilisin).

Subtilisin cleaves SLF into 12kda form toxic to bacteria.

Bacteria develop mechanisms to survive SLF exposure
w/ switch in phenotype.
RODS to COCCI (20x slower growth, not motile)
also resistant to subtilisin, SLF.
also antibiotics
COCCI revert to rods if growth conditions are
favorable.

CLUSTERS— dynamic, long-lived, no inter-cluster
correlation (but spatially, orientationally correlated
w/in cluster).
Clusters are dynamic (bacteria constantly join,
leave clusters).

BACTERIA in large clusters move faster—

\[ \text{Graphs showing mean speed} \]

\[ \text{Graphs showing fluctuations} \]
more nutrients, more phase space (growth from a physicist's POV).

DYNAMICS OF CELLS & CELL GROUPS, WOLFGANG LOSERT. NSF Physics of Living Systems. Propel across surface, chemical inhibition, collective motion:
- Energy savings (bird flocks)
- Wound healing (skin cell cooperation)

PV - features of skin cells during wound healing (one cell dies, others move in, function as a sheet).

DICTYOSTELIUM - model for chemotaxic collective behavior.
- Signaling pathways & neutrophils (white blood cells).

DICTYO aggregation - spiral wave formation, they form centers, break apart, form new centers.

AMP - generates waves that occur every 6 minutes.
- Cells sense AMP, use cells that don't sense AMP to show this (aca-).
Growing actin filaments - propel cells.
Actin filaments push against membrane, moves cell in direction.

What guides actin polymerization?

Round up (immobilize) cells, use protein label, introduce cAMP (red).
* cAMP translocated to membrane, then falls off.

* triggers actin motion

<table>
<thead>
<tr>
<th>cAMP</th>
<th>ACTIN</th>
<th>MOVEMENT</th>
</tr>
</thead>
</table>

Reference state: chemokinesis

Uniform dose of cAMP - constant, random movement.

**Directional Persistence:**

\[ \langle \Delta r^2 \rangle \propto t^{2\alpha - 2} \]

Diffusive exponent \( \alpha \)

- \( \alpha = 2 \) WT
- \( \alpha = 1 \) aca-

Mean Squared Displacement (MSD)

Directional persistence over 14 min, cAMP controls this but what about short timescales? Diffusion is Gaussian noise, ballistic is patterned.
MEASURING LOCAL BOUNDARY MOTION:

- Front protrudes, sometimes shifts in different directions
- "Waves" of actin polymerization?
- Protrusion & retraction measured. Signal relay (color-coded) does not affect speed
- Cells = persistent random walk on short timescales

CAMP wavelength — reaction-diffusion problem.

CHANGES IN SOLUTION SET IN IDEALIZED GENE-NETWORK MODEL, HEATHER HARDAWAY.

Fruit fly development, pattern formation.

Positional, relative information about body plan.

14 distinct segments — scaling w.r.t. embryo length.

HOUCHMANZADEH, 2002

Embryos stained for bicoid, hunchback, segmental genes: 9% of total embryo length.

BICOID — determines "midpoint"

GREGOR et al, 2005 — patterns scale with embryo length
\( c_{ij} > 0 \rightarrow p_i \text{ activates } p_j \)
\( c_{ij} < 0 \rightarrow p_j \text{ activates } p_i \)
\( 0 < g < 1 \text{ (g smooth, monotonic)} \)

**Effect of protein** \( i \) on protein \( j \):
\[
R_1 g (c_{11} p_1 + c_{21} p_2)
\]

**HENRIKES et al.** restrict to single variable concentration parameters: diffusion, decay, production.

**Symmetric parameters:**

\[
\sum a_t \rightarrow \bar{a} \quad \frac{d}{dt} \rightarrow \frac{a}{b}
\]

**Steady-state solutions** (even or odd about the midpoint).

**Pitchfork bifurcation** - dependence on \( g'(0) \)

\( \frac{1}{\alpha} \)

Taking \( g = H \) (Heaviside function) \( \rightarrow \) idealized gene network model (gene network calibratory) collapses to one solution.
STABILITY: for increasing values of \( g'(z) \)
As \( g' \) goes to infinity, solution goes to infinity as well.

\[ \phi(z) = c z^2 \tanh(z) + \tanh(z) - 2 \]

find locations of Eigenvalues w/in complex plane.
Using \( \lambda = \mu^2 - 1, \mu \in \mathbb{R}, \) all eigenvalues \( \lambda \)
lies in left-half of complex plane.

HEURISTIC FUNCTION \rightarrow EIGENVALUES \rightarrow \text{two proteins used to establish scale invariance.}

GENOMIC CODE FOR NUCLEOSOME POSITIONING, JOHNATHAN WIDOM

Information that controls 3-D chromosome in space—nucleosomes.

Folding (30-nm chromatin fiber of packed nucleosomes).

Nucleosome positions are specific—written into DNA \rightarrow \text{stereo competition between nucleosome + protein for a specific locus of DNA.}

DNA → NUCLEOSOME → DNA sterically excluded & sharply bent.
Nucleosome unwrapping vs. protein binding.
Cells control number of nucleosomes → stretches of DNA "compete" for nucleosomes (self-competition), access of protein to target site is hindered.

* In vitro selection of nucleosome-favoring DNA
* Isolation of natural nucleosome DNA
  * Strongly non-random features.

Nucleosomes like 'TA' basepair followed by 'AT'
basepair (or 'AA' or 'TT'). Protases like Gs & Cs.

New sequencing techniques: $10^6$ x more data
atolation of natural nucleosome DNA: via digestion

Use Solexa short tags & short tags from each end.

(Fields et al., 2008) Nucleosome position in yeast.

\[
\begin{align*}
\text{GC} & \quad \Delta 0.0 \quad \text{G+C signal out-of-phase with AT signal,} \\
2 & \quad 8 & \quad 12 & \quad 40 & \quad 16 & \quad \# \text{ of reads, abundance of collective property of all nucleosomes.}
\end{align*}
\]

FAVORED 5-mers in in vivo nucleosomes.

\[
\log \left[ \frac{5\text{-mer in linker}}{5\text{-mer in nucleosome}} \right] \rightarrow \text{create a free energy landscape, not just score at threshold,}
\]

* one good score cluster of good scores, periodicity.
Nucleosomes equilibrate location in genome. Solve (atequilibrium):

- \( P_{R}(\text{placing nucleosome at starting position}) 
- \( P_{R}(\text{placing nucleosome at any site i}) 

**Selection Experiment:**

* pure histones * pure genomic DNA
* sequence undigested DNA
* compare in vivo vs. in vitro (indifferent growth media).

Genomic DNA explicitly encodes potential to wrap around nucleosomes. Prediction is mostly based on bioinformatics.

![Diagram](true_pos_false_pos)

78% in C. elegans genome, (not a good proxy for human). Nucleosome positioning delineates these functional & non-functional TF sites.

Different promoter architectures cause different expression dynamics. Universal genomic code for positioning (organism invariant)?
VISNAFUU & GREENE, 2009
Nucleosome present in living yeast → predictions in humans.

Viral DNA (phage 2) → show where nucleosomes might be (experiment that's never been done in nature).

SANDMAN & REEVE, CURR. OP. MICROBIOL. 2006
Archaeal histone-like proteins
Archaeal use histones in a way analogous to middle tetramers of eukaryotic nucleosome.

METHANOBACTERIUM → Archaeal histones & nucleosomes → positioning experiments.

IN VIVO, IN VITRO Eukaryotic & Archaeal DNA all have some nucleosome → prefer binding sites (highly conserved, arose early).

Multiplexing?
• nucleosomes not evolved for highest affinity → many ways for suboptimal affinity over 147 bp.
• protein-coding/gene regulator sequences is degenerate
• A+T, G+C pairs can be anywhere in target region, good enough.

3 modes of degeneracy:
Nucleosome velocity of diffusion; semi-random walk (utilize catalysts).
Higher levels of genomic structure (1-D vs. 3-D positioning information).

Nucleosome coverage (%) varies across species & cell types in organism. Biological meaning (highly regulated)?

Classify low vs. high occupancy BPs

True Pos.

False Pos.

Energy landscape for folding & molecular motors: Kinesin story, Jose Onuchic
c.top.ucsd.edu

Energy landscape - rough landscape - random heteropolymer

Proteins - try to understand landscape

If $\alpha$ stability $\rightarrow$ principle of minimum frustration, (Wolyenes)

Hydrophobic, hydrophilic components - give many low-energy states.
States are hard to find, not robust (uninterpretable proteins).

"STABILITY GAP" - how do we measure this?

Volume/surface ratio is an important concept.

Folding funnel - idealized system

\[ \phi_i = \frac{\Delta \Delta G_i^+}{\Delta \Delta G_i} x = \frac{-RT \ln(k_i/k_{wt})}{\Delta \Delta G_i} \]

Not free energy per se.

* measure populations - states around 5 kT barriers.

Configuration entropy

Free energy

Break homogeneity:
- energetics
- geometry

Contacts have 50% probability, same free energy.

Off-lattice model (Jim 2000)

Protein = interactive chain in 3-D space.

2-state model: mutate into functional structures analogous to experimental results.

Probability of contact formation:
- very robust to mutation
- predicts funnel of folding

<table>
<thead>
<tr>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>

\( \alpha \)-helix
Second problem: SH3 domain - contacts must be formed early. No energetic frustration, must be due to geometry.

**Folding routes for SH3.**

* Proteins fold independent of energetic frustration.
* Nature can minimize frustration, should be apparent in molecular motors.

**Kinesin Dynamics:** Vale and Milligan, Science (2000)

- ADP release
- ATP hydrolysis (regulating energy production)

**Mechanical step**

- ATP binding

**Rice et al., Nature (1994).** States of kinesin, nucleotide, MT, mech-linked or kinesin motor. With MT being bound (one step):
- ATP hydrolysis 10x increase, ADP dissociation 3000x increase.

**Internal strain regulates binding site of kinesin head.**

5 nm separation

\[ \text{RMSD} = 1.6 \text{ Å} \]

\[ \text{SEQ. ID} = 40\% \]

**ENERGY LANDSCAPE**

NOT JUST FOR FOLDING,

BUT FOR ALL FUNCTION.

---

**Two-head-bound kinesin on MT binding sites.**

**NATURE CONTACT MAP:**

---

**Strain disorders compensate for energetics of inertial forces.**


**ORDER-DISORDER connection** → bound ATP determines completion of step.

**KINESIN uses rearward tension to create disorder.**

---

**MICROTUBULE SURFACE** - kinesin steps from one cell to another

\[ \lambda = 0 \rightarrow \lambda = 1 \text{ (ungipped to zipped)} \]

contacts on/off: \( \lambda = 0 \) (mech-linker disorder), \( \lambda = 1 \) (mech-linker order).

Partial unfolding facilitates binding (unfold, twist, fold instead of elastic motion).
TIME-DELAY MODEL FOR PROTEIN SYNTHESIS,
Luis Mier-Y-Teran
APPLICATION TO GENE NETWORKS.

ELOWITZ, NATURE (403) 2000 - REPRESSILATOR,
3 genes w/ mutually inhibitory dynamics
(oscillatory) describes switching behavior,
but not much molecular detail.

POLYSOME PACKING fraction: Translation occurs in polysomes.

RIBOSOME DYNAMICS - HEINICHT & RAPAPORT, 1980

\[ \frac{d}{dt} x_i = V_i - V_i \quad i = 2 \ldots N \]

production of mRNA

\[ \frac{d}{dt} x_j = V_j - V_j \]

presence of protein.

\[ \eta(t) = \eta \left( \mu - \int_{-\infty}^{t} \eta(t') dt' \right) \]

parameters mapped directly
(modelling),

\[ x_j(t) = \sum_{i=1}^{j} \text{continuous} \]

distribution for density.

Degradation of mRNA - factor in loss of ribosomes from templates.
ODE MODEL → use time-delay for oscillations in single gene (ODE models),
MONK (heuristic delay model),
production of proteins → delay of mRNA production,
SELF-REPRESSING gene

TIME-DELAY MODEL (molecular detail).
oscillations will eventually cease.

TIME-SCALE for sustained oscillation:
vary parameters of Hill function — HOPE surface will allow you to time
oscillations, adjust parameters.

MITOCHONDRIAL MODULATION INTRACELLULAR Ca²⁺ SIGNALING,
CHRIS FALL.

Endoplasmic reticulum Ca²⁺ (compartments, gradient),
channels, FB, pumps, messengers,
BISTABLE "TRAP WAVE"
EXCITABLE MEDIUM "SPIRAL WAVES" ± response curve.

IP₃, IP₃, HODGKIN-HUXLEY-like Ca model:
IP₃: activation, inactivation 2000:10:1
L-ROZEL, 1994
MITOCHONDRIA
RIUZTO et al., 1998 - networks not "sausages."

CHEMIOSMOTIC TRANSDUCTION

\[ \text{Na}^+ / \text{Ca}^{2+} \text{ exchanger} \]

\[ \Delta \psi \text{ across membrane} = 150 \text{ mV.} \]

\[ \text{Ca}^{2+} \text{ feedback on } MT \text{ metabolism} \]
(ROBB-GASPERS, et al., 1998).

MT dominate Ca\(^{2+}\) clearance in some cells
(as opposed to EA), canalicular shape
regenerative Ca\(^{2+}\) signaling.

MT are excitable organelles exhibiting CICR
ICHAS et al., 1997.

Slow series of Ca pulses in curtail, somewhat
pH dependent, MT can support wave

CYCLOSPORIN - keeps cell from massively
depolarizing.
MT exhibit catastrophic depolarization events
MWPL - pressure release
MTPH - cell death, apoptosis.

* Sensor of health, based on ROS.

\[ \text{pH} \]

- Low
- High (SUICIDE STATE)
Modular physiological model;
MAGNUS-KEIZER MT Ca/physiology
* built in a box (pH buffering)
* pulse Ca at fast rate, catastrophic depolarization

PTP mechanism coupled by Ca diffusion → creates
waves, propagation, multidimensional phenomenon.

APOPTOSIS: MT are obligate participants (via MTP).

MT genome → electron transport chain →
 excess free radicals.

(FALL & BENNETT, 1999) * huge amount of
stochasticity.

Reduce model to a simple dynamic system
approach in realistic geometries.
“Pulsing” of Ca²⁺ in substantia nigra (ROS →
death in Parkinson's).

INFINITELY MANY CASCADES — CONNECTING PERIOD-
DOUBLING TO CHAOS.

LOGISTIC MAP

\[
X' = \mu X (1 - X),
\]

Feigenbaum — if it
exists, it will have a
period-free regular scaling.
n-dimensional systems, triple-well

Periodic orbits of $F(M,x)$

$(x,x)$ periodic ($p$) if $F^p(x,x) = x$

Eigenvalues are derived.

Why is cascade there?
CASCADING STems up to period 6 well-understood
Each stem extends to $M = \infty$.

Flip of regular orbits

$R^1 \rightarrow$ map's derivative is $< -1$

Two pairs of cascades in Henon Map

$(x,y) \rightarrow (1.25 - x^2 + My, x)$

Path of regular orbits connect "paired" cascades.

CASCADED - continuous path of regular periodic orbit 2p, 4p, 8p for all p
can be 2p, 4p, 8p, 4p, 8p...

"PAIRED" vs. "SOLITARY" cascaded.
Large perturbation:
\[ F(\mu x) = \mu - x^2 + 1000 \cos(\mu x) \]

Each generic \( F \) = one solitary period-3 cascade & 1 solitary period-1 cascade, 3 solitary cascades of period-5.

Periodic orbits for forced damped pendulum (DYNAMICS FOR WINDOWS).

Generic Maps - smooth parameterized maps \( F(\beta, x) \)

\( F : \mathbb{R} \times \mathbb{R}^N \rightarrow \mathbb{R}^N \quad (N = 1, 2, \ldots, n) \)

Can have symmetry-breaking bifurcations, nontypical system.

All period orbit bifurcations typical (e.g., saddle node).

Saddle node, period-doubling, Hopf bifurcations.

What is chaos? Elephant \(ightarrow\) picture DNA sequence (different but equivalent).

Chaos - defined as periodic orbits.

No chaos \quad Almost uniform chaos
(Definite # of \# of regular periodic \# of regular periodic orbits).
(orbits) \quad (Explosive growth in orbit)
PENDULUM - chaos to no chaos to chaos.
SANDER YORKE in arXiv.
Periodic orbits vs cascades (essential aspect of dynamics).
DETECTING RESONANCE & RECURSIVE FILTERS
BADII, 1988 - recursive filters cause dimension increase.
RECURSIVE FILTERS vs DYNAMICAL SYSTEMS
Finite impulse response (FIR) - sum of delayed values
Infinite impulse response (IIR) - recurring
FB, dynamical systems
FIR - infinite plate.
IIR - $\lambda_{1,2} = \alpha, \beta$
Chemical, magnetical resonance line.
CHAOTIC SIGNAL: LORENTZ SYSTEM
Pecora, Chaos, 17-0131 (2007)
$R^d \rightarrow R^c$ large e-f map
$\varepsilon$-ball $\varepsilon$-interval
\[ f : \mathbb{R}^d \to \mathbb{R} \] add dimension (not clear mapping).
Apply IIR filter.

Plot average of \( e^x \) vs. dimension:

- FIR filter
- IIR filter: \( e^x \) no dimension increase
- IIR filter: \( e^x \) sum of unfiltered + IIR signals - intermediate result

Unfiltered \( e^x \)

Noise handling: use points & delays from IIR filtered signals.
Unfiltered curve moves up w/noise, down w/addition.

Long FIR can look like IIR filter.
* Dimension method distinguishes between them.
* Signal bandwidth can be smaller than filter bandwidth (w/ freq. modulation).

Cooling Classical Particles w/Szilard Engine,
Juan Parrondo,
Beating the 2nd Law.
* Energy cannot be extracted from isolated system along a cycle. How to extract energy?
Expansions: gas in chamber

\[ W = NKT \log \frac{V_{\text{fin}}}{V_{\text{ini}}} \]

Uncertainty \( W \) energy.
BENNERT (1981):

System coupled to a memory:

\[ W = n_{\text{steps}} kT \log 2 \]

\[ W \]

\[ W \]

\[ W \]

\[ W \]

\[ W \]

\[ W \]

\[ W \]

Expansion-volume doubles.

Quasi-cycle-extract energy, only price paid is uncertainty of memory.

Microcanonical initial condition:

Initial energy known, can we increase uncertainty of energy? By this uncertainty, can we extract energy?

\[ W = E_{\text{ini}} - E_{\text{fin}} \]

\[ H(q,p) \in [E_{\text{fin}}, E_{\text{fin}} + \Delta E_{\text{fin}}] \]

\[ H(q,p) \in [E_{\text{ini}}, E_{\text{ini}} + \Delta E_{\text{ini}}] \]

Cyclic quasistatic process with \( W > 0 \) for some \( E_{\text{ini}} \).

Yes for single d.o.f.
FOR 1 d.o.f.: Invariance of phase space problem

\[ \phi(E) = \int_{H(q,p) \leq E} dqdp \] volume is constant

When ergodicity broken, adiabatic invariance breaks as well, orbits collapse or split.

Energy of particle is higher than barrier.

Move barriers with slow, constant velocity, particle loses energy.

Increase volume by increasing width, create barriers

"MAXWELL'S DEMON 2" (covers S2LARD engine).

Let particle expand as barriers is raised, get work from particle, then compress chamber against vacuum.

STOCHASTICITY due to initial condition.
We can tune parameters to harvest energy (choose initial energy, set tancen):

\[ V_B(t) = k^n E_0, \quad w/k = \left[ \frac{1}{\beta} + \frac{1}{|G|} \right]^2 \]

divide by 2 over each cycle.

Cycle in parameter space (not periodic)

include the wall energy is still conserved.

1) Shuffling phase space

2)

3)

4)

get discontinuous parts, but volume is the same.

generalize to many particles (d.o.f.)?

May not be able to find Hamiltonian for this.

Two particles work in a limited case, many repetitions of same cycle possible but not replicable (a small degree of cooling).
Extra ingredient needed for Newtonian dynamics? Quantum version: level crossing.

Network Destabilizations w/ Negative Mech. Responses, Zack Nicolau


Braess Paradox in traffic control.

If you cut support strings, does linker support mass at bottom.

(e.g., congestion on road networks equilibrium vs. optimality).

Cut one string, load transferred to other two strings.
Can this be done reversibly? Evolving quasi-statically.

Destabilization: $U(\xi, F^*) = \xi^3 + F^* \xi \rightarrow$ snapping effect changes to $F$ cause minima of potential to

Finish.
SWAPPING undone by relaxing system (bring force back down).

"TWISTED" HYSTERESIS (many internal forces, measured for total h).

\[ h \]
\[ F \]

Internal displacements of particles.

Shape of loop constrained by positive energy dissipation.

For particles in 2 or more-D behavior, mimic using buckling linear springs.

Couple systems together, form a coherent material.

*STRESS-INDUCED*, SOLID-TO-SOLID phase transition.

Phase transitions are unique to nature.

*Thermal flux* → destabilization → phase transitions occur earlier.

*Thermal flux* small on scale of the subunits.

Will it move in mixed phases or distinct phases (across material). Phase transition exhibits a negative Young's modulus (no elasticity during phase transition).
PARADOX OF LATENCY IN E. COli GENE NETWORKS
SEan CORNELIUS. Metabolism network modeling

- Carbon
- Biomass
- Reactions/Enzymes
- Metabolic reactions
- Enzymes
- Genes

1000-D vector

CONSTRAINT-BASED MODELING:
Predict phenotype computationally
w/Flux Balance Analysis (FBA).

FBA is ineffective for v2 dynamics (not optimal output).

PREDICTED PHENOTYPE

ROOM (regulatory on/off minimization)
MOMA (minimal perturbation analysis)

Cell locally re-routes fluxes
to deal w/ metabolically
infeasibility due to perturbation.

Growth

Perturbation (Heat Shock, KO)

transient activation of a large
# of pathways → activity
returns to WT activity.

transient pathways are
not optimal for long-term
activity (short-term switching).

MOMA (minimization) / ROOM

RX

t
Heat shock → compensatory pathways.

\[ \text{FBA} \rightarrow \text{FBA} \]

\[ \text{moma} / \text{room} \]

Change in growth upon LP removal (better performance in silico)

* Latent pathways may not be easily adaptive advantage

Room minimizes large changes from WT.

Each perturbation defines set of latent pathways.

\[ \text{GENE A} \rightarrow \text{GENE B} \]

\[ \text{LP needed} \rightarrow \text{LP needed} \]

\[ \text{RANDOM WALK} \rightarrow \text{feasible flux space} \]

* No LPs, growth rate is maximal

Synthetic lethality -
Delete A or B - lives
Delete A & B - dies
(A is original, B is knockup).

* LPs, growth rate approaches 0.

MOTTER, 2008

KO A alone - sick or lethal
KO A & B - rescue

Disabling latent pathways targets low-growth states (relates to availability of microstates).
Latent pathways \(\rightarrow\) no adaptive advantage
(\(\text{short-term solution is sub-optimal}\)).
*force network to make good choices\).

**Bryce Paradox in Metabolic Networks.**

**Wednesday Morning Sessions:**

**Spiral Wave Chimeras, Steve Strogatz.**
Spiral states, rare, 2002 (Kuramoto bound in computer science).

How are they possible?
Chimera - population of identical oscillators
 coupled by waves (can occur in 1, 2, 3-D). Not yet found in experiment.
Erik Martens, Carlo Laing.

EPSTEIN, PNAS, 103, 15777 (2006)
Spiral Waves (Winfree)
BZ reaction (oxidation propagates like grassfire)
Slime mold (2-D plate), Density of

Universal features of excitable media:
- arrhythmias (heart), cortical slices (brain)
- epilepsy


Modeled w/ reaction-diffusion PDEs (local coupling)
Local regions are coupled
limit cycle via diffusion
oscillators

What if coupling is non-local?
Chimeras: spiral wave (on infinite region)

* incoherent core (w/ diffusion, this would not occur - spatial continuity + 0 amplitude of oscillator - chimaera spiral exhibits neither of these

* synchronized & desynchronized oscillators in tandem (constant phase difference between different types of oscillators)

* Phase desorganization at core, phase organization on outer edges

INITIAL = 2π phase (phase at t=0 is 0) polar.

* Relaxes almost immediately into incoherent core.

* Arises when coupling is non-local (range of coupling, standard deviation of Gaussian kernel).

* Strange core: full amplitude, random phases

INFLUENCED BY NEIGHBORING SPIRAL/DECAY

CHIMERA - incongruous parts, phase locked arms, desynchronized co-existing oscillators

NUMERICAL SIMS - BATTOGTOKH, SHIMA (2002,4)

Fitzhugh-Nagumo, diffusively coupled, non-local limit.

DIFFUSION (doesnt fully diffuse), REACTION (doesnt fully react), DIFFUSION & REACTION interact. Diffusion term can be replaced.

* QUORUM SENSING
* effective non-locality (neurons)

* phase models
SELF-CONSISTENCY EQUATIONS:

Analytical solution - predictions of core (radius), rotation rate of spiral arm

* Stability & bifurcations, experimental results (OPEN AURAS)

Governing equations

\[
\frac{\partial \phi}{\partial t} = \omega - \int_{\mathbb{R}^2} G(|x-x'|) \sin[\phi(x,t) - \phi(x',t) + \pi] \, dx'
\]

* 2D normalized Gaussian kernel

\[ G(|x-x'|) = e^{-\frac{1}{2}(x-x')^2} \]

* Conspicuity between a (non-zero) & non-local, non-global coupling

* Length scale - width of kernel

KURAMOTO & SHIMA (2003, 4) use different G,

Small \( \lambda \):

spiral arm rotation - increasing \( \lambda \) (aim)

\[
\begin{align*}
\psi &= \omega - \alpha + O(\lambda^2) \\
\rho &= \frac{2\pi}{4\lambda^2} + O(\lambda^2)
\end{align*}
\]

odd bifurcation

ORDER PARAMETER:

\[
R(x,t)e^{i\phi(x,t)} = \int_{\mathbb{R}^2} G(|x-x'|) e^{i\phi(x',t)} \, dx'
\]

Local coherence & average phase of oscillators near \( x \)
\[ \frac{d\phi(x, t)}{dt} = \omega - R(x, t) \sin[\phi(x, t) - \Theta(x, t) + \phi] \]

flows on a circle, governing equations

SPATIAL VARIATION OF ORDER PARAM.

\[ \sin\phi(x) \] small core

\[ R(x) \] concentric circles

\[ \sin\Theta(x) \] no discontinuity at core

ROTATING FRAME - order parameter becomes time-independent (stable steady state).

LOCKED VS. DRIFTING OSCILLATORS

Self-consistency equations (R, \Theta related to themselves), solve for \Theta using perturbation theory.

Core moves around, bifurcation (traditionally a Hopf bifurcation).

SPIRAL WAVE ANSATZ

\[ R(x) = A(r) \rightarrow \theta \text{ drops out, solvable with Gaussian theme.} \]

Phase locking & preferential attachment (too many choices at center, caught up in waves at edges).
Response of Oscillator Networks, Hiroshi Uchida

Oscillator network:
- Slightly detuned, matched, order → reaches a stable synchronized state.

Emergence of spatiotemporal order
- Response to external inputs
- Control function

To give stronger effects on collective dynamics, which components should be forced?

Coupled oscillators, weak:
\[ \phi_i = \omega_i + \sum_{j=1}^{N} \Gamma_{ij} (\phi_j - \phi_i) + \rho_i(t) \]

Phase-locked solution for \( \rho_i(t) = 0 \)
\[ \phi_i(t) = \Omega t + \Theta_i, \Theta_i \text{ constant} \]

Linearize:
\[ \dot{x} = Lx + \rho \quad (L \text{ is Jacobian}) \]

* L is Laplacian in complex networks
* L is weighted asymmetric

Diffusion network

Long-range behavior:

Translational mode: relative motion
- No relaxation, infinitely
- Long-time scale
- Zero-eigenvectors of L (for Laplacian L)
COLLECTIVE MODE DYNAMICS:

\[ \dot{x} = Lx + p(t) \]

Decomposition:

\[ x(t) = y(t)u + p(t) \]

Collective mode relative modes

Non-external forcing \( \dot{x} = LX \)

Ex. 1: symmetric \( L \) (not asymmetric)

\[ UDiV = \begin{bmatrix} 1/N & 1/N & \cdots & 1/N \end{bmatrix} \text{ democratic} \]

Who is most influential? Most "selfish" mode more influential

Ex. 2: COUPLED DISSIMILAR:

Anatomically symmetric, Jacobian is asymmetric. Uncoupled, diffuse over time; coupled, diffuse.

\[ (2, 4, 3, 1) \rightarrow 2 > 3 > 1 > 4 \]

Eigenvector

[connectivity]
COLLECTIVE FLUX
When noise is weak, linearize
Brownian noise sole.

AUTOCRATIC NETWORKS (feedback network)

DEMOCRATIC NETWORKS - fluctuations decrease with network size N

DIRECTED SCALE-FREE NETWORKS

INFLUENCE INDEX (PRE, 2009); (AJP, 2009
ENTRAINMENT OF A PACEMAKER (PRE 2009)
NETWORK STRUCTURE - COLLECTIVE FLUX (ARXIV)

Can you do better than \( 1/\sqrt{N} \) in coupled oscillators?

VISUAL ANALYTICS, TAKASHI NISHIKAWA,
Discover group structure in networks.

NETWORK ANALYSIS - TYPE OF STRUCTURE
Small-world (Watts & Strogatz)
Scale-free (Barabasi & Albert)
Community structure (Newman & Girvan)
(dense within group, sparse between groups)

Discover an unknown structure.

Visual interaction between human users & analytical tools,
Use to discover unknown group structure among nodes.
NODE PROPERTIES: measure many of these standards $\rightarrow \mathbb{R}^p \rightarrow$ is there group structure embedded in these?

* RANDOM 2D PROJECTION: randomly-chosen subspace, user decides if there is structure (accept/reject) $\rightarrow$ criterion is collective across many users. User also can divide dataset into groups, quantify how separate groups are.

* Human-assisted machine learning.

COMMUNITY GROUP STRUCTURE

MIXED-GROUP STRUCTURE

PACS network $\rightarrow$ ARXIV paper
Can we substitute human perception with 2-means clustering or unsupervised two-class SVM?

EXPLORING SPATIOTEMPORAL CHAOS, JERRY GOLUB

Space-time chaos (STC)
* topological features characterize
* understanding particle motion in flows

STC's common in fluids, will particles follow such flows?
Using curvature to study STC, no good definition.

*Nonperiodic in time, nonfixed spatial structure
*Large phase space dimension

Drive flow with EM forces
*electromagnetic
*regions of local vorticity, change structure over time (transience)

Magnetically-driven flow. Low Reynolds' number, flows constant \( \to \) more interesting behavior w/higher Reynolds' number.

**HYPERBOLIC**

\[ \frac{\partial}{\partial t} \]

**ELLIPTIC**

\[ \frac{\partial^2}{\partial x^2} \]

\[ \frac{\partial^2}{\partial y^2} \]

*measure using particle tracking. Compute velocities as \( f(t) \), also get accelerations.

**CURVATURE FIELDS** locate topological points.

\[ K = \frac{\text{lux} \text{u}^2}{1u^3} = \frac{a_n}{u^2} \]  

(Points of high curvature)

For steady flows: hyperbolic (\(+\))

Elliptic (\(-\)) features periodic

U/turbulence, annihilation

Nucleation of structures, float around to become periodic

Can use patterns of special features to reconstruct flows.

Criterion for hyperbolic/elliptic points:
- \( V \) rotates by \(-2\pi\) (clockwise) \( \rightarrow \) elliptic
- \( V \) rotates by \(2\pi\) (counterclockwise) \( \rightarrow \) hyperbolic

"Other points exist that aren't \(2\pi\) or \(-2\pi\)"

* Elliptic points, isotropic regular paths
* Hyperbolic points move along stable manifolds until nucleation allows movement
* Fluctuation moves along only one axis

**Creation - Annihilation rates vs. Reynolds # (Re)**

- \( Re = 60 \) (onset of chaos)
- \( Re = 28.182 \), \( Re = 30, 201 \), \( Re = 21, 300 \)

Flows (cellular, Kolmogorov, random array). Less symmetry reduces the critical Reynolds #.

- **Cellular**
  - \( Re = 60 \)
- **K-flow**
  - \( Re = 25 \)
How well can flow field be reconstructed?

* Particles of different density as underlying fluid do not follow flow.

**KEY PARAMETER:** Stokes # (dimensionless).

\[ \text{St} = \left( \frac{2}{4} \right) \left( \frac{a}{L} \right)^2 \quad \text{Re} < 0.07 \text{ for } a = 2 \text{mm} \]

* Particles do not necessarily follow the flow.

**LAGRANGIAN dynamics.**

**MAXEY-RIFE** equation (Phys. Fluids, 26, 1983).

**Rod dynamics - alignment.**

- Rods follow a trajectory, but touch trajectory at different points.

Advanced pole balancing problem (control theory)？

**PRL, 2008 (Statistical measurements)**

**CLUSTERING PHASE TRANSITIONS, COMPLEX NETS, PETER GRASSBERGER.**

- Null models (time-series = surrogate)
- Strauss model
- Graph Hamiltonian

**Fixed-degree ensembles with enhanced clustering.**

**CLUSTERING - transitivity**
links tend to cluster, form triangles.
Random graphs - very few loops, no clustering.

CLUSTERING graphs hard to model mathematically.

"MOTIF" - subgraph topology, overrepresented in large networks.

PROTEIN - PROTEIN in yeast (Krogan, 2006)
2559 nodes, 7031 links.

How to interpret this?
* Compare "overrepresentation" to null model.

* Monte Carlo "surp" random links (Maslov & Sneppen, 2002)

V-shaped & triangle

Vast majority of subgraphs overrepresented.

Graph Hamiltonians - ensemble = Gibbs-Boltzmann distribution

C = configuration \rightarrow P(C) \propto e^{-\beta H(C)}
$H = \text{Hamiltonian (energy, cost function)}.$

**STRAUSS MODEL (PARK & NEWMAN, 2005).**

$B H_{\text{straus}}(C) = -\theta L - Bn_\Delta$

$L = \# \text{ links}$

$n_\Delta = \text{fully-linked triangle}$

$\theta, B = \log \text{arithms of "fugacities"}$

1) small $\theta, B \rightarrow$ few $\Delta$'s, gas phase
2) large $\theta$, small $B \rightarrow$ Erdos-Renyi-like graphs (many links, few $\Delta$'s),
3) large $\theta, B \rightarrow$ densely-connected graphs, "condensation" of links.

**Between 2 & 3** $\rightarrow$ first-order phase transition

no phase w/broad degree distribution $\rightarrow$ no good null model. MILO, ALON (2002).

$B H_{\text{null}} = B n_\Delta - n_0$

$n_0 = \# \Delta$'s in graph, fixed degree sequence.

If $B > B_c$, then $n_\Delta \geq n_0$

**BIASED REWRITING MODEL (FOSTER)**

Simulation — link swapping, based on energy (new link has smaller probability, then replace).
Large \( N \), hysteresis & phase transitions.

\( k = 3 \) (degree)

\( k \geq 3: \)
* 1st-order phase transition
* \( B_c \sim \log N \) (\# nodes)

* For \( B > B_c \): disjoint \((k+1)\) cliques form.
* For \( B < B_c \), \( n_A \sim \frac{(k-1)^3}{6} e^3 \)

* Strong hysteresis, increases \( n/N \).
* Phase transition due to cooperativity, presence of first link encourages more links.

**Non-regular graphs**
- Critical value \( B_c \) depends on \( k \)

Different parts of graph, transitions at different values of \( B \).
- (Set of phase transitions, highly vs. less connected).

(Cavin, 2005)
Degree of randomness in complex networks: characteristics (modularity, assortativity, clustering, 4-clique clustering) exhibit jumps.

Re-arrangement during jumps: graphs do not become disjoint.

- # of triangles for which links participate.
- Run MCMC. Sim, vary B, → whole groups of nodes decide they want to join in at specific point in time.

First clusters "dense" (once formed, extremely robust).

- quasi-broken "ergodicity" (makes this dubious as a null model).
- Declining avalanches, SOC models (indirect links), Birkhoff jumps as well.

Self Organization of Dynamic Patterns (Non-uniform), Hiroka Nakao.

Coupled oscillators on random nets - important in Yamaguchi, Science, 2003 (Biology/Physiology)

Waves & patterns in addition to dynamics.

Limit-cycle oscillators - e.g. Brusselator


Network Laplacian

Diffusively-coupled oscillators.
PHASE REDUCTION:
1) Introduce phase along limit cycle, increases w/ constant freq.
2) Reduction - averaging for small heterogeneity & diffusion.
3) Original ODE reduced to amplitude equation
4) Weakly nonlinear analysis.

AMPLITUDE REDUCTION:
Ginzburg-Landau model used

Typical coupling schemes:
1) Local (NN interaction)
2) Global (mean field, equal among nodes)
3) Random network
4) Non-local coupling

KURAMOTO TRANSITION:
Reaction-diffusion in continuous media:
\[ x(t+\tau) = x + D \nabla^2 x + f(x) \]
Space-time chaos exists.

DIFFUSION-INDUCED INSTABILITY ON NETWORKS:
\{ Laplacian eigenvalues/vectors
Linear stability analysis
Diffusion-induced instability when Benjamin-Feir condition is satisfied.
In Benjamin-Feir stable regime, oscillators stabilize.

In "unstable" regime, chaos can emerge (middle-class oscillators = turbulent).

PARTIAL AMPLITUDE DEATH - Benjamin-Feir is unstable w/ weak coupling. CLUSTERING - B-F is unstable w/ coupling (strong).

SINUSOIDAL MEAN FIELD APPROXIMATION

Network chaos vs. bifurcation diagram using mean field normalizes oscillators.

Nakao, PRE, 79, 036214 (2009)

Periodic mean-field approximation can explain some dynamical states.

COMMUNITIES IN NETWORKS, MASON PORTER.

BINARY EDGES (0-1)
BIPARTITE EDGE (cannot connect to itself)
TIME-DEPENDENCE
MULTIPLEXITY (Social Science concern),

"BASEBALL STERIOR network" community structure
CalTech FACEBOOK network

Structure in hierarchical & modular, cohesive subgroups.
Larger #s of internal connections (compare to model)
MODULES - parallel.

HIERARCHY - relative size.

REVIEW:

NOTICES OF AMS, 56(9), 1082, 1164

AGGLOMERATIVE - linkage clustering

DIVISIVE - spectral methods

LOCAL METHODS -

MODULARITY & Potts Model -

\[ \text{MINIMIZE} = \sum_{i,j} H_{ij} \delta(\delta_i, \delta_j) \]

Potts Hamiltonian

FACEBOOK NETWORKS -
Quantitative comparison
PAIR-COUNTING, PERMUTATION
\[ S_R = \frac{(W_{ii} + W_{00})}{M} \]
\[ S_J = \frac{W_{ij}}{(W_{ii} + W_{00} + W_{jj})} \]
\[ S_{FM} = \frac{W_{ij}}{\sqrt{(W_{ii} + W_{00})(W_{jj} + W_{00})}} \]

All connections have comparable Z-scores tell us how network is organized (based on demographic criterion).

MULTISCALE "COMMUNITY" DETECTION - use
adjacency tensors to connect time-steps & different types of connections.
RANDOM WALK Across slices, within slices

U.S. Senate voting (consider time slices—not all Senator positions same at every t).

Methods exist to define structure, but more to do anything with.

Binary trees exist in nature. Voter model is a “toy” problem.

Compute modularity of any partition you want, compare to best split, derive quality function.

Observations of Boolean Chaos: Dan Gauthier.

Small networks/Boolean rules applications to circuit boards.

"Large" network in lab that you can build—2 modes.

- Large network w/explicit control.
- Time delays: (beyond topology)
  - Fast systems {propagation}
  - Communication {delay}

Speed-of-light propagation, large size \( \rightarrow \) time delay is important in most networks.

Want 100s of modes:

- Semiconductor laser w/feedback
- Opto-electric oscillator
- Speed up analog electronics circuits

{Drawbacks}
"Fast" dynamical system - Boolean nets.

2-state continuous time delays.
* No clocking system (autonomous Boolean time-delay system).

**BOOLEAN DELAY EQUATIONS:**
SIAM J. APPL. MATH, 44(11) 1984
J. STAT. PHYS., 41(175) 1985

$$x(t) = f(t - T_1, \ldots, x(t - T_n))$$

mapping input to output using Boolean rules, continuous process.

Infinite # Boolean networks display complexity.

**XOR rules at each node (does not exist in biological networks).**

$$Y = A \oplus B = A \cdot \overline{B} + \overline{A} \cdot B$$

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th>XOR</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

# Switching events per unit time increases w/ powerlaw.
X₁(t) = x₂(t-T₂)
X₂(t) = X₁(t-T₂) ⊕ x₂(t-T₁)

Switching gets increasingly dense as time goes on.

Does a finite response time destroy complexity?
Use commercial logic gates (CMOS gate)
> 100 psec rise/fall time.
> 2 nsec propagation delay.

3-node network:
Nodes 1 & 2 do XOR, 3 does an XNOR
PRE, 80, 045202 (2004).

Boolean net, temporal evolution:

V

Time (nSec)

Transient UV catastrophe (starts slow, runs up fast to a limit).

Behavior understood using perturbed Boolean model.
The performance of logic depends on $V_{cc}$ (supply voltage) — a bifurcation parameter.

Periodic windows — not just a noise oscillator.

Very large class of networks show "complexity" using Boolean rules.

Apps. of sensor networks, systems biology, programmable networks, evolutionary networks.

GRNs — for gene expression.
MICROSCOPIC MODEL — lots of ODEs.

COARSE-GRAINED — time-delay equals 0.

BOOLEAN NETS — genes on and off w/ a clock, to what extent are these autonomous.

NON-Ideal Behaviors:
Universal — from EE to Systems Bio
1. Short-pulse rejection (reject fast pulses).
2. Asymmetry between logic states.
3. Degradation effect (dependent on recent gate history).

PRE 72, 055101 (2005)
PRE 76, 046122 (2007)

Data assimilation (how good is model?)
adjust to account for non-ideal behaviors.
prediction possible for nsec scale.

**Boolean Distance & Lyapunov exponent**

\[ d(s) = \frac{1}{T} \int_0^T x(t + t_s) \Theta x(t) \, dt \]
\[ d(s) = d(0) e^{\lambda s} \cdots \]

will assume to infinitely diverge.

\[ \lambda_{max} = 0.16 \text{ ns}^{-1} (\pm 0.02 \text{ ns}^{-1}) \]

**Phase space**
in Boolean
+ time delays

**Origin of Chaos?**
short-pulse rejection (due to degradation)

\[ \begin{align*}
\xi_i^T &= \xi_i^t \\
\end{align*} \]

Degradation alone can cause chaos. Pulse width/evolution equations

No Chaos.

NOT gate that feedback on itself - chaos.
+ Boolean Delay Equations (BDE).
+ Arrays of periodic oscillators possible

**Broad power spectrum-high dimensional?**

Biologists don't want XORs, but artificially washes out complexity (XORs chaos -> perhaps chaos in important m'dology; XOR doesn't map to phenotype, for example).
FILAMENT TURBULENCE & CARDIAC FIBRILLATION
JORN DAVIDSEN
SPIRAL WAVES IN 2D MEDIA (SCOTT, 1991)

CO-oxidation, heart tissue, glycolysis in yeast.

SPIRAL - periodic signal in 2D coordinate space

\[
\frac{\partial u}{\partial t} + u \frac{\partial u}{\partial x} = 0
\]

TOPOLOGICAL THEOREM \[ \sum_i I_i = 0 \]
(sum of topological charges)

\[ I_i = \pm 1 \] HAGAN 1982 for oscillatory media

created/annihilated at boundaries of spiral arms.

DEFECT-MEDIATED TURBULENCE
defects \( \rightarrow \) stationary # of defects
pairs (bar-field or core instabilities)
(BETA, 2003)
(BAR, 2004)

HISTOGRAM of system defects.


defect pairs are stat. independent
creation \( a \times c(n) = const \)
annihilation \( a \times \alpha(n) = an^2 \)

dependent on noise & boundary conditions

VENTRICULAR FIBRILLATION (FENTON, 2002)
Dynamical pacemaker (spiral wave).

NORMAL PACING PATTERNS
FIBRILLATION

Defect-mediated turbulence.

GEOMETRY OF HEART -
2-D or 3-D approximation
3-D - scroll waves,
2-D - spiral waves.

Scroll waves & filaments (Lengo, 2004)

Negative line tension instability -
(Winfree, 1994; Alonso, 2003)

No 2-D analogue

Scroll wave in cardiac tissue (size, action of instability).

Filament-induced surface spiral turbulence

scroll wave turbulence -
Excitable Barkley (3-D) model.

Creation & Annihilation of filaments.

Creation rates # of filaments in medium

\[
\frac{c(n)}{n} = \text{creation rate} = \text{annihilation rate}
\]

\[
\text{surface defect } a(n)
\]

\[
\text{pairs}
\]

\[
\text{systems}
\]
Ae/C: SURFACE DENSITY & Ae/C: VOLUME

interaction between two,

$10^4 \times \rho$

- complex Ginzburg-Landau
- more rings, more instability
- creation-annihilation rates (linear)
- filament turbulence vs. long-lived, stat. stationary regime
- mechanisms for creation & annihilation are different for 2D & 3D models
- statistical problems: properties of surface dynamics distinguish between 2D, 3D turbulence (linear contribution to $c(0)$)
- persistence of turbulent & absorbing state.

PUBLISHING IN NATURE PHYSICS:
Whole family of Nature journals

ACCEPTED: Structure of DNA, discovery of neutron, laser, MRI, human genome sequence

REJECTED: Nuclear cycle, B decay, Pauli's work
Nature Life Science Journals:
- BIOTECH (1983)
- GENETICS, etc. (1990s)
- PHYSICS (2002)
- NATURE CLIMATE CHANGE (2010)

Journal:
- Highly selective
- High impact
- Full-time ed. staff
- Editorial independence
- "Front half" (letters, etc.)

"Surprise factor"
- CLEVER & USEFUL *
- NOT EXPECTED *

NEW EXP./THEOR. RESULTS

SUBSTANTIAL/NOVEL ADVANCES

DON'T SALAMISUCCE (make paper rock solid & consolidate results)

7-10 d first decision

If one editor will read, get another
- Look at informal advice from experts (4-6 wk.)
JAMES YORKE, CHAOS.

Gave chaos its name
* characterized orbits of chaos.
* weather prediction, disease transmission.

SENSITIVITY TO INITIAL DATA:
Poincare, 1890 (first paper on chaos).
All systems are chaotic, even the solar system.
* Martian precession
Geometric chaos.

TABLE - is not chaos (only 3 kinds of bounded motion: steady state, wobbles).

COUPLED PENDULUM - when will it stop?
Pauses & flips many times depends on initial condition.
Chaos is about prediction
exhibits an appearance of randomness.
SENSITIVITY - split-second differences completely changes the outcome (choosing one option over the other)
Chaos is about instabilities throughout our lives.

3 kinds of behavior (ignore transient)
A) steady state
B) periodic/quasi-periodic
C) chaotic $a \rightarrow 2a \mod 1$

Is $23 \times \frac{1}{3}$rd? 1 part in 300 $\rightarrow$ after time evolution $\rightarrow$ outcome is totally different
Doubling process - multiplicative growth. Differences will be magnified over time (doubling time).

CHAOS - state is sensitive to initial state, condition; very tiny perturbations get magnified.
Butterfly effect assumes no dampening of amplification

Mission to comet (NASA)! ISEE multiple lunar swing-by trajectory.
How do you get spacecraft to travel 60 million miles carrying 200 lb of fuel (to study comet's tail)?

10 mph change in velocity

Control chaos (correct orbit)

2 bodies that we have non-chaotically, 3rd

5 mean passes of the moon. Fuel used for occasional rocket boosts.
Circular planar restricted 3-body problem
\[ (\text{kinetic + potential energy}) = \text{angular momentum} \]

Basins of attraction - set of initial points whose trajectory goes to specific attractor
\[ \theta'' + a\theta' + \sin \theta = b \cos \theta \]
Forced damped pendulum
\( a = 0.2, b = 1.6 \) bouncing

Compute 1000 initial speeds, 10^6 experiments, see which state it goes to.

If you draw a map, 3 regions meet at a point.

WADA property - any point will have both red & green boundaries of all 3.

Final pendulum - bands of 3 colors in rings of Saturn, no matter how finely you scale.

Chaotic pendulum, steady-state motion.

UNSTABLE MANIFOLDS -
Are solar system's major planets (gas giants) chaotic?

Neptune's position varies by 1000 miles, leads to vastly different positions.

ODE solvers - gave both "fast" & "slow" divergence (depending on initial condition).
THURSDAY MORNING SESSION:
STRUCTURE OF BORDERS IN A SMALL WORLD, DANIEL CRARY.

www.wheresgeorge.gag → MOBILITY NETWORK
+ Indirect measure of human travel.
+ Identify effective communities (mobility neighborhoods).
+ Model (large-scale) of Milgram experiment.
+ Overlay outcomes onto single map.

Initiated in 1998 by Hank Eakin; > 100 million bills registered, 10 million bills with hit.

* Captures movement on all modes of transportation, all spatial scales.
* Distances are scale-free (no average length for single trajectory).

Los Angeles & New York are “closer” than Los Angeles & Omaha. What are meaningful local neighborhoods?

meaningful neighborhood - major cities as a series of disjoint modes.

MODULARITY - given some partitioning, how do groups random (based on connectivity)?

would optimum be meaningful (many near-optimal groups)?

SIMULATED ANNEALING algorithm:
+ Spatially - compact groups w/o a priori geog. knowledge
44% of state boundaries match w/effective boundaries, compared to long-distance connections, gravity law (both quite different from first network).

Short-range traffic is essential, gravity laws don't give same structure.

EMERGENCE OF LARGE-SCALE CONNECTIVITY IN NETWORKS, ELIZABETH LEICHT. Networks that interact w/each other.

Power grid & internet are coupled. Systems of interacting networks?

BUILD RANDOM NETWORK (ERDOS & RENYI) take n unconnected nodes, connect w/ prob p, gives a degree distribution of \( P_k \) (Poisson distribution).

"Ensemble" of models, connected components, \( p_n \rightarrow \) order of network

avg. degree = 1, phase transition \( p_{crit} = 1/n \) "giant component"

ARBITRARY DEGREE DISTRIBUTION MOLLOY & REED (1995)

NEWMAN, STROGATZ, WATTS (2001)

When 2nd order connectivity exceeds first-order (giant component).
MULTIPLE ERDOS-Renyi

Add internal edges w/rate $\lambda(a-a)$
$\lambda/\ell, w/\ell > 1$ (b-b)
Intra-group $(a-b)$ w/rate $N\ell_0^2, w/\ell_0 > 1$

Multi-degree distribution $P^a_{k_a}P^b_{k_b}$
Generating function for:
$G_a(x_a,x_b) = \sum_{k_a,k_b} P^a_{k_a} x_a^{k_a} x_b^{k_b}$

Calculate moments - average degree.
Deriving new distributions (for generating functions we don't already know).
Giant component emerges simultaneously in both networks (assuming connectivity).

Edge $\eta_{k_a,k_b} \propto k_b \beta_{k_a,k_b}$

Distribution of connected components - assume local tree-like connectivity.

POFs
$\{ H_{ab}(x_a,x_b) = x_a G_a[H_{aa}(x_a,x_b),H_{bb}(x_a,x_b)] \}$
$\{ H_a(x_a,x_b) = x_a G_a[H_{aa}(x_a,x_b),H_{ba}(x_a,x_b)] \}$

Calculate when giant component emerges.

Fraction of nodes (a)

$\frac{k_{bb}}{k_{bb}}$

Have we really enhanced connectivity?
(remove node degree) $k = k_a + k_b$

Fewer nodes, giant component occurs sooner.
$\frac{k_{bb}}{k_{bb}}$

b nodes participate more, and play role.
can manipulate phase transition, still get giant component
* interacting network, change onset of phase transitions.
* can be used in multi-attribute datasets.
* devises change features of network.

PHASE TRANSITIONS IN RANDOM NETWORK
PERCOLATION, JAN NAGLER.
Discontinuous phase transitions.
Competition, percolation

PERCOLATING SYSTEM - adding links as a process

\[
\text{max component} = \text{each link induces jump in largest (max) component}
\]

2nd order phase transition - giant component

COMPONENT VS. COMPEITION - links two subgraphs create giant component.

Discontinuity in percolation - can we prove discontinuity?

No.

What are dynamics?
Prove continuity of largest

Losting transition (based on competition)
1) NO COMPETITION: Link 2 clusters at random.

2) EDGE m=2

3) EDGE m=3

4) CLIQUE k=3

2, 3, 4 are all competitive.

RENyi case - continuous
2nd-order phase transition

SCALING OF LARGEST GAP

\[ \frac{\Delta C_{\text{max}}}{N} \]

Small exponent?

\[ B = 0.01 \]

\[ N = 10^{10} \rightarrow \]

DISCONTINUITY:

for \( N \to \infty, B = 0 \)

strongly

for \( B > 0, N \to 0 \)

weakly

\[ \Delta C_{\text{max}} / N \approx N^{-B} \]

Largest cluster cannot grow

strongly discontinuous in percolation
Largest clusters cannot grow. Smaller clusters overtake & cause transition.

* Largest join with smallest prob (p)

* Two smallest clusters join prob (1-p) (prevents strong discontinuity)

Competition control dynamics & transition type (size of largest cluster)

Small & catastrophe v competitive phase transition in percolation

* Phase transitions & SOC in neuronal systems, Theo Geisel
  Application of nonlinear dynamics, neither mathematics nor physics, applications to neuroscience
  Two issues:
  1) Neuronal synchronization (binding)
  2) Neuronal maps (representations)

Self-organized criticality (SOC):
  Avalanches of neural activity
  Fully-connected networks of integrate & fire neurons
  Single cell recordings
  Functional role? Critical state = memory storage, information transfer

Single parameter - synaptic strength

PRE, 2002 (Erlang)
Slowly delivered external input, separation of time-scales

\[ \text{PRE } 2002 \rightarrow \text{prediction: static synapses (not self-organized).} \]

\[ t_1 \]

\[ t_2 \]

MEA experiments - local field potentials, thresholded output signals

\[ t_3 \]

Avalanches occur in array

BECCS & PLAN2

Size distribution: exponent \((1.5)\) = same as model.

* Dynamics were robust, but something missing (more parameters).
* True SOC, find avalanche in larger

MARKRAM, NATURE, 1996 - Depressing Synapses

\[ j_{ij} = \frac{1}{t_j} (j_{0} - j_{ij}) = u \cdot j_{ij} \delta (t - t_{sp}) \]

\( u = \text{fraction of resources used} \) \( \Rightarrow \) Models synaptic

\( T_j = \text{recovery (time constant)} \) \( \Rightarrow \) Cleft dynamics -

\( j_{ij} = \text{total # of resources} \) \( \Rightarrow \) Fatigue

\( \frac{d}{dt} \text{parameter model} (T_s = \text{separating time-scale}, T_s \gg 1) \)

\( N = \# \text{of neurons}, x = \text{max. synaptic strength} \)
FINITE-SIZE SCALING:

\[ P_c (L, N) \sim N^{-\nu} \left( \frac{L}{N} \right)^{\frac{\beta}{\nu}} \exp \left( \frac{\lambda}{N^\delta} \right) \]

\[ \nu = 1 \quad B/\nu = 3/2 \]

\[ B = 3/2 \quad 2\nu - B = 1/2 \]

There is infinite-size scaling.

FACILITATORY SYNAPSES - repeated firing
increase of response.

DEPRESSION

\[ J = \frac{1}{\tau} (U - U_0) - \frac{1}{\tau} S(t - t_{sp}) \]

RECOVERY

\[ \tau_u, \tau_j = \text{time constant} \]

FACILITATION

\[ U = \frac{1}{\tau_u} (U_0 - U) + (1 - U) U_0 S(t - t_{sp}) \]

related to Ca^2+ dynamics in opening up vesicles.

DISCONTINUITY (FIRST-ORDER PHASE TRANSITION)
MEAN FIELD ANALYSIS -

$\Delta isi$ - inter-spike interval
$wij$ - synaptic strength

$\langle \Delta isi \rangle = F(\langle wij \rangle)$

Self-consistency equations shows this.

$\Delta isi$ for $\alpha = 1.0, 1.2, 1.4, 1.6, 1.8$

DEPRESSING SYNAPSES

if $isi$ becomes longer, $wij$ becomes larger.

Neurons get less input, $isi$ gets longer, time between avalanches gets longer.

DEPRESSING & FACILITATING

HYSTERESIS - sub-critical behavior continues, potential for phase transition as a changes its value.

BIFURCATION DIAGRAM

$wij$ - $isi$

critical solution

hysteresis points

$\alpha$ - sub-critical solution

THERMODYNAMICAL LIMIT.
thermodynamic limit

\[ 2 V_0 (1 - u) \]

\[ x^c \]

\[ \frac{x}{x^c} \]

1.0

Subcritical states - 1st & 2nd order phase transitions.

d) Brain in critical state?

No, but ensembles of neurons can be, still a hypothesis.

Use models other than integrate & fire, Hodgkin-Huxley?

More computationally expensive, harder to parameterize.

**DECODING NEURAL SIGNALS, SARA SOLLA.**

Neural signals contain information functional \( \rightarrow \) what is the info content

**SPATIOTEMPORAL PATTERNS -**

Brain-Machine Interfaces

![Diagram of brain and machine interfaces]

Brain sends signals to muscles, tap into this stream, activate muscles, control a wheelchair.

**SPECIFIC IMPLEMENTATION -**

1) Directional tuning \( \rightarrow \) linear dimensionality reduction.
2) task-specific, low-D manifolds → nonlinear dimensionality reduction.

Predictions of muscle activity & direction of movement manifolds vs. subspaces

CENTER-OUT REACH task, record neurons using multielectrode recordings.

If I look at this pattern can you infer behavior?

Order of 10^2 neurons involved (size of population that start control, only record from small subject).

ENSEMBLE ACTIVITY - single target → most neurons are quiet most of the time (<10 Hz), so pattern of activity most important. These neurons 2 synapses away from motor neurons. Doesn't matter when firing, spiking takes place, but rather effect on population average.

MULTIPLE REACHING TARGETS - ensemble displays different patterns. Look at specific neuron & firing pattern (target-dependent pop. activity).

\[ f^* = (f_1, f_2, \ldots, f_N) \]

Dish

Rate (kHz)

3 different neurons activity moves on N-dim. space
How do points move in space? Does not fully explore space, because neurons work together.

This implies activation space can be restricted / decomposed to low-D space.

**Direction of Movement**
(preference in M1, neurons fire more strongly for left-side reaches, regulates

**Tuning** - cosine tuning model
(George Poulos)

\[ r_{ij} = b_i + a_i \frac{1}{2} (1 + \cos(\theta - \phi_i)) \]

Assume three parameters:
- \( b \) = baseline activity
- \( a \) = amplitude of modulation

In \( N \)-dimensional space, this form many neurons \( \rightarrow \) 2-D plane.

- Should see this plane in data for all reach directions.
  - PCA analysis: does not yield this in eigenvalues.
**ISOMAP** method DOES yield 2-D structure → data live in curved 2-D manifold (still high-D).

**ISOMAP** (nonlinear dimensionality reduction) → based on MDS (multidimensional scaling)

Can you derive a Euclidean distance between high-D data points?

\[ \tilde{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \]  

\( \tilde{x} \) is data for M + K clusters → M x N matrix

If distances are Euclidean, construct scalar product matrix.

\[ \text{data matrix can easily be obtained.} \]

\( M \) data points which are \( K \)-rather than \( M \)-dimensional (equivalent to PCA).

\[ E(x) = \|x^T x - y\|_F \]  

*best approximation for distances*  

**TENENBAUM, 2000** (ISOMAP: a nonlinear embedding).

<table>
<thead>
<tr>
<th>RESID.</th>
<th>VARIANCE</th>
<th>PC1</th>
<th>PC2</th>
</tr>
</thead>
<tbody>
<tr>
<td>DIMENSIONS</td>
<td></td>
<td>8</td>
<td>7</td>
</tr>
</tbody>
</table>

Partially solves "curse of dimensionality" problem.

Why is manifold curved? Interactions between neurons → generalized linear model (GLM) as generative model of spiking activity.
GLM
\[ \lambda_i(t) = \exp\left( a_i + \sum_j^m \delta_i j \right) \]

**Interaction Kernels** - tell us something about effective connectivity.

**Neural Interaction Kernels** - use muscle activity as covariates.

Data lives in curved space → neurons interact & all data must live in that space.

Solves "capacity problem" in brain → allows for \( 10^{12} \) neurons to control 100s of muscles.

**Curved Manifold**

Create low-D manifolds that are task-dependent → creates representations for each task → no more capacity problem.

Spatially-Distributed Kuramoto Model, Wai Shing Lee.

N oscillators in spatial domain

\[ \theta_i, \omega_i, T_i \]

Response time

\[ k_{ij} \]

Natural freq.

\[ \frac{d\theta_i}{dt} = \omega_i \]

Adjustable constant
How do we analyze? What characteristic behavior result?


**Spatio-Temporal Interaction with Finite Resp. Time**

- Interactions spatially local ($q_{ij} \to 0$)
- Delay ($\tau$), time for oscillator to react (not propagation time).

**Course-grain Continuum Limit**

1. Course-graining:
   - Interaction length $>>$ spacing between oscillators
   - Discrete to continuous (density) description
   - Distributions are homogeneous and constant in time.

2. **Kinetic Equation** for evolution of $F(\theta, \omega, x, t)$
   - Dynamical problem for evolution of distribution function $F$.
   - Go from kinetic to macroscopic description of $F(x, t)$.

3. Reduction to an invariant manifold in $F$-space
   - Fourier expression of $F$

   Solution of $\Phi_n \to \Phi_n(\omega, x, t) = \mathcal{X}(\omega, x, t)$

   Invariant manifold in $F$-space.
Frequency distributions, interaction kernels are models to study.

\[ h(t) = \begin{cases} \frac{4}{\pi} e^{-\frac{t}{\tau}}, & t \geq 0 \\ 0, & t < 0 \end{cases} \] delay distribution

**MACROSCOPIC DESCRIPTION**

**B** \((x,t) = e^{it \theta} x\)

**KINETIC \rightarrow EVOLU. DISTALB. \rightarrow MACROSCOPIC EVOLUTION**

Inexact solution.

Spatially homogeneous case: 2 possible solutions (incoherent \( B = r = 0 (e^{i\theta}) \), & coherent).

Bi-stability & hysteresis effects:

**Hysteretic behavior**

\[ |r(x,t)| \]

1-D analogue of chimeric wave-state.
2-D case:
SPIRAL WAVES \rightarrow INCOHERENT CORE
simulate coherent \& incoherent states as adjacent stripes (continuous) \rightarrow
interaction between coherent \& incoherent regions.

"TOY" MODEL VS. OBSERVATIONS, ERIC BOLT,
when is a toy model appropriate
CONJUGACY \rightarrow equivalence test.
CHAOS, 8, 3, 702 (1998)

Simplification \rightarrow what do you want to
learn? APPROXIMATE REAL SYSTEM \rightarrow
how do you know a "good" from a "bad"
model?

SPLINE, CUBIC MOVING SPLINE \rightarrow both fit
data, but how is model quantified

TOPOLOGICAL CONJUGACY

\[ x \xrightarrow{g_1} x \quad \text{with } n = 1:1, \text{onto, continuous,} \]
\[ h \downarrow \quad h \quad \text{continuous inverse.} \]

LOGISTIC MAP TYPES

---

\[ g_1(x) = 4x(1-x) \quad g_2(x) = 1 - 2|y_1 - \frac{1}{2}| \]

defects of
homeomorphism
mostly conjugate
measure conjugacy
defect of commutators

EQUIVALENT

Don't look at transformations,
instead look at functions.
DETECT MEASURE:
conjugacy defect

defects/mismatches on a small scale.

QUADWEB - cobweb for commuters.
change of coordinates
affect both domain and range.

\[ f_{n+1}(x) = g_2 \circ f \circ g_1(x) \]

converges by contraction mapping.
*when systems are not conjugate.

FIXED-POINT ITERATION \rightarrow application of Banach contraction mapping principle.

\[ \lambda_0(f) = \text{not onto } (f) \]
\[ \lambda_{1-1}(f) = \text{not } 1-1 (f) \]
\[ \lambda_C(f) = \text{not continuous } (f) \]
\[ \lambda_{C-1}(f) = f^{-1} \text{ not continuous} \]

HOW TO COMPARE DYNAMICAL SYSTEMS:
* compare transformations between them.
* Defect approach is a high-O similarity measure.
LAGRANGIAN COHERENT STRUCTURES

LAGRANGIAN - study of particle trajectories in phase space.

Passive tracers can follow particle trajectories as curves in 2- or 3-space that are solutions of

\[ \dot{x} = v(x,t) \]

General time-dependence

- Invariant sets (fixed points, periodic orbits) cannot be used.
- Velocity field is only known over a finite-time interval (usually approximate otherwise, as in Navier-Stokes).
- Flows with general time-dependence emergent qualities \( \rightarrow \) coherent structures.
- Coherent structures in terms of quantities derived from fluid trajectories \( \rightarrow \) Lagrangian Coherent Structures.

FTE, FSLE (finite-time / finite-size Lyapunov exponent) \( \rightarrow \) how many or how long it takes for particles to separate after a given interval of time or specified separation distance.
FTLE: $\lambda > 0$

FSLE: $d_o$

solve for distance  solve for time

HAVER—hyperbolic time approach.

LCS is defined by local extrema of hyperbolic time field (show long each trajectory remains hyperbolic).

hyperbolic

parts?

Lyapunov exponent quantifies asymptotic behavior of close particles in a dynamical system.

* contours of finite-time Lyapunov exponent fields approximate stable manifolds for time-independent & periodic systems

* structures = invariant tori (time-periodic flow)
FORMAL DEFINITION: LCS is a ridge of FTLE field.

RIDGES - special gradient lines of the FTLE field transverse to direction of minimum curvature.

Well-defined LCS of flux across structure $\nabla \phi$ structures are invariant manifolds transport barriers.

For given FTLE field, scalar function $L(x,t)$.

$LCS$ given as $L(x,t) = 0$.

Flux across LCS: $\Phi(t) = \int_{LCS} \frac{dl}{dt} ds$

Estimate for $dl/dt$ based on FTLE & velocity fields:

$$\frac{dl}{dt} = \left( \frac{\partial}{\partial t}, \nabla \phi \right) \left( \frac{\partial}{\partial t}, \frac{\partial}{\partial A} \right) + \mathcal{O}(\frac{1}{T^2})$$

Term A  Term B  Term C

A = how well defined the ridge is.

B = difference between local rotation rate for LCS & local rotation rate for Eulerian velocity field. $[\text{LRR}_{\text{LCS}} - \text{LRR}_{\text{Euler}}]$

C = scales as $\frac{1}{T^2}$, where $|T|$ = length of time FTLE is evaluated.

FURTHER READING:


