

# Experiments on Large Fluctuations and Optimal Control

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# Outline

- 1 Introduction
  - Theory (conceptual basis)
  - Experiments
- 2 Experimental results
  - Equilibrium systems
  - Nonequilibrium systems
  - Chaotic systems & control
- 3 Conclusion
  - Summary

How do **large fluctuations** occur?  
What are **optimal paths**? How do they manifest in **reality**?



Mark Dykman (1951 – )



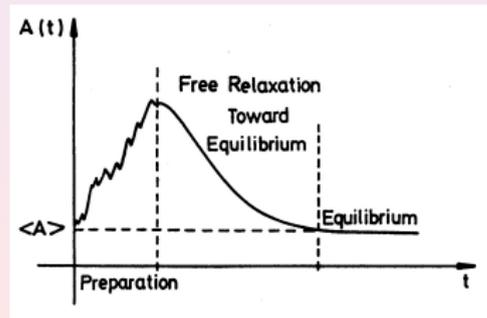
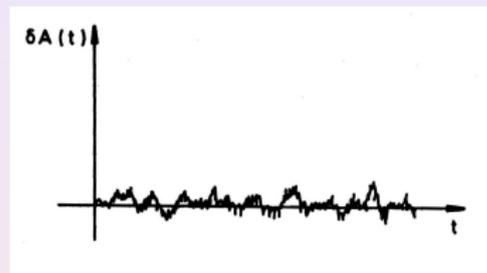
- Fluctuations and nonlinearity are of course **universal**, affecting all macroscopic physical systems.
- **Rare** large fluctuations are often the most important, for e.g. –
  - Chemical reactions
  - Mutations in DNA sequences
  - Failures of electronic devices, lasers
  - Stochastic resonance
  - Protein transport in Brownian ratchets
- Aim is it investigate large rare fluctuations, and how they happen –
  - Use an **experimental** approach
  - Measure, understand, predict
  - Control, exploit?
- Although rare, when large fluctuations arise, they occur in an almost **deterministic** manner.



# Physical picture

Consider overdamped Brownian motion of a particle in the force field  $\mathbf{K}(\mathbf{x}, t)$ , driven by weak white noise of intensity  $D$ ...

- Mostly, system fluctuates near a stable state  $S$  at  $x = x_S$  (N.B. figure from book uses  $A(t)$  as state variable).
- Very occasionally, a large rare fluctuation takes the system to a remote state  $x_f$  – from which it may then return.
- But **how** does the event occur? One idea, from the 1994 textbook by a distinguished authority...



# Problem to be solved

- **Problem:** to describe the form of the trajectories to and from  $x_f$ .
- **Assumption:** the noise is **weak**,  $D \rightarrow 0$  (no assumption of adiabaticity). Hamiltonian (or equivalent path-integral approach) –
- Many researchers: Cohen & Lewis (1967), Ventzell & Freidlin (1970), Ludwig (1975), Dykman et al (1979), Graham & Tell (1984), Jauslin (1986), Day (1987), McKane (1989), ...and numerous others, over the last 30 years.
- Start from the **Fokker-Planck** equation... use the weak noise assumption...
- We consider the simplest one-dimensional example – but the formalism is easily extended.



## Finding the “auxiliary system”

Fokker-Plank equation (FPE) for probability density  $P(\mathbf{x}, t)$  is

$$\frac{\partial P(\mathbf{x}, t)}{\partial t} = -\nabla \cdot (\mathbf{K}(\mathbf{x}, t) P(\mathbf{x}, t)) + \frac{D}{2} \nabla^2 P(\mathbf{x}, t).$$

Near a stable stationary state  $S$ , for  $D \rightarrow 0$ , use **WKB (eikonal) approximation**

$$P(\mathbf{x}, t) = z(\mathbf{x}, t) \exp\left(-\frac{W(\mathbf{x}, t)}{D}\right).$$

where  $z(\mathbf{x}, t)$  is a **prefactor**, and  $W(\mathbf{x}, t)$  is a classical **action** satisfying the Hamilton-Jacobi equation, which can be solved by integrating the **Hamiltonian** equations of motion

$$\dot{\mathbf{x}} = \mathbf{p} + \mathbf{K}, \quad \dot{\mathbf{p}} = -\frac{\partial \mathbf{K}}{\partial \mathbf{x}} \mathbf{p},$$

$$H(\mathbf{x}, \mathbf{p}, t) = \mathbf{p} \mathbf{K}(\mathbf{x}, t) + \frac{1}{2} \mathbf{p}^2, \quad \mathbf{p} \equiv \nabla W,$$

with Hamiltonian  $H(\mathbf{x}, \mathbf{p}, t)$  for appropriate boundary conditions.



# Minimum action solutions

In seeking **extreme trajectories** that minimise the action, we find **two** different types of solution –

- 1 Set of Hamiltonian trajectories **approaching S**  
≡ stable invariant manifold of S, with  $\mathbf{p} = 0$ .
- 2 Set of Hamiltonian trajectories **leaving S**  
≡ unstable invariant manifold of S, with  $\mathbf{p} \neq 0$ .

## Note:

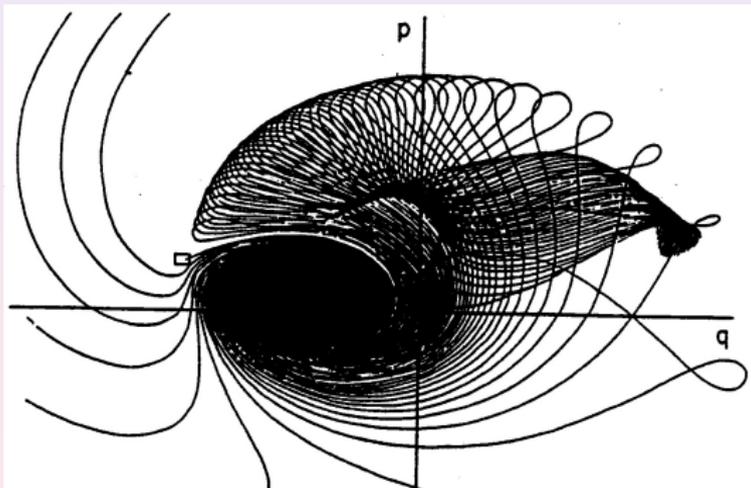
- The theory is now **deterministic** (no  $D$ ).
- But real physical systems have **finite  $D$** .
- Extremal paths are not necessarily **optimal** paths.
- Non-equilibrium systems have **singularities**.
- Beautiful **patterns** of extreme trajectories can be drawn.
- Without experiments – not obvious how all this relates to reality!



# Example of extreme paths

Chinarov et al, *Phys. Rev E* **47**, 2448 (1993).

- Extreme paths for a nearly resonantly driven nonlinear oscillator.
- **Caustics** are clearly evident.



# Example of extreme paths

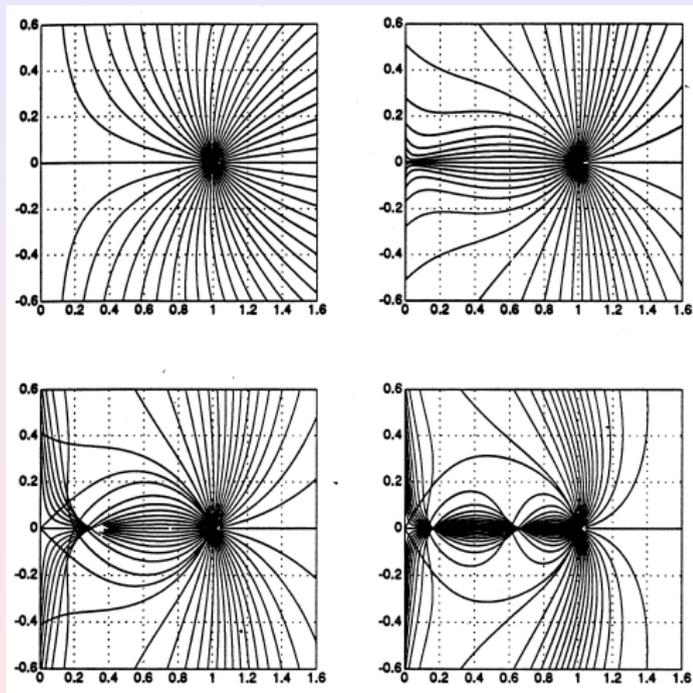
Maier & Stein, *J. Stat. Phys.* **83**, 291 (1996).

Extreme paths for  
non-potential gradient  
system

$$K_x(x, y) = x - x^3 - \alpha xy^2$$

$$K_y(x, y) = -\mu(1 + x^2)y$$

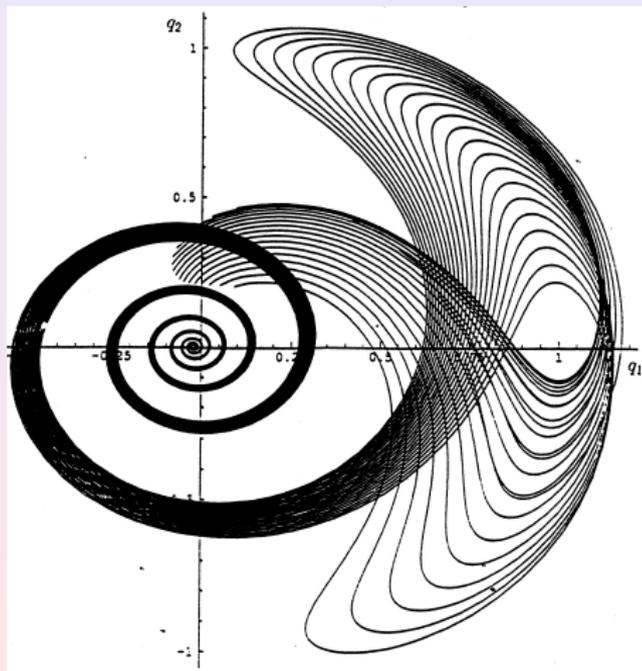
- Shows outgoing paths from stable point for  $\alpha = 1, 4, 5, 10$ .
- Note **focussing** for  $\alpha > 4$ .



# Example of extreme paths

Dykman et al, *Phys. Lett. A* **195**, 53 (1994).

- Periodically driven nonlinear oscillator.
- Again, caustics evident.
- But do **real** fluctuations ever look like this?
- Where do **caustics** come from?
- What **experiments** are possible?



# Generation of singularities

Dykman et al, *Phys. Lett. A* **195**, 53 (1994).

- Singularities arising from **folds** in the Lagrangian manifold.
- Caustics arise because paths cannot go beyond fold.
- A **pair** of caustics emanate from a **cuspl point**.
- Two families of extreme paths: 1 go below cusp; 2 go round above cusp.
- Paths cannot cross **switching line**, so caustics are not experimental observables.
- But **cusp** and **switching line** should be observable.

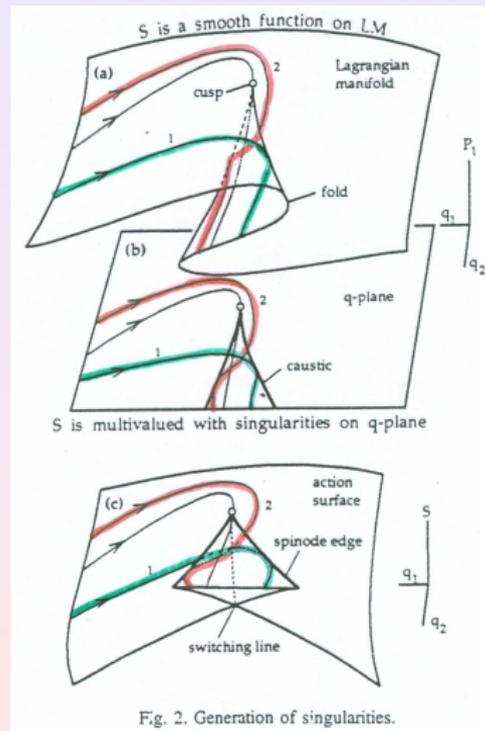
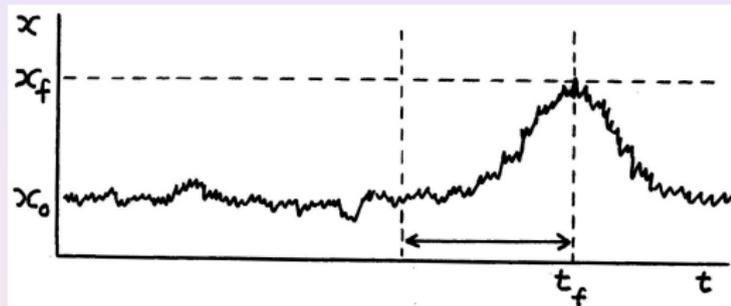


Fig. 2. Generation of singularities.



# Experiments on large fluctuations – basic procedure

- 1 Build model of system –
  - Analogue electronic, or
  - Numerical
- 2 Apply relevant forces, e.g. noise, periodic force...
- 3 Measure response –
  - Await arrival at  $x_f$
  - Record arrival path
- 4 Repeat, ensemble-average, to find **prehistory** probability distribution  $P_h(x, t; x_f, t_f)$ .



If system departs stable state at  $t = -\infty$  and arrives at  $x = x_f$  at time  $t = t_f$ , then  $p_h(x, t; x_f, t_f)$  gives probability of being at  $x$  at time  $t$ .



# Very simple example

- Consider overdamped double-well Duffing oscillator driven by zero-mean white noise of intensity  $D$ .

$$\dot{x} = -U'(x) + \xi(t),$$

$$U(x) = -\frac{1}{2}x^2 + \frac{1}{4}x^4,$$

$$\langle \xi(t) \rangle = 0, \quad \langle \xi(t)\xi(t') \rangle = D\delta(t - t').$$

- Interested in rare fluctuations to a particular final position  $x_f$ , **far from** the equilibrium state.
- Catch segment of path leading to  $x_f$ , build the **prehistory probability distribution**  $p_h(x, t; x_f, t_f)$ .
- Guess that  $p_h(x, t; x_f, t_f)$  is closely connected to the **optimal path** of the  $D \rightarrow 0$  theory.

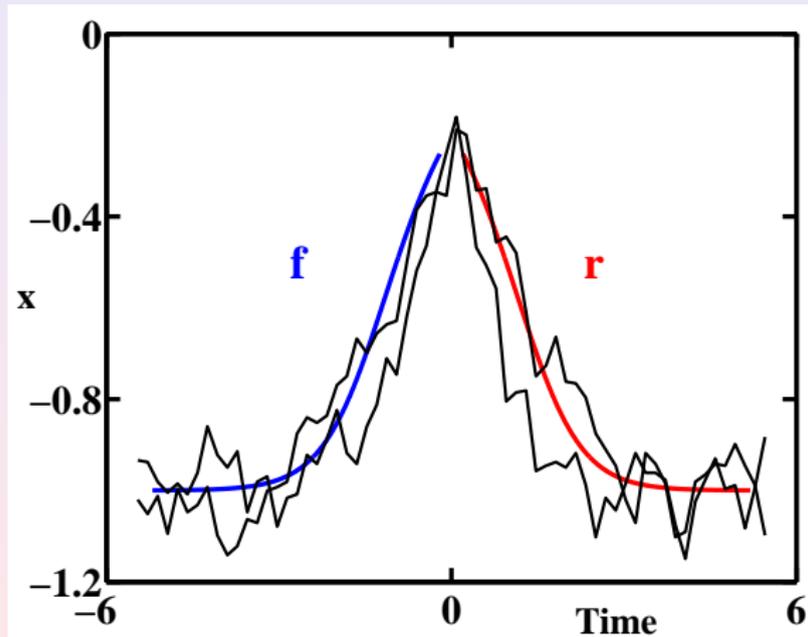


# Examples of 2 large fluctuations in circuit model

Differs from earlier sketch –

- **Symmetric** in time.
- Small fluctuations similar on both **fluctuational** and **relaxational** parts of path.

Construct ensemble average to measure **prehistory** (or posthistory) probability density.



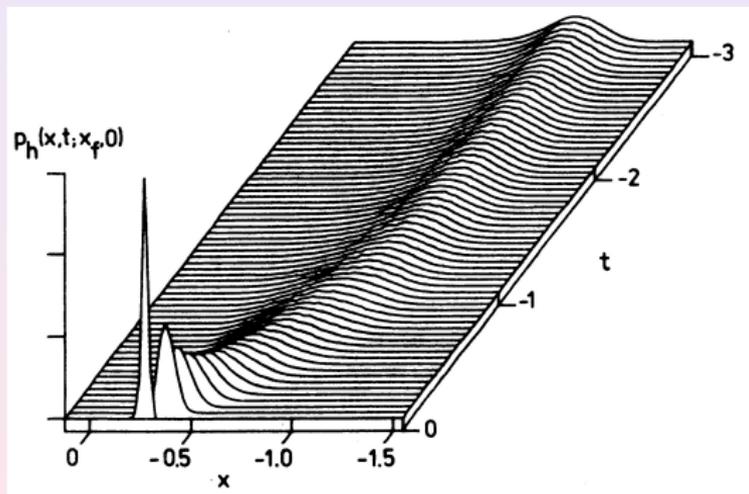
# Observation of an optimal path

Dykman et al, *PRL* **68**, 2718 (1992).

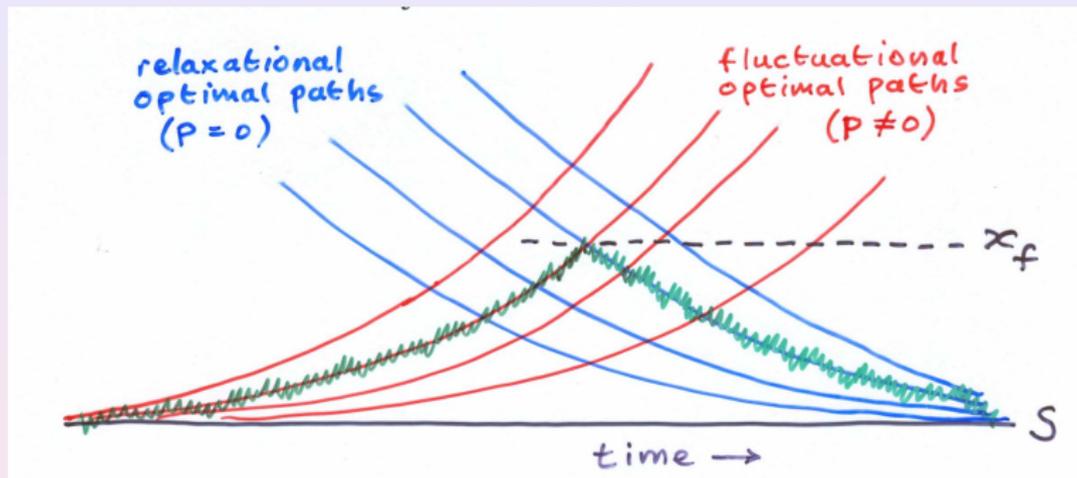
- Identify **ridge** (locus of maxima) with the **optimal path** of the  $D \rightarrow 0$  Hamiltonian fluctuation theory.
- Note (unpredicted) **dispersion** just before  $t_f$ .

Q: What happens to fluctuation after reaching  $x_f$ ?

A: It **dies!**



# Physical significance of optimal paths

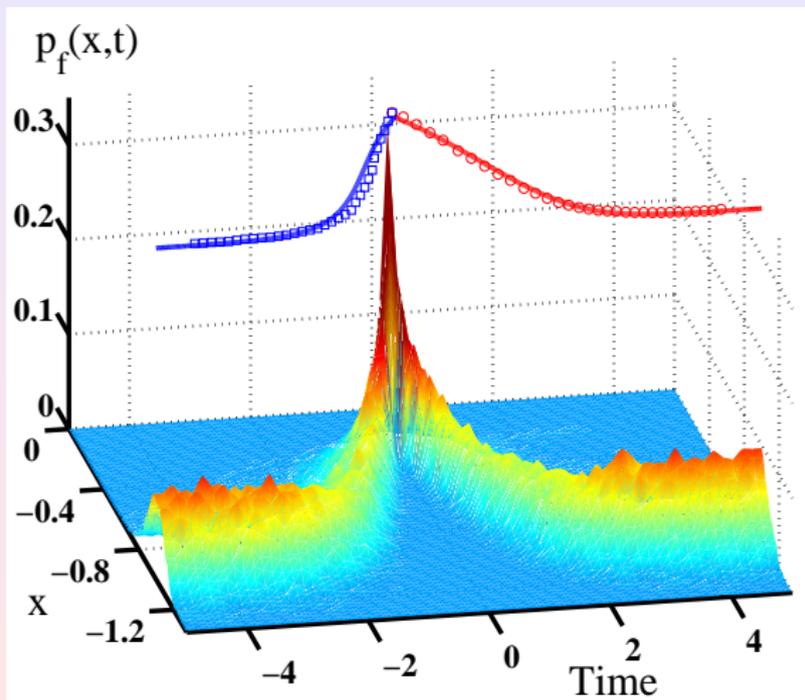


- Determinism only works **backwards** for fluctuational paths.
- Relaxational paths are **deterministic**.
- If system is “caught” at  $x_f$  then, with overwhelming probability, it **switches** to relaxational path and returns to S.



# Time-reversal symmetry in equilibrium

- Prehistory & posthistory densities.
- Optimal paths plotted in top-plane.
- Blue and red curves are theory.
- Prediction of time-reversal symmetry is verified.



# Physical significance of $p$ ?

- What is the **physical significance** of  $p$ ?
- An “effective momentum” in the theory – is it just a theoretical **abstraction**?
- No:  $p$  represents the **force** provided by the noise – the rare special noise history producing the rare fluctuation.
- In electronic experiments, can measure  $p$  during fluctuation, so can ask –

**Q:** Is it true that  $p \neq 0$  during fluctuational path, and  $p = 0$  during relaxation, as predicted by Hamiltonian theory?

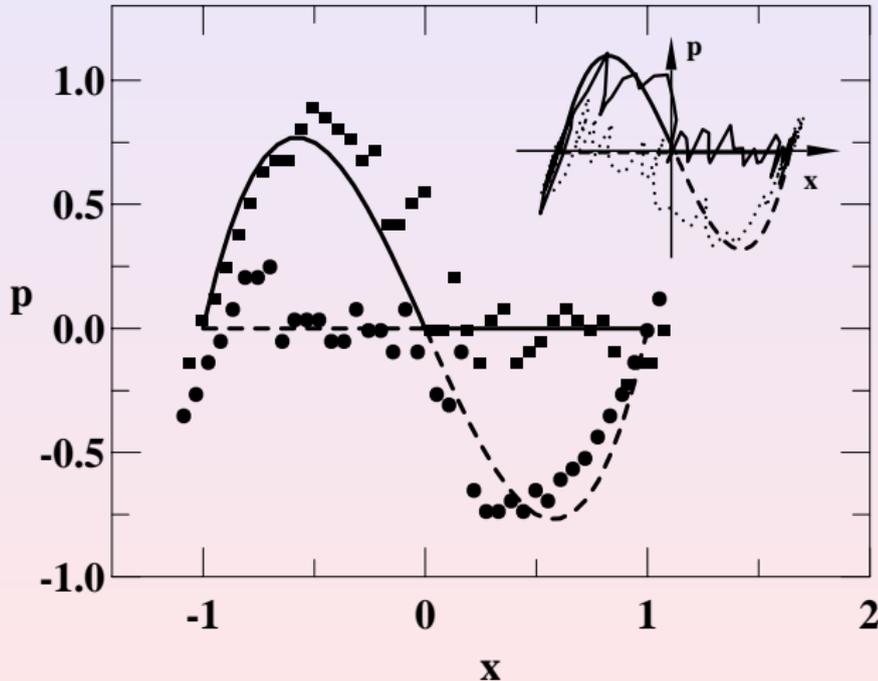
**A:** Find out answer from **experiment**.

(N.B. Unclear how to measure  $p$  in a thermal system)



# Observation of the optimal force

- Double-well Duffing.
- Densities and (inset) paths.
- Lines are theory.
- Clearly  $p \neq 0$  in fluctuational path.
- But  $p = 0$  during relaxation.



# A very simple example

- Consider simplest example – system **driven from equilibrium** by a periodic force –

$$\dot{x} = -U'(x) + A \cos \omega t + \xi(t),$$

$$U(x) = -\frac{1}{2}x^2 + \frac{1}{4}x^4,$$

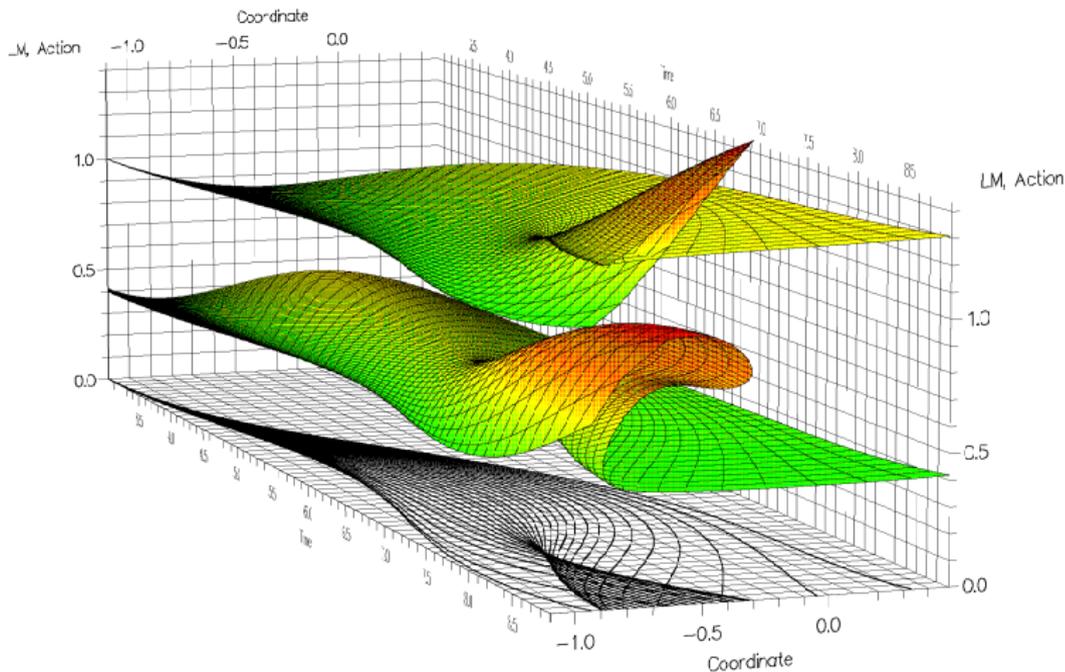
$$\langle \xi(t) \rangle = 0, \quad \langle \xi(t)\xi(t') \rangle = D\delta(t - t').$$

i.e. an overdamped bistable oscillator driven by zero-mean white noise of intensity  $D$  and a periodic force of amplitude  $A$ , frequency  $\omega$ .

- Interested in fluctuations to  $(x_f, t_f)$ , via  $(x, t)$ , where the time  $t$  now determines the **phase**  $\phi$  of the periodic force.
- The Hamiltonian fluctuation theory is easily worked out...



# Hamiltonian theory for double-well Duffing

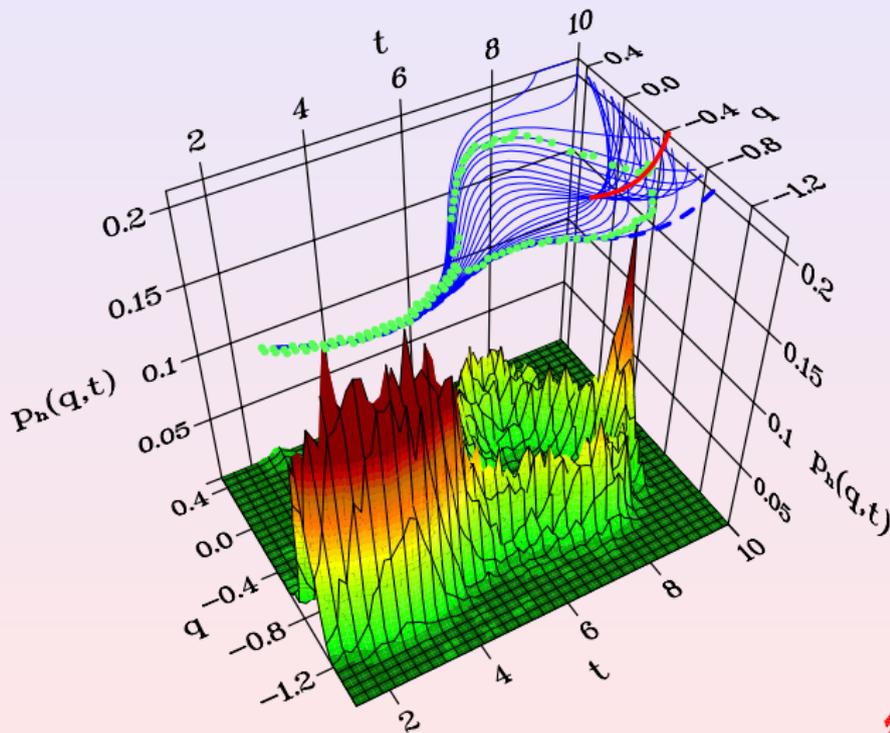


Action surface, Lagrangian manifold, and extreme paths, calculated for periodically-driven double-well Duffing.  
*D G Luchinsky, Contemporary Phys. 45, 379 (2002).*



# Measurements on driven double-well Duffing

- $(q_f, t_f)$  on (red) switching line.
- Hence **corral** of optimal paths.
- Sensitive to small departures from switching line.
- Top-plane shows experiment (green dots) and theory (blue lines).



# Maier and Stein system

- Consider Maier & Stein's system – an overdamped oscillator driven from equilibrium by a stationary nongradient field –

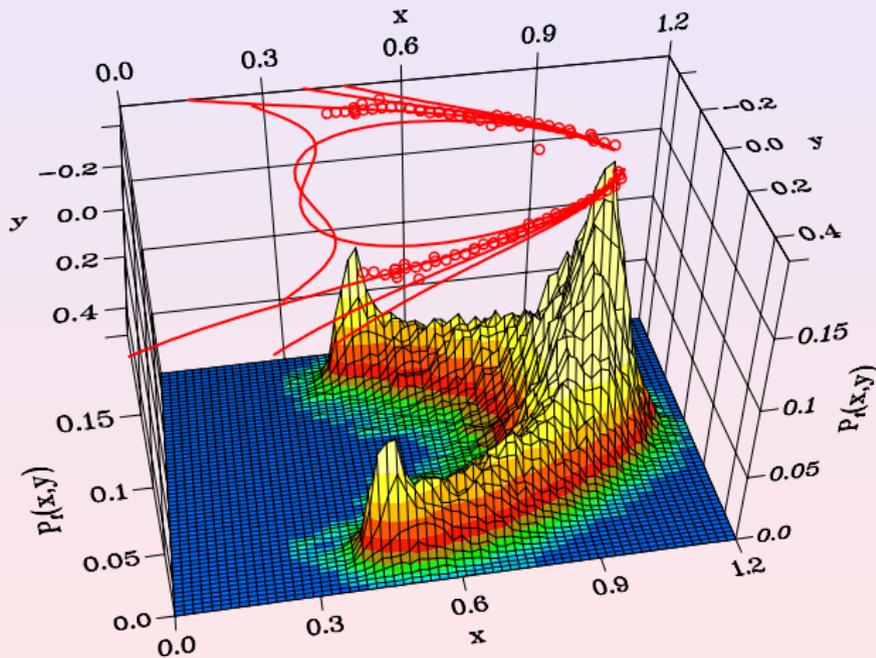
$$\begin{aligned}\dot{x} &= x - x^3 - \alpha xy^2 + f_x(t) \\ \dot{y} &= -\mu y(1 + x^2) + f_Y(t) \\ \langle f_i(t) \rangle &= 0, \quad \langle f_i(s)f_j(t) \rangle = \epsilon \delta_{ij} \delta(s - t)\end{aligned}$$

- A nongradient system (unless  $\alpha = 1$ ), so dynamics not governed by detailed balance.
- Investigate an electronic model.



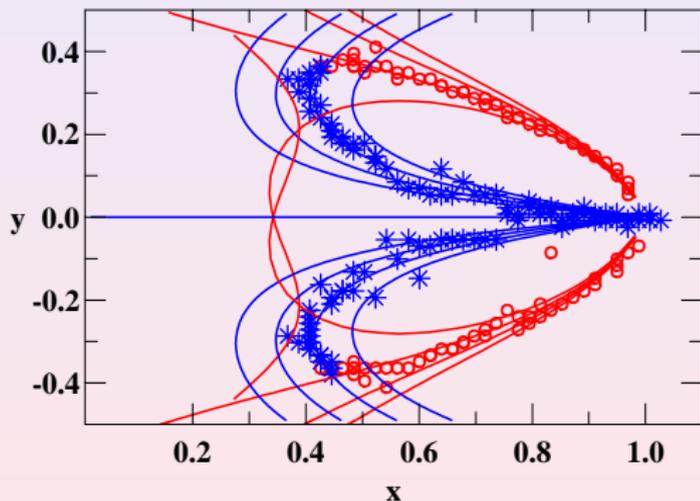
# Maier & Stein system prehistory densities

- Combination of data from **two** experiments with  $\pm y_f$ , same  $X_f$ .
- **Points** on top-plane from ridge of prehistory density.
- **Lines** on top-plane from  $\epsilon \rightarrow 0$  theory.



# Maier & Stein optimal paths

- Again, two experiments.
- Showing both outgoing **fluctuational** paths (red) and returning **relaxational** paths (blue).
- Lines are Maier & Stein theory, points are Lancaster experiment.
- **Rotational flow** of the probability density (predicted by Onsager).



# Fluctuational escape from a chaotic attractor

- Escape from point attractors and limit cycles has been intensively studied over many years.
- But how does fluctuational escape take place from a **chaotic** attractor?
- No theory exists – but **experiments** are entirely feasible.
- Have used both digital and analogue simulation.
- So far, we have studied –
  - Tilted Duffing oscillator.
  - Lorenz attractor.
  - Class-B laser equations (control).
- Summarise results from the tilted Duffing...



# Tilted Duffing oscillator (TDO)

Consider the periodically-driven, tilted, underdamped, Duffing oscillator,

$$\ddot{x} + 2\Gamma\dot{x} + \omega_0^2 x + \beta x^2 + \gamma x^3 = A \cos(\Omega t) + \xi(t),$$
$$\langle \xi(t) \rangle = 0, \quad \langle \xi(t)\xi(0) \rangle = 4kT\Gamma\delta(t),$$
$$\Gamma \ll \omega_f, \quad \frac{9}{10} < \frac{\beta^2}{\gamma\omega_0^2} < 4.$$

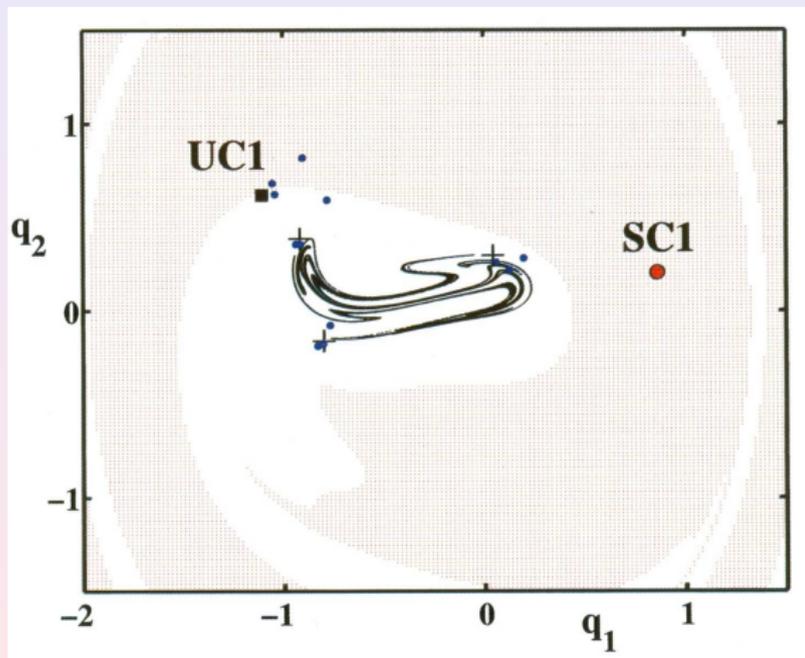
For the chosen parameter range –

- **Chaos** appears at relatively small driving amplitude,  $A \simeq 0.1$ .
- A **quasi-attractor** then coexists with a **stable limit cycle**.
- We examine **fluctuational escape** from the quasi-attractor.



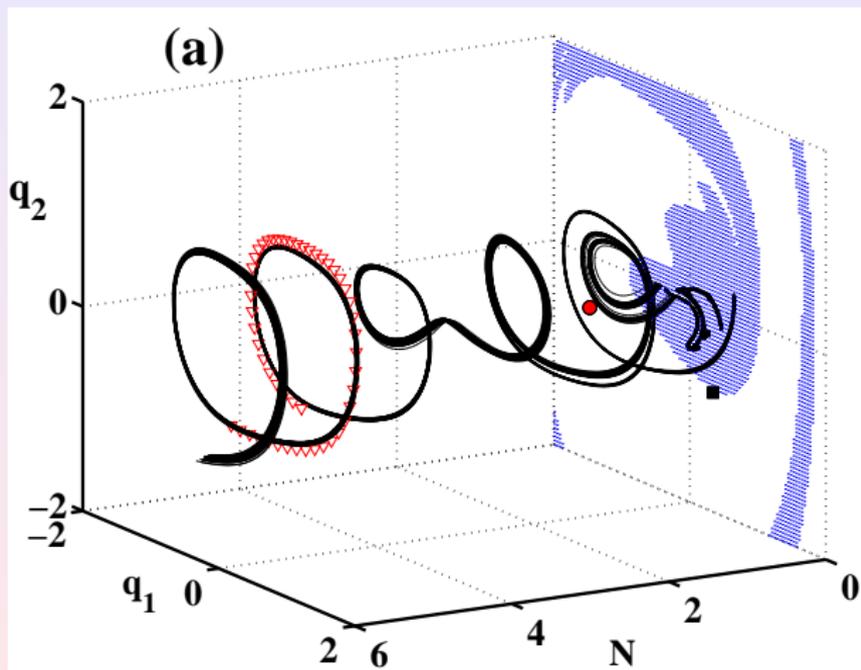
# Basins of attraction

- Basins of stable limit cycle SC1 (shaded) and chaotic attractor (white).
- The unstable saddle cycle of period 1 (UC1) marks the boundary between the basins.
- Saddle cycle of period 3 is marked with +s.



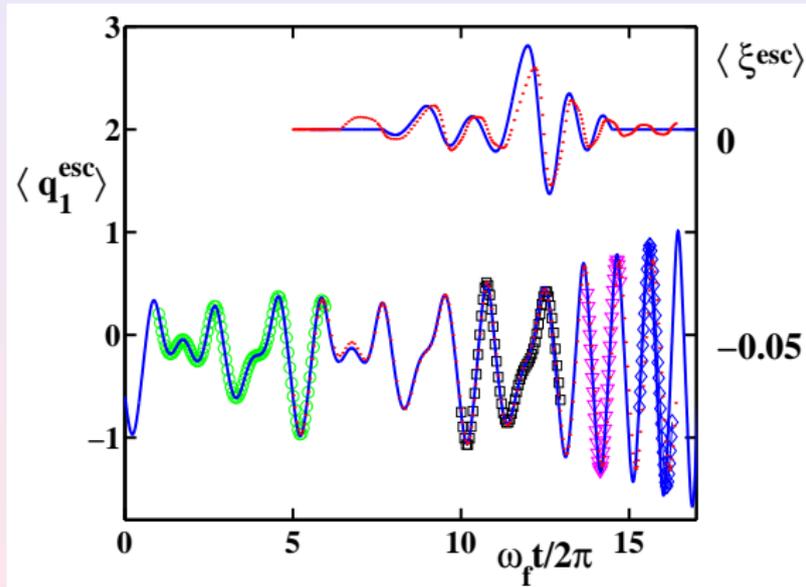
# Existence of an optimal escape path

- Analogue simulation, showing a bunch of escape paths.
- They are nearly coincident, implying existence of an **optimal path** for escape.
- Red triangles show calculated saddle cycle of period 1.



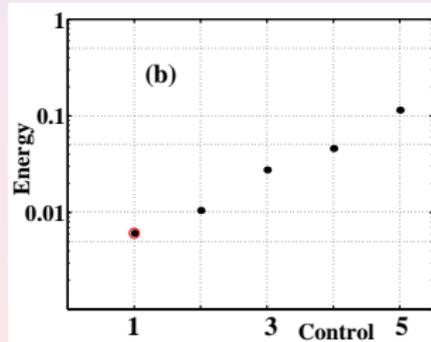
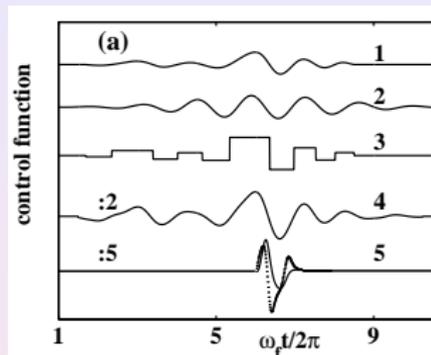
# Escape goes via saddle cycles

- Escape evidently goes via **saddle cycles**  
UC5 (green) UC3 (black) and UC1 (red).
- Driven by **optimal force** (inset).
- Once on UC1, no more force is required to reach stable cycle SC1 (blue).



# Control of noise-free system??

- Does the experimentally-determined optimal force (1) cause escape in the **noise-free** system?
- Yes! (1) is applied at increasing amplitude until escape occurs.
- Approximations to (1) also cause escape, but **cost extra energy** –
  - Approximated with sine-waves (2).
  - And with rectangular pulses (3).
  - Optimal force distorted by an arbitrary perturbation (4).
  - Standard open-plus-closed-loop (OPCL) control (5).
- The measured optimal force really does seem to be **energy-optimal**.



# Laser – single-mode rate equations

We consider the single-mode rate equations -

$$\begin{cases} \frac{du}{dt} = vu(y - 1), \\ \frac{dy}{dt} = q + k \cos(\omega t) - y - yu + f(t), \end{cases}$$

where –

- $u \propto$  density of radiation
- $y \propto$  carrier inversion
- $v$  is ratio of photon damping and carrier inversion rates
- Cavity loss is normalised to unity
- Pumping rate has constant term  $q$  + periodic component
- $f(t)$  is an additive unconstrained control function



# Map

- For class-B lasers,  $\nu \sim 10^3 - 10^4$ ; get spiking regimes for deep modulation of pumping rate.
- Obtain solutions from corresponding 2-D Poincaré map –

$$\begin{cases} c_{i+1} = q + G(c_i, \psi_i)e^{-T} + K \cos(\omega T + \psi_i) + f_i, \\ \varphi_{i+1} = \varphi_i + \omega T, \text{ mod } 2\pi, \end{cases}$$

- $G(c_i, \psi_i) = c_i - g - q - K \cos \psi_i$ ,  $K = k(1 + \omega^2)^{-1/2}$ , and  $\psi_i = \varphi_i - \arctan(\omega)$ .
- Control function  $f_i$  is now defined in discrete time.
- $g = g(c_i)$  is positive root of

$$g - c_i(1 - \exp(-g)) = 0$$



# Map and its range of validity

- $T = T(c_i, \varphi_i)$  is positive root of
 
$$(q-1)T + G(c_i, \psi_i)(1 - e^{-T}) + K\omega^{-1}[\sin(\omega T + \psi_i) - \sin \psi_i] = 0.$$
- $c_i, \varphi_i$  correspond to the inversion of population  $y(t_i)$  and to the phase of modulation  $\varphi_i = \omega t_i, \text{ mod } 2\pi$  at the moments  $t_i$  of pulse onset when  $u(t_i) = 1, \dot{u}(t_i) > 0$ .
- $g(c_i)$  denotes the energy of the pulse.
- $T(c_i, \varphi_i)$  gives the time interval between sequential pulses.
- Map was derived by asymptotic integration to accuracy  $O(v^{-1})$ , so it is valid for –
  - $q, k, \omega \ll v$
  - $c_i > 1 + O(v^{-1})$



# Generalized multistability of map

- Fixed points of the map determine spiking solutions at multiples of the driving period, at  $T_n = nT_M$ , where  $T_M = 2\pi/\omega$  is the driving period.
- They are born through a saddle node bifurcation at modulation threshold

$$k_{sn} = \sqrt{1 + \omega^2} [q - C_n - g_n(e^{T_n} - 1)^{-1}].$$

- The stable cycles undergo period-doubling bifurcations beyond

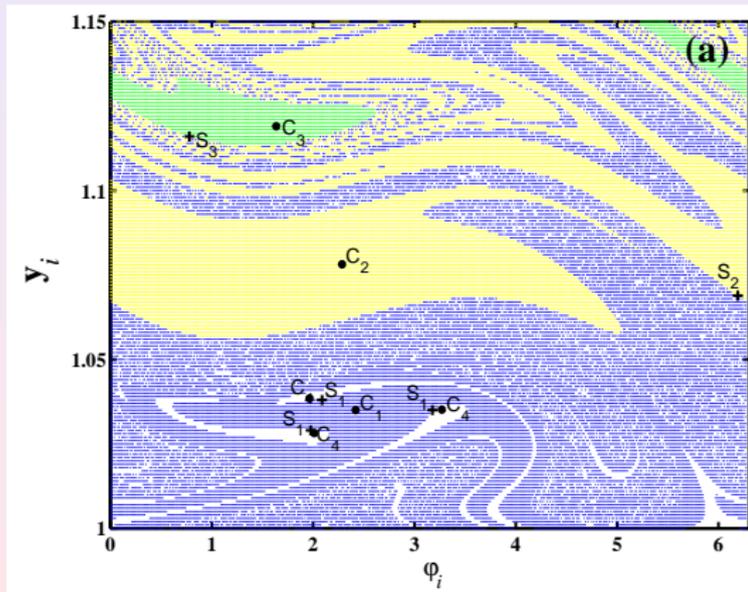
$$k_{pd} = \frac{\sqrt{1 + \omega^2}}{\omega} (q - 1) \left[ 1 + 2\pi \left( \frac{qnT_n}{12} \right)^2 + O(T_n^4) \right].$$

- Hence we determine analytically regions of generalized multistability, numbers of coexisting cycles, and approximate locations of the saddles and stable cycles.



# Basin of attraction for flow system

- Study controlled migration from stable cycle  $C_3$  to saddle cycle  $S_3$ .
- After reaching  $S_3$ , system no longer needs an applied force.
- Two kinds of force are considered –
  - Continuous
  - Impulses



# The control problem

- Consider the energy-optimal control problem –
  - How can system with unconstrained control function  $f_c(t)$  or  $f_d(t)$  be steered between coexisting states such that its “cost” functional

$$J_c = \inf_{f \in F} \frac{1}{2} \int_{t_0}^{t_1} f^2(t) dt, \quad \text{or} \quad J_d = \inf_{f \in F} \frac{1}{2} \sum_{i=1}^N f_i^2$$

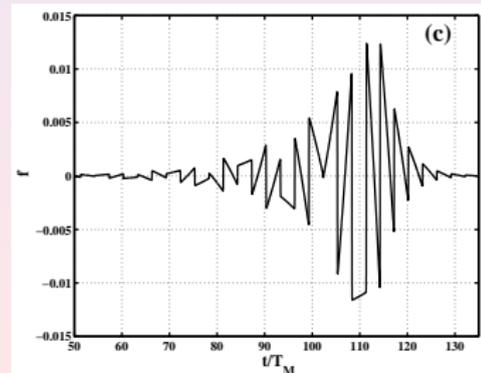
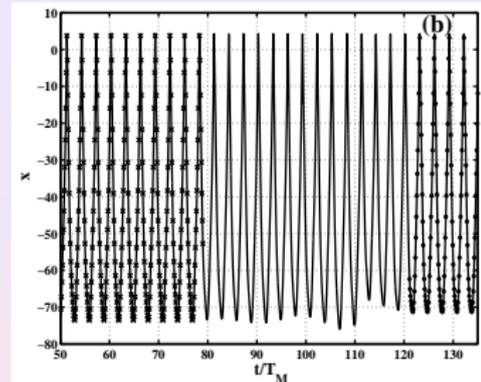
is minimized? Here  $t_1$ ,  $N$  are unspecified and  $F$  is the set of control functions.

- In general, a *very* challenging problem.
- Tackled it via ideas from optimal escape – correspondence of Wentzel-Freidlin Hamiltonian in fluctuation theory with Pontryagin’s Hamiltonian in control theory.



# Continuous control results

- Problem was solved by **prehistory** approach and numerical solution of boundary value problem.
- Variation of the coordinate  $x(t)$  during migration from stable cycle  $C_3$  to saddle cycle  $S_3$ .
- Variation of the control force  $f(t)$  during the migration.
- In **noise-free** system, showed that direct application of the optimal force as a control force **does** cause  $C_3 \rightarrow S_3$  migration.



# Summary

- 1 Large fluctuations do occur via **optimal paths**
- 2 Patterns of optimal paths and some singularities (not caustics) are physical **observables**.
- 3 For electronic models, the **optimal force** can be measured.
- 4 In equilibrium, fluctuations display **time-reversal symmetry** (if the p-dimension is ignored).
- 5 Fluctuations in nonequilibrium systems are **irreversible**.
- 6 Escape from **chaotic** attractors also occurs via optimal paths.
- 7 Intimate connection between the optimal fluctuational force and the energy-optimal **control force** in the noise-free system.



# Acknowledgements and references

## Acknowledgements

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