

Lecture 1: Stirring & Mixing

Stirring: mechanical action (cause)  
Mixing: homogenization of a scalar (effect)

$\theta(\underline{x}, t)$  = concentration,  $\underline{u}(\underline{x}, t)$  given

Advection-Diffusion eq.  $\frac{\partial \theta}{\partial t} + \underline{u} \cdot \nabla \theta = \kappa \nabla^2 \theta$ ,  $\nabla \cdot \underline{u} = 0$  in  $\Omega$

(AD) Boundary conditions:  $\hat{n} \cdot \nabla \theta = 0$   
 $\hat{n} \cdot \underline{u} = 0$  } on boundary  $\partial \Omega$

Let  $\langle \cdot \rangle = \int_{\Omega} \cdot dV$

Multiply AD by  $m \theta^{m-1}$ , integrate:

$\langle m \theta^{m-1} \partial_t \theta \rangle = \partial_t \langle \theta^m \rangle$

$\langle m \theta^{m-1} \underline{u} \cdot \nabla \theta \rangle = \langle \underline{u} \cdot \nabla \theta^m \rangle = \langle \nabla \cdot (\underline{u} \theta^m) \rangle$   
 $= \int_{\partial \Omega} \theta^m \underbrace{\underline{u} \cdot \hat{n}}_0 dS = 0$

$\langle m \theta^{m-1} \kappa \nabla^2 \theta \rangle = \kappa m \langle \nabla \cdot (\theta^{m-1} \nabla \theta) - \nabla \theta^{m-1} \cdot \nabla \theta \rangle$   
 $= \kappa m \int_{\partial \Omega} \theta^{m-1} \nabla \theta \cdot \hat{n} dS - \kappa m(m-1) \langle \theta^{m-2} |\nabla \theta|^2 \rangle$

$$\partial_t \langle \theta^m \rangle = -\kappa m(m-1) \langle \theta^{m-2} |\nabla\theta|^2 \rangle$$

$m=0$  is trivial

$m=1$ :  $\partial_t \langle \theta \rangle = 0$  Total amount of  $\theta$  is conserved

$m=2$ :  $\partial_t \langle \theta^2 \rangle = -2\kappa \langle |\nabla\theta|^2 \rangle$   $\langle \theta^2 \rangle$  non-increasing!

Let variance  $\text{Var} = C_2 = \langle \theta^2 \rangle - \langle \theta \rangle^2$

$$\partial_t C_2 = -2\kappa \langle |\nabla\theta|^2 \rangle$$

↑  
constant

Scenario:



- Variance can only decrease.
  - Slows down as  $\langle |\nabla\theta|^2 \rangle \rightarrow 0$
  - But  $\langle |\nabla\theta|^2 \rangle = 0$  iff  $\theta = \text{constant}$ .
- ↑  
in some sense

Hence the system is "driven" towards a homogeneous state where

$$\theta(\underline{x}, t) = \langle \theta \rangle = \text{constant.} \quad (C_2=0, \langle \theta^2 \rangle = \langle \theta \rangle^2)$$

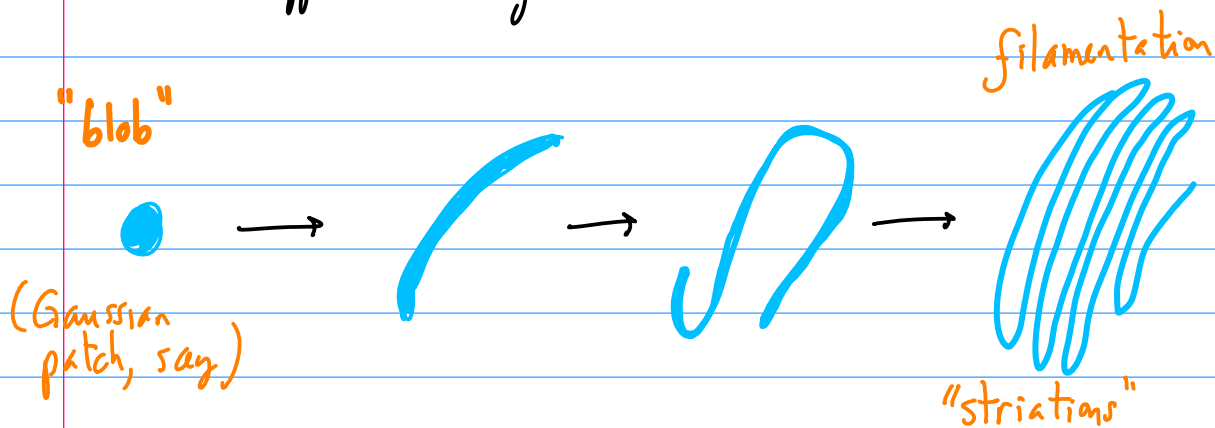
Assume  $\langle \theta \rangle = 0$   
WLOG

No fluctuations from the mean! When  $C_2$  is small "enough", we say the system is mixed.

Big Q: Where is  $u(\underline{x}, t)$  !? (stirring)

It doesn't appear in the variance equation!

But of course the variance equation is not closed: it depends on  $\nabla\theta$ .  
What happens when you stir?



This hints at the answer: stirring increases  $\nabla\theta$

$$\partial_t \langle \theta^2 \rangle = -2\kappa \langle |\nabla\theta|^2 \rangle$$

this becomes larger as we stir

By how much are gradients increased? After all, if  $|\nabla\theta|$  becomes too large, then  $\langle \theta^2 \rangle \rightarrow 0$ , so there are no gradients anymore!

Answer: for "good" stirring, the system is driven to a state where

$$\kappa \langle |\nabla\theta|^2 \rangle \rightarrow \text{independent of } \kappa$$

Hence,  $\nabla\theta \sim \kappa^{-1/2}$

This is the chaotic/turbulent mixing scenario:

$\frac{\partial \langle \theta^2 \rangle}{\partial t}$  becomes independent of  $\kappa$  after a "short" transient

(How short? Typically  $\sim \log \kappa$ )

This is the Platonic ideal of mixing

Furthermore, the smallest scales visible in the concentration field  $\theta(\underline{x}, t)$  have size  $\sim \sqrt{\kappa}$ . (missing a dimensional factor  $\rightarrow$  see later)

Note that  $\partial_t \langle \theta^2 \rangle$  independent of  $\kappa$  is crucial: in most applications,  $\kappa$  is tiny!

Heat:  $\kappa = 2.2160 \times 10^{-5} \text{ m}^2/\text{s}$  at 300K

10 m room: diffusion time  $\sim \frac{L^2}{\kappa} = \frac{(10\text{m})^2}{(2 \times 10^{-5} \text{ m}^2/\text{s})} \sim 4.5 \times 10^6 \text{ sec}$

So we better stir!  
Even thermal convection  
is often enough.

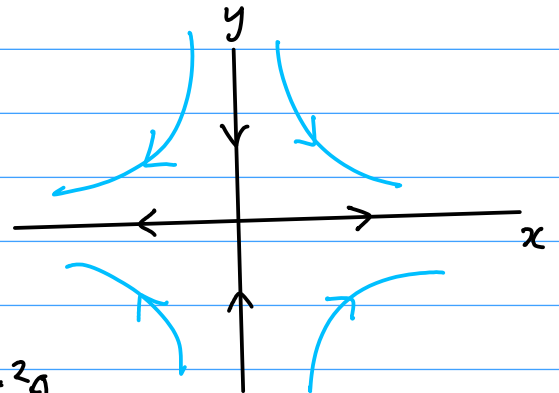
$\sim 1300 \text{ hours}$

$\sim 53 \text{ days!}$

Example of a good mixer:

$$\underline{u}(\underline{x}, t) = (\lambda x, -\lambda y)$$

"hyperbolic point"



AD:  $\partial_t \theta + \lambda x \partial_x \theta - \lambda y \partial_y \theta = \kappa \nabla^2 \theta$

Can solve this exactly (we'll say more next time), but let's do the simplest thing: look for an  $x$ -independent solution of the form:

$$\theta(\underline{x}, t) = e^{-\lambda t} f(y)$$

$$-\lambda f - \lambda y f' = \kappa f''$$

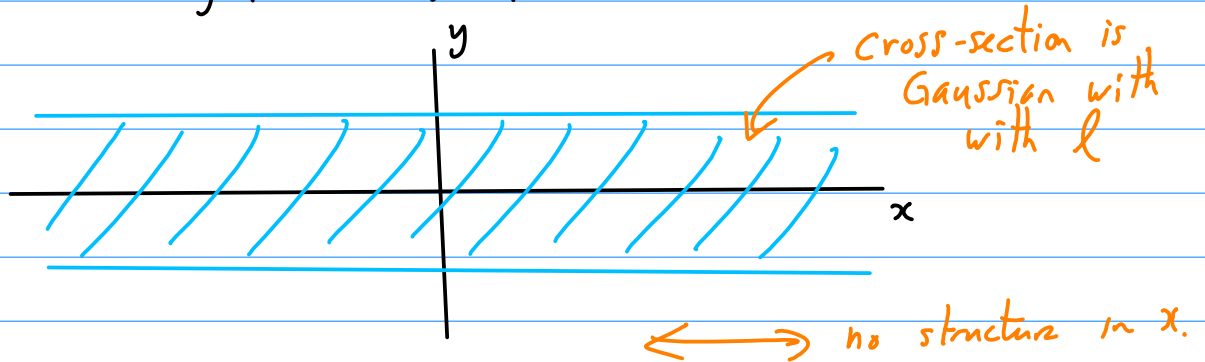
Boundary condition:

$$f \rightarrow 0 \text{ as } y \rightarrow \pm \infty.$$

Solution is:  $f(y) = e^{-y^2/2l^2}$ , where  $l^2 = \frac{\nu}{\lambda}$

Hence,  $\theta(x, t) \sim e^{-\lambda t} e^{-y^2/2l^2}$

This is the "filament" solution:



In fact, this solution tells us about the ultimate state of any compactly-supported initial condition:

"lob"



"filament"



"intensity fading" as  $e^{-\lambda t}$

central part

$\sim$  Gaussian cross-section

For this case, we know the length scale of "striations";

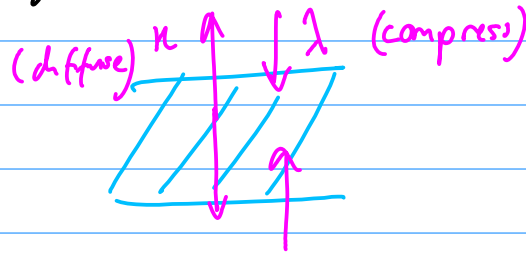
$$l = \sqrt{\frac{\nu}{\lambda}}$$

Batchelor length

Note  $l \sim \sqrt{\nu}$ , as necessary to make decay rate indep. of  $\nu$ !

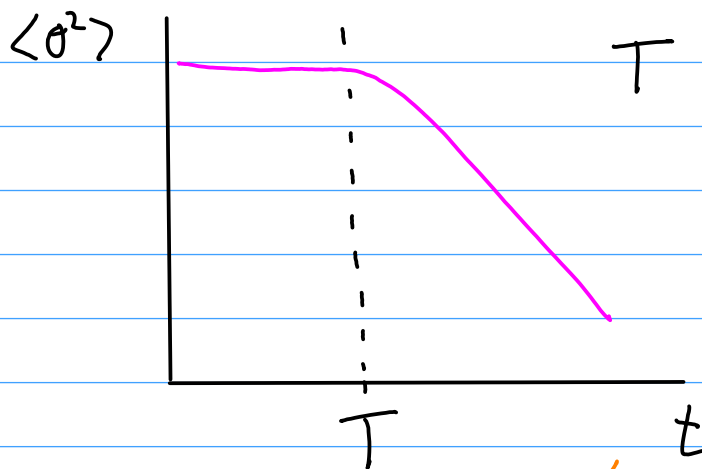
In practical applications,  $\lambda$  is often taken to be the local rate of strain.

$l$  is set by a balance between compression and diffusion



Summary: how mixing proceeds

- A blob is stirred  $\bullet \rightarrow$
- For a while,  $\langle \theta^2 \rangle$  is  $\sim$  constant, since  $\kappa$  is small
- When  $\nabla \theta$  reaches scales of order  $l$ , diffusion takes over
- After that,  $\langle \theta^2 \rangle$  decays at a  $\kappa$ -independent rate



$T$  given by:  $e^{-1T} \sim \sqrt{\kappa}$

$T \sim \lambda^{-1} \log \kappa$

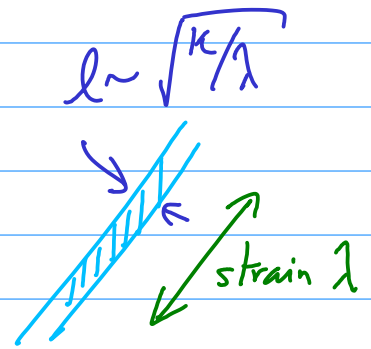
filamentation phase      mixing phase

## Effective Diffusivity

Recall: filaments in chaotic advection

Goal was to compute decay of variance,

$$\langle \theta^2 \rangle \sim e^{-\gamma t} \quad (\gamma = \lambda \text{ for uniform strain})$$



But when can we replace the advection-diffusion equation by an "effective" diffusion equation?

$$\frac{\partial \theta}{\partial t} + \underline{u} \cdot \nabla \theta = \kappa \nabla^2 \theta \implies \frac{\partial \theta}{\partial t} = K_{\text{eff}} \nabla^2 \theta ?$$

Diffusion arises from noise:  $x_n = x_{n-1} + \xi_n$

$$\text{Assume } \langle \xi_n \rangle = 0, \quad \langle \xi_n^2 \rangle = \sigma^2$$

$$x_n = \underbrace{x_0}_0 + \sum_{i=1}^n \xi_i, \quad \langle x_n \rangle = 0$$

i.i.d. (Gaussian)


$$\langle x_n^2 \rangle = \sum_{i=1}^n \langle \xi_i^2 \rangle = \underbrace{n}_{\sim \text{time}} \sigma^2 = 2\kappa t$$

In d dimensions,

$$\langle x_n^2 + y_n^2 (+z_n^2) \rangle = \underbrace{nd}_{t=nT} \sigma^2 = 2d\kappa nT$$

by definition

$$K_{\text{eff}} = \frac{\sigma^2}{2T}$$

Now if we take a "cloud" of points , and define a density

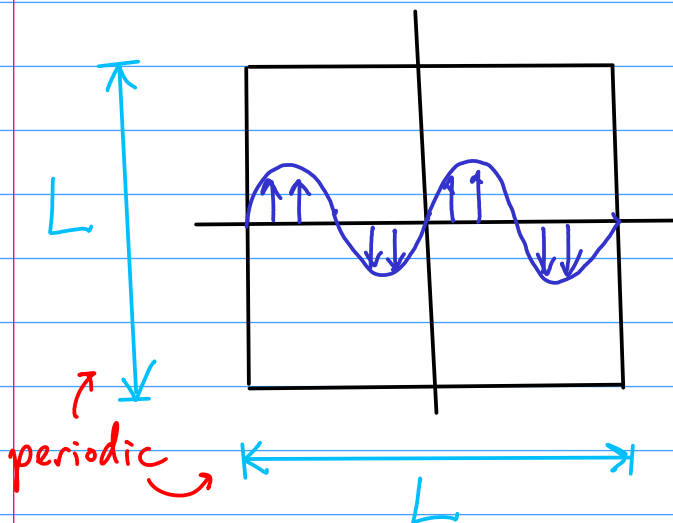
$$\theta(\underline{x}, t) = \text{density of points}$$

Then  $\theta$  satisfies  $\frac{\partial \theta}{\partial t} = K \nabla^2 \theta$  if each point evolves independently according to  $\underline{x}' = \underline{x} + \xi$ .

Of course, this requires "coarse-graining": it is only true if we don't look too closely (scales  $\lesssim \sigma$ ) or too often (time scales  $\lesssim T$ ).

This provides clues as to when the concept of an effective diffusivity makes sense.

Rest of lecture: look at an example, the famous SINE FLOW.



• Velocity field (shear flow)

$$\underline{u}_H = \left( U \sin\left(\frac{2\pi k y}{L}\right), 0 \right) \quad \text{STEP 1}$$

applied for  $0 \leq t < \tau/2$

$$\underline{u}_V = \left( 0, U \sin\left(\frac{2\pi k x}{L}\right) \right) \quad \text{STEP 2}$$

for  $\tau/2 \leq t < \tau$ .

Can solve  $\dot{\underline{x}} = \underline{u}$ ,  $\underline{x}(0) = \underline{x}_0$  exactly:

STEP 1:

$$x(\tau/2) = x_0 + U\tau/2 \sin\left(\frac{2\pi k y_0}{L}\right)$$

$$y(\tau/2) = y_0$$



STEP 2:  $x(\tau) = x(\tau/2)$   $x(\tau/2) = x(\tau)$   
↓

$$y(\tau) = y(\tau/2) + \frac{U\tau}{2} \sin\left(\frac{2\pi k x(\tau/2)}{L}\right)$$

Write as one map of period  $\tau$ :

$$\begin{aligned} x' &= x + T \sin(2\pi k y / L) \\ y' &= y + T \sin(2\pi k x' / L) \end{aligned}$$

$$T \equiv \frac{U\tau}{2}$$

Easy to iterate on a gazillion particles. ↑  
note  $x'$ ! Important for area-preservation (comes from incompressibility)

Example 1: Run Matlab script example (1).

$$L = k = 1, \quad T = 0.1$$

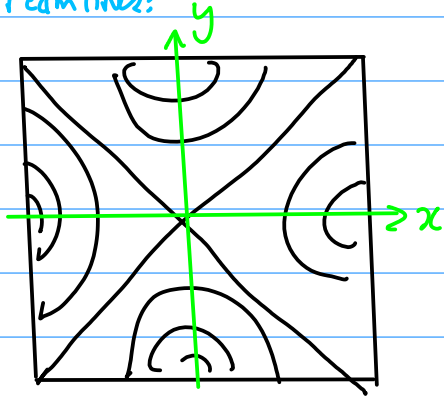
Note how regular the orbits are: for small  $T$  the map is effectively a symplectic integrator

$$\frac{x' - x}{T} = \sin\left(\frac{2\pi k y}{L}\right), \quad \frac{y' - y}{T} = \sin\left(\frac{2\pi k x'}{L}\right)$$

As  $T \rightarrow 0$ , this approximates  $\frac{dx}{dt} = \sin\left(\frac{2\pi k y}{L}\right), \quad \frac{dy}{dt} = \sin\left(\frac{2\pi k x}{L}\right),$   
 $= \partial\psi/\partial y \qquad \qquad \qquad = -\partial y/\partial x$

or flow with streamfunction:  $\psi = \frac{L}{2\pi k} \left( \cos\left(\frac{2\pi k x}{L}\right) - \cos\left(\frac{2\pi k y}{L}\right) \right)$

streamlines:



The streamlines aren't traced exactly because  $T$  is finite.

Example 2 adds a bit of noise.

$$x' = (\text{sine map}) + \sqrt{2D} \xi$$

↑  
Gaussian random var. with  $\langle \xi^2 \rangle = 1$ .

Example 3:  $T=1$ . Now doesn't approximate a flow at all → CHAOTIC.

Example 4:  $T=1, L=1, D=10^{-4}$ : "fat" filaments.

→ measure width by clicking

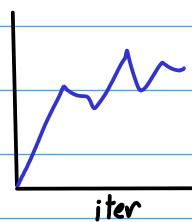
→ repeat for  $D=10^{-6}$

→ observe rough  $\sqrt{D}$  scaling for filament width

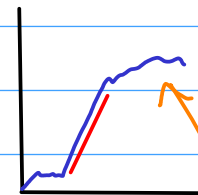
(see Lecture 1)

Example 5:  $T=1/2, k=1, D=10^{-6}$ , make  $L$  larger.

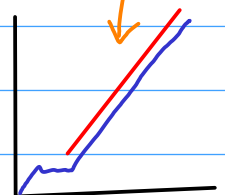
Plot  $\langle x^2 \rangle$  vs iteration



$L=1$



$L=3$



$L=25$

Hence, the concept of an effective diffusivity makes sense if we look at large scales, such that we cannot see the correlated small scale motions, and long times.


(but not too long!)

→ Useful for turbulence

particles are initially very close, so correlated  
"chaotic mixing" regime

particles reach sides of box

$$K_{\text{eff}} \sim 0.068 \gg D = 10^{-6}$$

Note that the "cross" shape  evident in the pattern is not captured.

## Lecture 2: Stirring by swimming organisms

Jean-Luc Thiffeault

Department of Mathematics  
University of Wisconsin – Madison

Summer Program in Geophysical Fluid Dynamics, Woods Hole  
23 June 2010

# Biomixing

A controversial proposition:

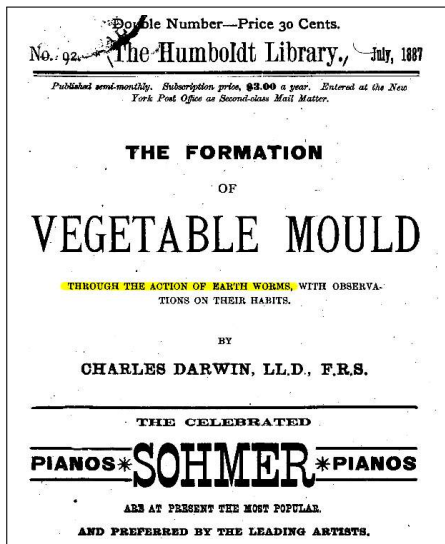
- There are many regions of the ocean that are relatively quiescent, especially in the depths (**1 hairdryer/ km<sup>3</sup>**);
- Yet mixing occurs: nutrients eventually get dredged up to the surface somehow;
- What if organisms swimming through the ocean made a significant contribution to this?
- There could be a **local** impact, especially with respect to feeding and schooling;
- Also relevant in suspensions of microorganisms (Viscous Stokes regime).

## Bioturbation

The earliest case studied of animals 'stirring' their environment is the subject of Darwin's last book.

This was suggested by his uncle and future father-in-law Josiah Wedgwood II, son of the famous potter.

"I was thus led to conclude that all the vegetable mould over the whole country has passed many times through, and will again pass many times through, the intestinal canals of worms."



## Munk's Idea

Though it had been mentioned earlier, the first to seriously consider the role of ocean biomixing was Walter Munk (1966):

### Abyssal recipes

WALTER H. MUNK\*

(Received 31 January 1966)

**Abstract**—Vertical distributions in the interior Pacific (excluding the top and bottom kilometer) are not inconsistent with a simple model involving a constant upward vertical velocity  $w \approx 1.2 \text{ cm day}^{-1}$  and eddy diffusivity  $\kappa \approx 1.3 \text{ cm}^2 \text{ sec}^{-1}$ . Thus temperature and salinity can be fitted by exponential-like solutions to  $[\kappa \cdot d^2/dz^2 - w \cdot d/dz] T, S = 0$ , with  $\kappa/w \approx 1 \text{ km}$  the appropriate "scale height." For Carbon 14 a decay term must be included,  $[ ]^{14}\text{C} = \mu^{14}\text{C}$ ; a fitting of the solution to the observed  $^{14}\text{C}$  distribution yields  $\kappa/w^2 \approx 200 \text{ years}$  for the appropriate "scale time," and permits  $w$  and

"... I have attempted, **without much success**, to interpret [the eddy diffusivity] from a variety of viewpoints: from mixing along the ocean boundaries, from thermodynamic and **biological processes**, and from internal tides."

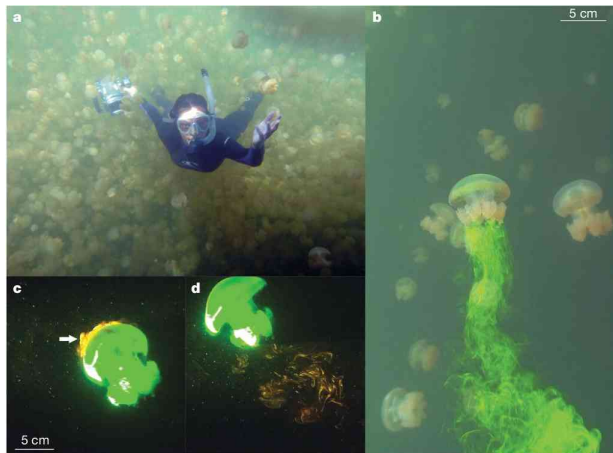
## Basic claims

The idea lay dormant for almost 40 years; then

- Huntley & Zhou (2004) analyzed the swimming of 100 (!) species, ranging from bacteria to blue whales. Turbulent energy production is  $\sim 10^{-5} \text{ W kg}^{-1}$  for 11 representative species.
- Total is comparable to energy dissipation by major storms.
- Another estimate comes from the solar energy captured: **63 TeraW**, something like 1% of which ends up as mechanical energy (Dewar *et al.*, 2006).
- Kunze *et al.* (2006) find that turbulence levels during the day in an inlet were **2 to 3 orders of magnitude** greater than at night, due to swimming krill.

## *In situ* experiments

Katija & Dabiri (2009) looked at jellyfish:



[movie 1] (Palau's Jellyfish Lake.)



# Displacement by a moving body

86

Mr. J. Clerk-Maxwell on

[Mar. 10,

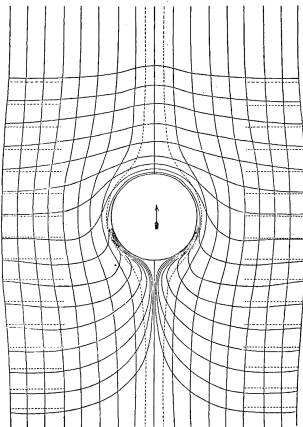


FIG. 1.

Fluid flowing past a fixed cylinder.

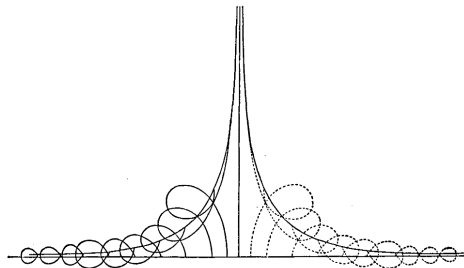
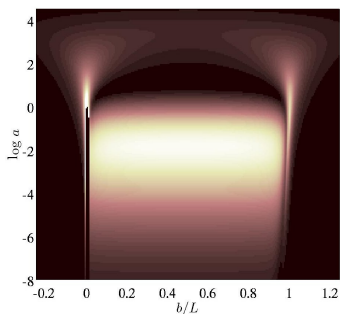


FIG. 2.

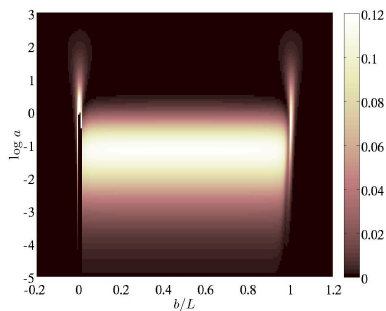
Paths of particles of the fluid when a cylinder moves through it.

Maxwell (1869); Darwin (1953); Eames *et al.* (1994); Eames & Bush (1999)

## Cylinders and spheres: Displacements



$$\Delta_L^2(a, b) a \text{ (cylinder)}$$



$$\Delta_L^2(a, b) a^2 \text{ (sphere)}$$

## Displacement for cylinders

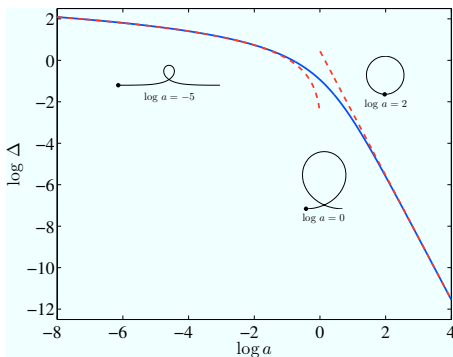
Small  $a$ :  $\Delta \sim -\log a$

Large  $a$ :  $\Delta \sim a^{-3}$

(Darwin, 1953)

$$\int_0^1 \Delta^2(a) da \simeq 2.31$$

$$\int_1^\infty \Delta^2(a) da \simeq .06$$

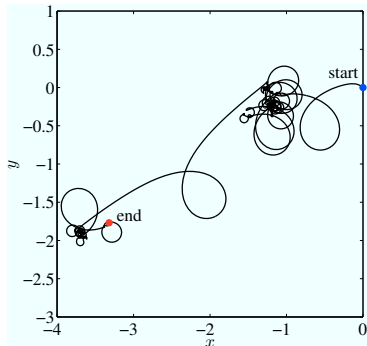
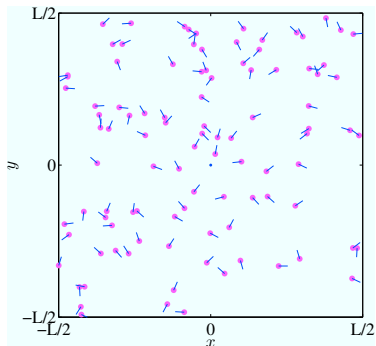


$\implies$  97% dominated by “head-on” collisions (similar for spheres)

## Numerical simulation

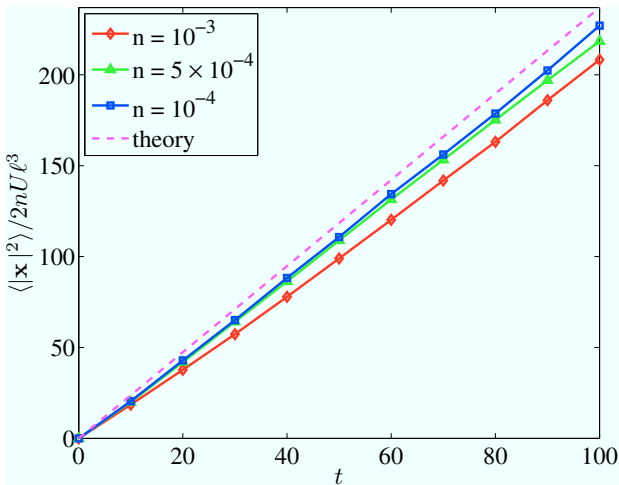
- Validate theory using simple simple simulations;
- Large periodic box;
- $N$  swimmers (cylinders of radius 1), initially at random positions, swimming in random direction with constant speed  $U = 1$ ;
- Target particle initially at origin advected by the swimmers;
- Since dilute, superimpose velocities;
- Integrate for some time, compute  $|\mathbf{x}(t)|^2$ , repeat for a large number  $N_{\text{real}}$  of realizations, and average.

# A 'gas' of swimmers



[movie 2]  $N = 100$  cylinders, box size = 1000

## How well does the dilute theory work?



# Cloud of particles

t=10



t=630



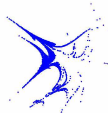
t=1255



t=1880



t=2505



t=3125



t=3750



t=4375

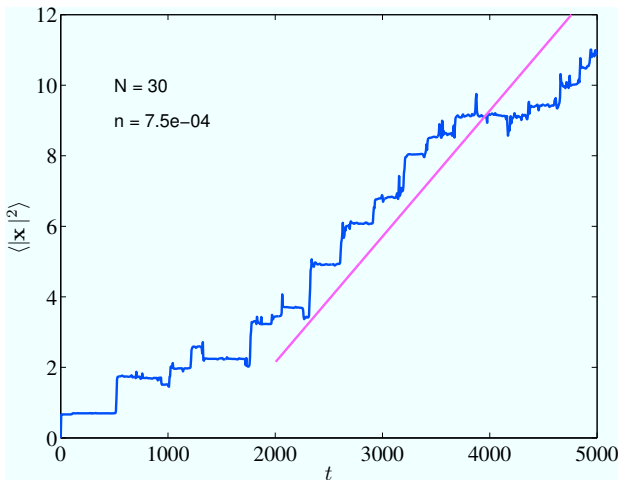


t=5000



[movie 3] (30 cylinders)

## Cloud dispersion proceeds by steps



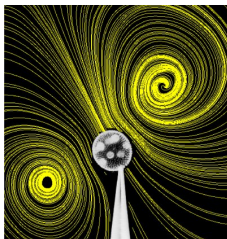


## Squirmers

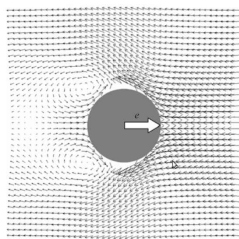
Considerable literature on transport due to microorganisms: Wu & Libchaber (2000); Hernandez-Ortiz *et al.* (2006); Saintillian & Shelley (2007); Underhill *et al.* (2008); Ishikawa (2009); Leptos *et al.* (2009)

Lighthill (1952), Blake (1971), and more recently Ishikawa *et al.* (2006) have considered **squirmers**:

- Sphere in Stokes flow;
- Steady velocity specified at surface, to mimic cilia;
- Steady swimming condition imposed (no net force on fluid).



(Drescher *et al.*, 2009)



(Ishikawa *et al.*, 2006)

## Typical squirmer

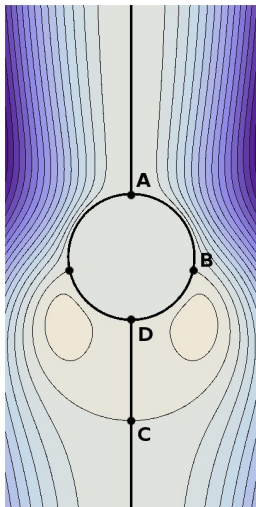
3D axisymmetric streamfunction for a typical squirmer, in cylindrical coordinates  $(\rho, z)$ :

$$\psi = -\frac{1}{2}\rho^2 + \frac{1}{2r^3}\rho^2 + \frac{3\beta}{4r^3}\rho^2 z \left( \frac{1}{r^2} - 1 \right)$$

where  $r = \sqrt{\rho^2 + z^2}$ ,  $U = 1$ , radius of squirmer = 1.

Note that  $\beta = 0$  is the sphere in potential flow.

We will use  $\beta = 5$  for most of the remainder.

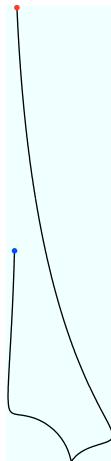


## Particle motion for squirmer

A particle near the squirmer's swimming axis initially (blue) moves towards the squirmer.

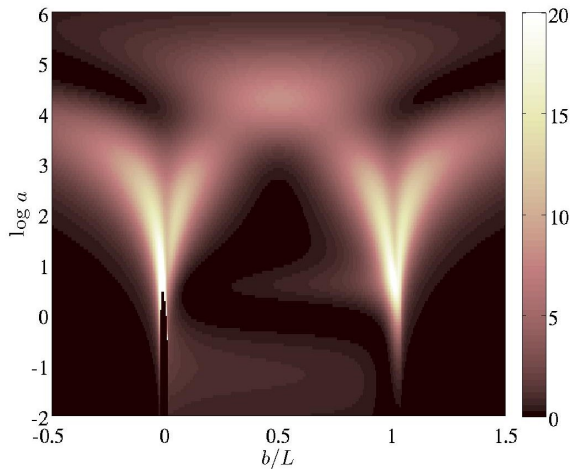
After the squirmer has passed the particle follows in the squirmer's wake.

(The squirmer moves from bottom to top.)

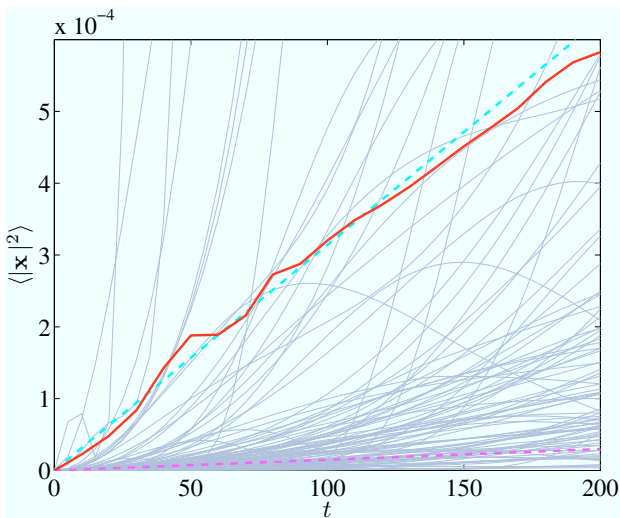


[movie 4]

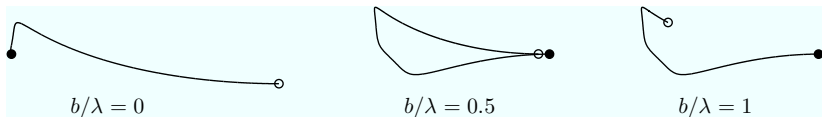
# Squirmer displacements



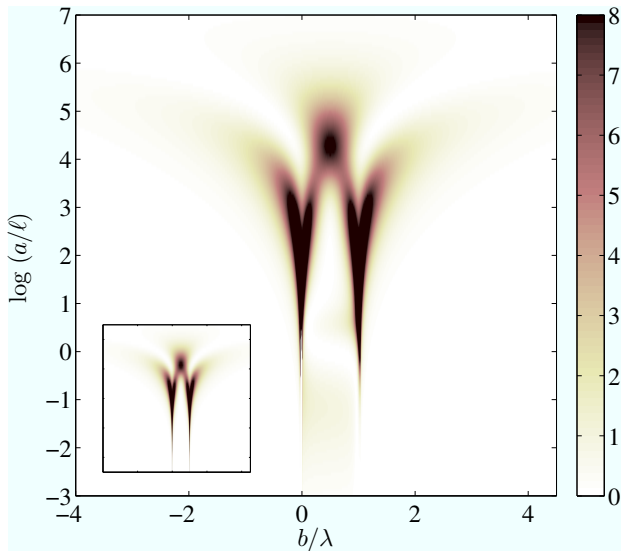
# Squirmers: Transport



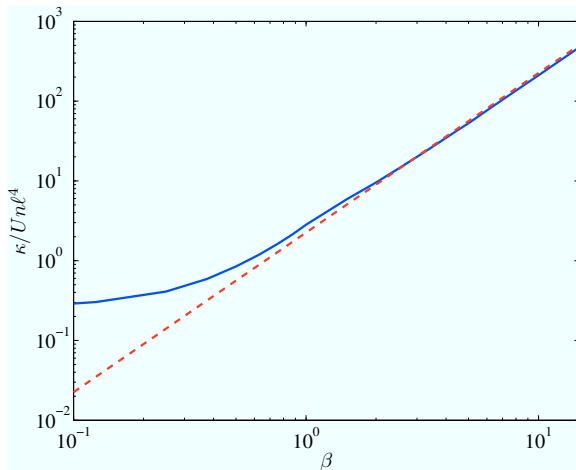
# Squirmers: Trajectories



## Far field: Displacements

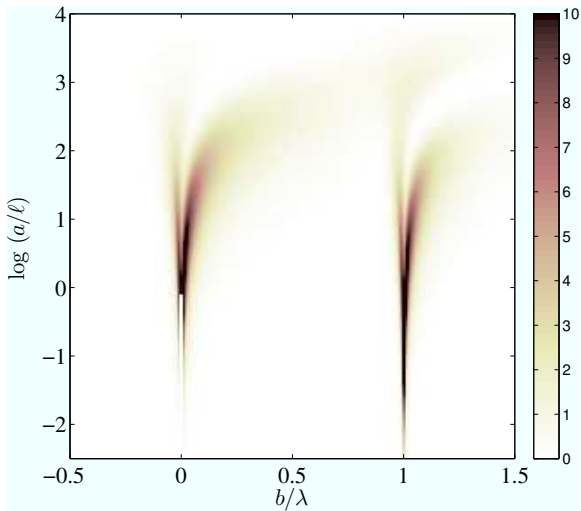


## Far field: transport

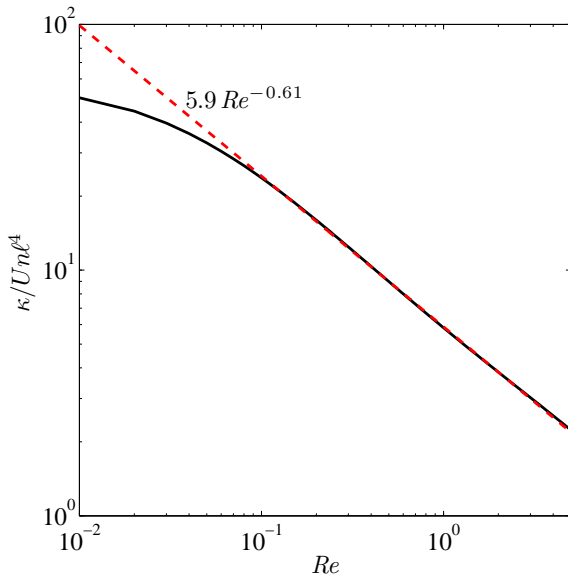




## Finite Reynolds number: Displacements



## Finite Reynolds number: Transport

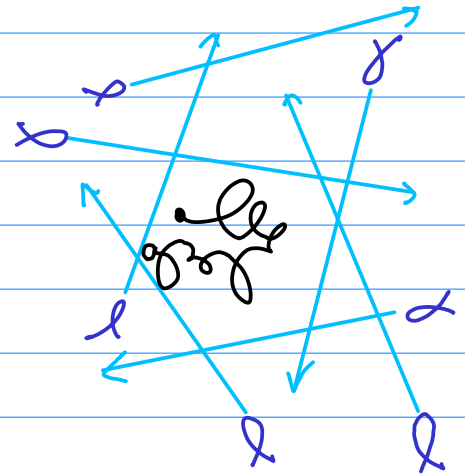
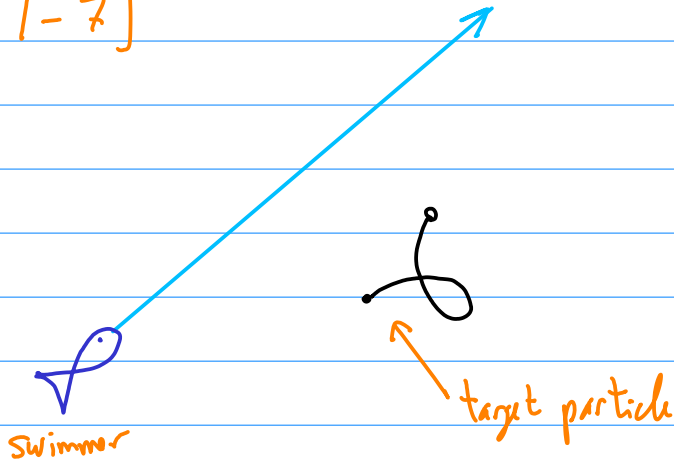


- BLAKE, J. R. 1971 A spherical envelope approach to ciliary propulsion. *J. Fluid Mech.* **46**, 199–208.
- DARWIN, C. G. 1953 Note on hydrodynamics. *Proc. Camb. Phil. Soc.* **49** (2), 342–354.
- DEWAR, W. K., BINGHAM, R. J., IVERSON, R. L., NOWACEK, D. P., ST. LAURENT, L. C. & WIEBE, P. H. 2006 Does the marine biosphere mix the ocean? *J. Mar. Res.* **64**, 541–561.
- DRESCHER, K., LEPTOS, K., TUVAL, I., ISHIKAWA, T., PEDLEY, T. J. & GOLDSTEIN, R. E. 2009 Dancing *volvox*: hydrodynamic bound states of swimming algae. *Phys. Rev. Lett.* **102**, 168101.
- EAMES, I., BELCHER, S. E. & HUNT, J. C. R. 1994 Drift, partial drift, and Darwin's proposition. *J. Fluid Mech.* **275**, 201–223.
- EAMES, I. & BUSH, J. W. M. 1999 Longitudinal dispersion by bodies fixed in a potential flow. *Proc. R. Soc. Lond. A* **455**, 3665–3686.
- HERNANDEZ-ORTIZ, J. P., DTOLZ, C. G. & GRAHAM, M. D. 2006 Transport and collective dynamics in suspensions of confined swimming particles. *Phys. Rev. Lett.* **95**, 204501.
- HUNTLEY, M. E. & ZHOU, M. 2004 Influence of animals on turbulence in the sea. *Mar. Ecol. Prog. Ser.* **273**, 65–79.
- ISHIKAWA, T. 2009 Suspension biomechanics of swimming microbes. *J. Roy. Soc. Interface* **6**, 815–834.
- ISHIKAWA, T., SIMMONDS, M. P. & PEDLEY, T. J. 2006 Hydrodynamic interaction of two swimming model micro-organisms. *J. Fluid Mech.* **568**, 119–160.
- KATLA, K. & DABIRI, J. O. 2009 A viscosity-enhanced mechanism for biogenic ocean mixing. *Nature* **460**, 624–627.
- KUNZE, E., DOWER, J. F., BEVERIDGE, I., DEWEY, R. & BARTLETT, K. P. 2006 Observations of biologically generated turbulence in a coastal inlet. *Science* **313**, 1768–1770.
- LEPTOS, K. C., GUASTO, J. S., GOLLUB, J. P., PESCI, A. I. & GOLDSTEIN, R. E. 2009 Dynamics of enhanced tracer diffusion in suspensions of swimming eukaryotic microorganisms. *Phys. Rev. Lett.* **103**, 198103.
- LIGHTHILL, M. J. 1952 On the squirring motion of nearly spherical deformable bodies through liquids at very small Reynolds numbers. *Comm. Pure Appl. Math.* **5**, 109–118.
- MAXWELL, J. C. 1869 On the displacement in a case of fluid motion. *Proc. London Math. Soc.* **s1-3** (1), 82–87.
- SAINTILLIAN, D. & SHELLEY, M. J. 2007 Orientational order and instabilities in suspensions of self-locomoting rods. *Phys. Rev. Lett.* **99**, 058102.
- THIFFEAULT, J.-L. & CHILDRESS, S. 2009 Stirring by swimming bodies, <http://arxiv.org/abs/0911.5511>.
- UNDERHILL, P. T., HERNANDEZ-ORTIZ, J. P. & GRAHAM, M. D. 2008 Diffusion and spatial correlations in suspensions of swimming particles. *Phys. Rev. Lett.* **100**, 248101.
- WU, X.-L. & LIBCHABER, A. 2000 Particle diffusion in a quasi-two-dimensional bacterial bath. *Phys. Rev. Lett.* **84**, 3017–3020.

Lecture 2: Stirring by swimming organisms

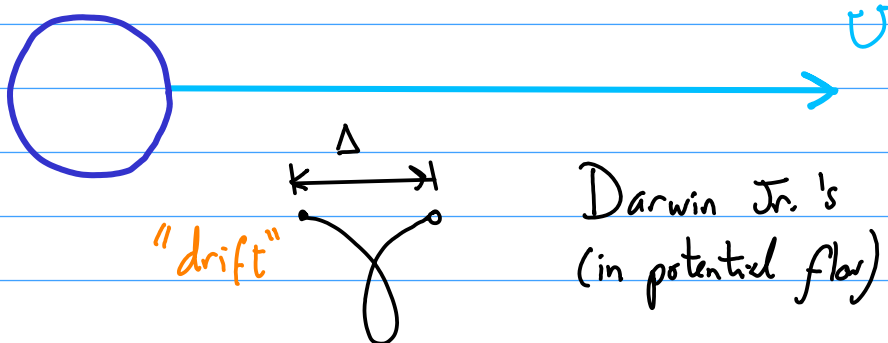
[Slide 1-7]

Vision:



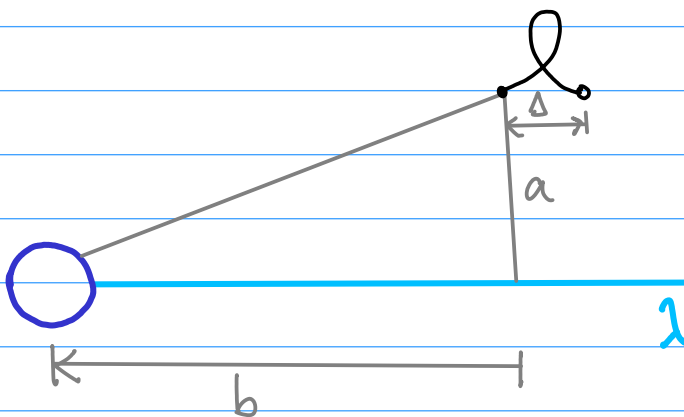
Target particle moves under the influence of many swimmers

Single swimmer: take a cylinder



Darwin Jr.'s "elastica"  
(in potential flow)

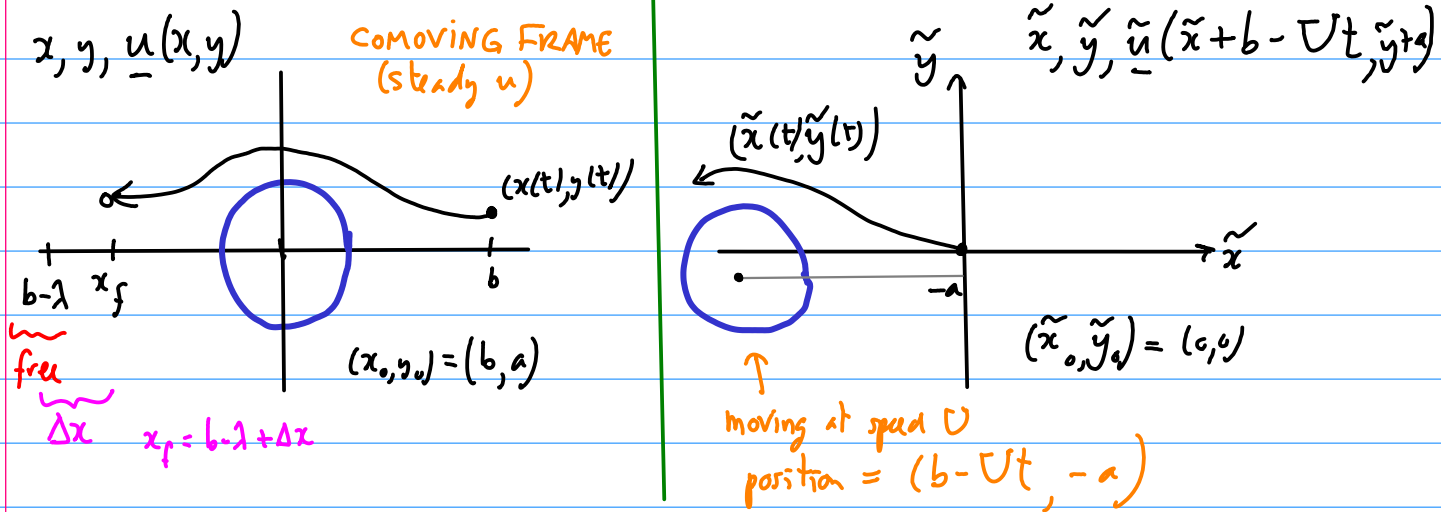
How do we compute  $\Delta$ ?



- Swimming velocity is  $U$  (const.)
- Straight line for distance  $\lambda$ .
- Axially-symmetric, steady swimmer
- $a, b$  are "impact parameters" ( $a > 0$ )

Compute  $\Delta_\lambda(a, b)$

Do 2D case (axisymmetric 3D similar):



$$\frac{d\tilde{x}}{dt} = \tilde{u}(\tilde{x}(t) + b - Ut, \tilde{y}(t) + a), \quad x = \tilde{x} + b - Ut$$

$$\frac{dx}{dt} + U = \tilde{u}(x, y) \Leftrightarrow \frac{dx}{dt} = -U + \tilde{u}(x, y) = u(x, y)$$

$$-\lambda + \Delta x = \int_0^{T=\lambda/U} u(x(t), y(t)) dt$$

need both

autonomous (better!)

For y:  $\frac{dy}{dt} = \tilde{v}(x, y)$

Alternate form:  $T = \frac{\lambda}{U} = \int_b^{x_f} \frac{dx}{u(x, y)}, \quad x_f = b - \lambda + \Delta x$

$$\frac{\lambda}{U} = \int_b^{b-\lambda+\Delta x} \frac{dx}{u} = - \int_b^{b-\lambda+\Delta x} \frac{dx}{|u|} = \int_{b-\lambda+\Delta x}^b \frac{dx}{|u|}$$

how far particle moves when "free-streaming"

$$= \int_{b-\lambda}^b \frac{dx}{|u|} + \int_{b-\lambda+\Delta x}^{b-\lambda} \frac{dx}{|u|}$$

← If particle doesn't move much and  $|b-\lambda|$  "large", then  $|u| \approx U$

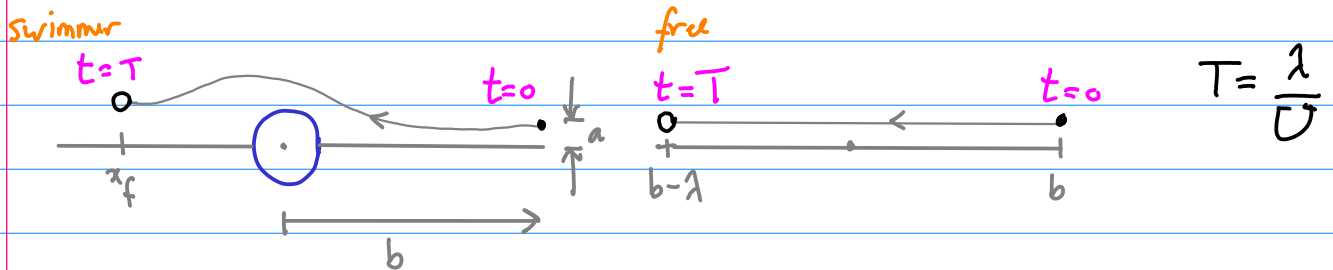
$$\frac{\lambda}{U} \approx \int_{b-\lambda}^b \frac{dx}{|u|} - \frac{\Delta x}{U} \Leftrightarrow \Delta x = \int_{b-\lambda}^b \frac{dx}{|u|} - \frac{\lambda}{U}$$

$$\Delta x \approx \int_{b-\lambda}^b \left( \frac{1}{|u|} - \frac{1}{U} \right) dx$$

Better form, since now can take  $b \rightarrow \infty$ ,  $b-\lambda \rightarrow -\infty$  if we want.

"Rayleigh form"

Intuitively, this formula measures the "lag" behind a free-streaming particle:



2D incompressible:  $u = \frac{\partial \psi}{\partial y}$ ,  $v = -\frac{\partial \psi}{\partial x}$

$$\psi(x_f, a + \Delta y) = \psi(b, a) \quad \text{Same streamline}$$

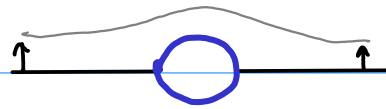
$$\psi(b-\lambda + \Delta x, a + \Delta y) = \psi(b, a) \quad \text{solve for } \Delta y, \text{ given } \Delta x$$

If  $|b-\lambda| \gg \Delta x$ ,  $\psi(b-\lambda, a + \Delta y) \approx \psi(b, a)$  solve for  $\Delta y$

If also  $\Delta y \ll a$ ,  $\psi(b-\lambda, a) + \Delta y \underbrace{\partial_y \psi(b-\lambda, a)}_{u(b-\lambda, a)} \approx \psi(b, a)$

$$\Delta y \approx \frac{\psi(b, a) - \psi(b-\lambda, a)}{u(b-\lambda, a)}$$

Now for infinite  $\lambda$ , we have:



$$\Delta y = \frac{\psi(\infty, a) - \psi(-\infty, a)}{U} = 0!$$

$\Delta y = 0$  for  $\lambda \rightarrow \infty, b-1 \rightarrow -\infty$

Cylinder in potential flow:

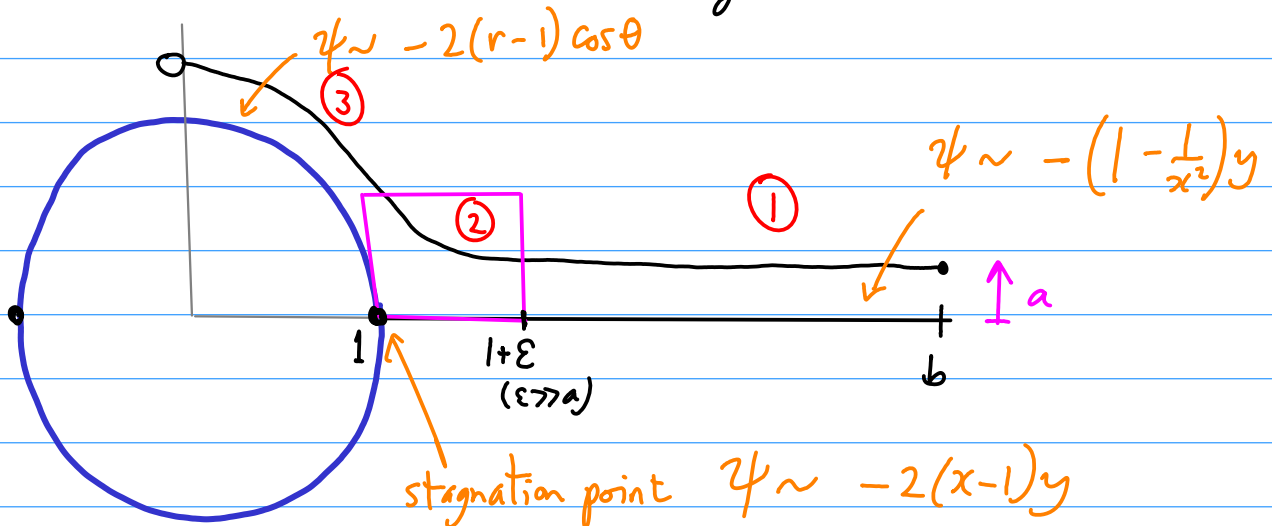
$$\psi(x, y) = -Uy \left( 1 - \frac{l^2}{x^2 + y^2} \right) \quad \text{Set } U = l = 1$$

Far away,  $\tilde{\psi} \sim \frac{y}{r^2}$ , so  $\tilde{u} \sim \frac{1}{r^2}$  in fixed frame

However, trajectories are almost closed,  $\frac{1}{a}$

Net result is  $\Delta(a) \sim \frac{1}{a^3}$  Much smaller  $\frac{1}{a^3}$  than overall excursion!

The limit  $a \ll 1$  is more interesting:



free flow  $\cup$  (to the left)

Need to calculate  $\int \left(\frac{1}{u} + 1\right) dx$  over each region ①, ②, ③.

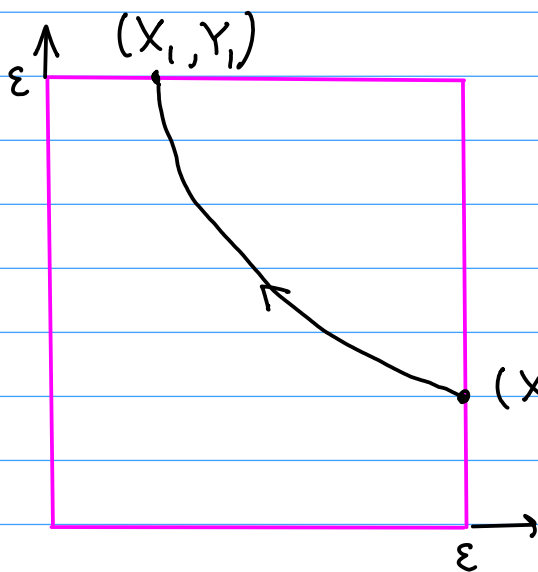
Region 1:  $\psi_0 = \psi(b, a) = -(1 - b^{-2})a$

$$u = -(1 - x^{-2}), \quad T_1 = \int_b^{1+\varepsilon} \left(\frac{1}{u} + 1\right) dx = \int_b^{1+\varepsilon} \frac{dx}{1 - x^2}$$

transit time

After using  $\varepsilon \ll 1, b \gg 1$ :  $T_1 \approx \frac{1}{2} \log(2/\varepsilon) + \varepsilon/4 - b^{-1} + O(\varepsilon^2, b^{-2})$

Region 2:



$$X = x - 1, \quad Y = y$$

$$\psi = -2XY$$

At  $X_0, Y_0$ ,

$$\psi = -2X_0Y_0 = -(1 - b^{-2})a$$

$$\Rightarrow Y_0 = \frac{a}{2\varepsilon}$$

$$(X_0, Y_0) = (\varepsilon, a/2\varepsilon)$$

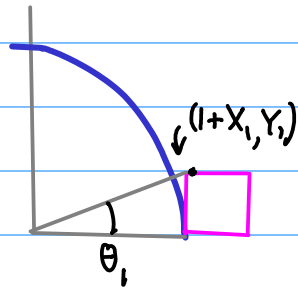
But also  $Y_1 = \varepsilon$ , so  $X_1 = a/2\varepsilon$ .

$$T_2 = \int_{X_0}^{X_1} \left(\frac{1}{u} + 1\right) dx = \int_{\varepsilon}^{a/2\varepsilon} \left(\frac{1}{(-2X)} + 1\right) dx = -\frac{1}{2} \log\left(\frac{a}{2\varepsilon}\right) + \frac{a}{2\varepsilon} - \varepsilon$$



$$u = -1 + \frac{\cos 2\theta}{r^2}$$

Region 3:



$$T_3 = \int_{\theta_1}^{\pi/2} \left( \frac{1}{u} + 1 \right) \frac{dx}{d\theta} d\theta$$

$$= \frac{1}{2} \int_{\theta_1}^{\pi/2} \frac{\cos 2\theta}{\sin \theta} d\theta, \quad \theta_1 \text{ small.}$$

*u = -r \sin \theta*

$$T_3 \approx -1 + \frac{1}{2} \log 2 - \frac{1}{2} \log \theta_1 + O(\theta_1^2)$$

$$\tan \theta_1 = \frac{Y_1}{1+X_1} = \frac{\varepsilon}{1+a/\varepsilon} \approx \varepsilon (1 - a/\varepsilon) = \varepsilon - a$$

$$\therefore T_3 \approx -1 + \frac{1}{2} \log 2 - \frac{1}{2} \log \varepsilon + \frac{1}{2} \frac{a}{\varepsilon} + O((a/\varepsilon)^2)$$

Add everything together:

$$T = T_1 + T_2 + T_3 = \left( \frac{1}{2} \log(2/\varepsilon) - 6^{-1} \right) + \left( -\frac{1}{2} \log(a/2\varepsilon) \right)$$

*divergent log ε terms cancel*

$$T = -\frac{1}{2} \log a - 1 + \frac{3}{2} \log 2 - 6^{-1} \quad \text{to leading order.}$$

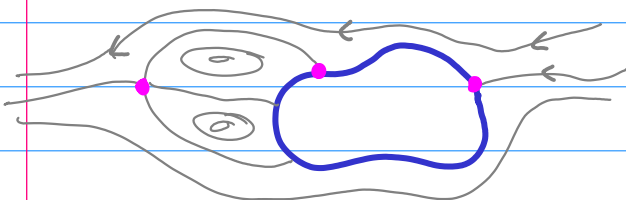
*Dominant term for small a.*

*Comes only from region 2, near stagnation point.*

*T → ∞ for a → 0.*

*particle gets stuck!*

The total drift is given by  $2T$ , since the body is fore-aft symmetric.



In general, the coefficient of  $\log a$  is given by summing over the linearization coeffs for each (hyperbolic) stagnation pt. encountered. *(not true for no-slip!)*

Note that to pick up the  $-\log a$  contribution, the target particle must come in the vicinity of the stagnation points

$$\Delta_{\lambda}(a, b) = \begin{cases} -\log a & , 0 \leq b \leq 1 \\ \text{(neglect)} & , \text{otherwise} \end{cases}$$

Effective diffusivity:

What we have:  $\Delta_{\lambda}(a, b)$       Need: effective diffusivity

Constants:  $U, l, \lambda, n$       Random:  $a, b$

↑  
number  
density

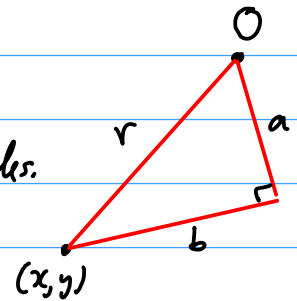
If we pick a random point in space, what is PDF of  $a, b$ ?

$$\frac{1}{V} dx dy \rightarrow p(a, b) da db$$

Volume →

Assume target particle at origin:

- Hard way: compute  $(a, b)$  from  $(x, y)$ , transform variables.
- Easier: note  $(a, b)$  just like  $(x, y)$ , but rotated, and  $a > 0$ .



↓  
irrelevant, by isotropy

Hence:  $\frac{1}{V} dx dy = \frac{1}{V} 2 da db$       2D

In 3D,  $\frac{1}{V} dx dy dz = \frac{1}{V} 2\pi a da db$  3D ← like cylindrical coordinates, integrated over  $\theta$ .

Now, assume target particle is "kicked" by swimmer:

$$\underline{x}_N = \underbrace{\underline{x}_0}_0 + \sum_{k=1}^N \Delta_{\lambda}(a_k, b_k) \hat{r}_k \quad a_k, b_k, \hat{r}_k \text{ random independent \& identical}$$

On average, particle goes nowhere:  $\langle \underline{x}_N \rangle = 0$

$$\langle |\underline{x}_N|^2 \rangle = \sum_{k=1}^N \langle \Delta_{\lambda}^2(a_k, b_k) \hat{r}_k \cdot \hat{r}_k \rangle + \text{vanishing cross terms } \langle \hat{r}_k \rangle = 0$$

$$= N \langle \Delta_{\lambda}^2(a, b) \rangle$$

$$= \frac{N}{V} \int \Delta_{\lambda}^2(a, b) 2 da db$$

2D elapsed time

What is  $N$ ? # of "collisions"  $N = t/T$  ← "mean free time"

$$T = \lambda / U \quad \lambda = \text{mean free path}$$

Hence,  $\langle |x(t)|^2 \rangle = \frac{Ut}{\lambda} \frac{1}{V} \int \Delta_{\lambda}^2(a, b) 2 da db$  Only one swimmer, so  $\frac{1}{V} = n$ , the number density

What about this?

$$\langle |x(t)|^2 \rangle = \frac{2Ut}{\lambda} \int \Delta_{\lambda}^2(a, b) da db = 2 d n t = 4 n t$$

↑ dimension of space      ↑ effective diff

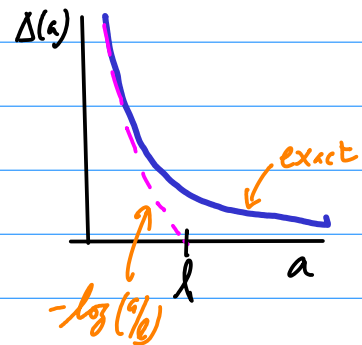
This depends on integral of squared displacement.  
Actual mass displaced could be 0!

$$\kappa = \begin{cases} \frac{U_n}{2\lambda} \int \Delta_\lambda^2(a,b) da db & \text{2D} \\ \frac{\pi U_n}{3\lambda} \int \Delta_\lambda^2(a,b) a da db & \text{3D} \end{cases}$$

effective diffusivity

Recall our approximate form for cylinder:  $\Delta_\lambda(a,b) = \begin{cases} -\log a & 0 \leq b \leq \lambda \\ 0 & \text{otherwise} \end{cases}$

Cylinder.  $\kappa \simeq \frac{2 U_n}{\lambda} \int_0^\lambda \log^2\left(\frac{a}{\lambda}\right) da$



$$\int \log^2 x dx = x \log^2 x - 2x \log x + 2x$$

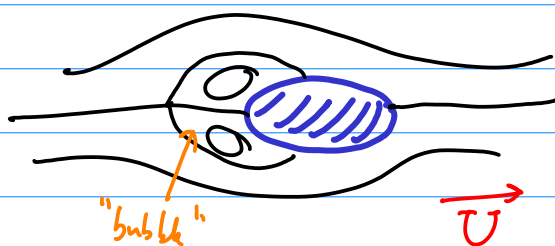
$$\int_0^1 \log^2 x dx = 2 \quad (\text{numerical answer: } 2.37)$$

$$\kappa \simeq U_n l^3 \quad (\text{numerical: } \kappa = 1.19 U_n l^3)$$

Note that this is completely independent of  $\lambda$ !

⇒ see computer simulations

Another example: consider a swimmer with a bubble "wake":



If a particle is trapped in the bubble, moves by  $\lambda$ .

$$\Delta_\lambda(a, b) = \begin{cases} \lambda, & \text{particle inside bubble} \\ \text{neglect}, & \text{otherwise} \end{cases}$$

↙ Total volume of bubble

$$6\kappa = \frac{2U_n}{\lambda} \int_{\text{inside bubble}} \lambda^2 da db = U_n \lambda V_{\text{bubble}}$$

↑ The 2 goes away since  $2 da db$  is volume element

$$\kappa = \frac{1}{6} U_n \lambda V_{\text{bubble}}$$

$V_{\text{bubble}} = \text{area in 2D}$   
 $= \text{volume in 3D}$

Now this depends on path length  $\lambda$ . This can be much larger than for untrapped fluid. Real swimmer probably in between

(Viscous swimmer with boundary layer:  $\kappa \sim \log \lambda$ )

swimmer	$\lambda$ -dependence	far/near field dominance
potential (slip)	none	near
viscous (slip) squirmers	none	far
viscous (no-slip)	$\log \lambda$	near
trapped	$\lambda$	near

More topics:

- Green-Kubo
- Wikus
- Far field
- Levy flights
- Stratification

# GFD Lectures: Swimming & Swirling

2010/06/24

## Lecture 3: Local Stretching Theories

Antonsen et al. '96  
Belkovich & Foxen '99

$$(AD) \quad \partial_t \theta + \underline{u} \cdot \nabla \theta = \kappa \nabla^2 \theta.$$

For this lecture, think of  $\theta$  as a "patch"

Last time we examined  $\underline{u} = (1x, -1y)$ . Let's try something more general:

$$\underline{u} = \underline{U} + \underline{x} \cdot A, \quad \nabla \cdot \underline{u} = \text{trace } A = 0.$$

const.

$$\text{Let } \langle f \rangle = \int_{\Omega} f \, dV \quad (\Omega = \mathbb{R}^2 \text{ or } \mathbb{R}^3)$$

Solve (AD) using moments:

$$c_i = \frac{\langle x_i \theta \rangle}{\langle \theta \rangle} \quad (\partial_t \langle \theta \rangle = 0)$$

$$(AD) \rightarrow \partial_t \langle x_i \theta \rangle + \langle x_i \nabla \cdot ((\underline{U} + \underline{x} \cdot A)\theta) \rangle = \kappa \langle x_i \nabla^2 \theta \rangle$$

$$\partial_t \langle x_i \theta \rangle - \langle (U_j + x_l A_{lj}) \theta \cdot \underbrace{\partial_j x_i}_{\delta_{ji}} \rangle = \kappa \langle 0 \rangle$$

$$\langle \theta \rangle \partial_t c_i - U_i \langle \theta \rangle - A_{li} \langle \theta \rangle c_l = 0$$

$$\partial_t \underline{c} = \underline{U} + \underline{c} \cdot A$$

Motion of center of mass

Next moments:

$$m_{ij} = \frac{\langle x_i x_j \theta \rangle}{\langle \theta \rangle} - c_i c_j$$

Again, multiply (AD) by  $x_i x_j$  and  $\langle \cdot \rangle$ .

$$\langle x_i x_j \nabla \cdot (\underline{u} \theta) \rangle = \langle x_i x_j \partial_h ((U_h + x_l A_{lh}) \theta) \rangle$$

$$= - \langle (U_h + x_l A_{lh}) (\delta_{ih} x_j + x_i \delta_{jh}) \theta \rangle$$

$$= -U_i c_j \langle \theta \rangle - U_j c_i \langle \theta \rangle - A_{li} \underbrace{\langle x_l x_j \theta \rangle}_{\langle \theta \rangle (m_{lj} + c_l c_j)} - A_{lj} \underbrace{\langle x_l x_i \theta \rangle}_{\langle \theta \rangle (m_{li} + c_l c_i)}$$

$$\begin{aligned} \partial_t (c_i c_j) &= c_i \partial_t c_j + c_j \partial_t c_i \\ &= c_i (U_j + A_{lj} c_l) + c_j (U_i + A_{li} c_l) \end{aligned}$$

$$\langle x_i x_j \nabla \cdot (\underline{u} \theta) \rangle = - (\partial_t (c_i c_j) + A_{li} m_{lj} + A_{lj} m_{li}) \langle \theta \rangle$$

That's the hard part! Next:

$$\langle x_i x_j \nabla^2 \theta \rangle = \langle \theta \nabla^2 (x_i x_j) \rangle = 2 \langle \theta \rangle \delta_{ij}$$

So finally:

$$\partial_t m_{ij} = A_{li} m_{lj} + A_{lj} m_{il} + 2\kappa \delta_{ij}$$

Let  $(M)_{ij} = m_{ij}$  (symmetric matrix)

$$\partial_t M = M \cdot A + A^T \cdot M + 2\kappa I$$

Moment of inertia equation.  
"spread" of patch

Time to solve these equations!

$$\underline{c}(t) = \underline{c}(0) \cdot e^{At} + \underline{U} \cdot \int_0^t e^{A(t-\tau)} d\tau$$

$$M(t) = e^{A^T t} \cdot M(0) \cdot e^{At} + 2\kappa \int_0^t e^{A^T(t-\tau)} \cdot e^{A(t-\tau)} d\tau$$

Can't write as  $e^{(A+A^T)(t-\tau)}$   
 unless  $[A, A^T] = 0$  Normal matrix

Let  $M = RDR^T$ ,  $R$  orthogonal,  $D$  diagonal

$$\dot{M} = \dot{R}DR^T + R\dot{D}R^T + R\dot{R}^T = RDR^T A + A^T RDR^T + 2\kappa I$$

$$R^T \dot{R} D + D \dot{R}^T R + \dot{D} = D \underbrace{R^T \dot{R} R}_{\tilde{A}} + R^T \underbrace{\dot{R} R}_{\tilde{A}^T} D + 2\kappa I$$

Now:  $\frac{d}{dt}(R^T R) = \dot{R}^T R + R^T \dot{R} = \frac{d}{dt}(I) = 0$ , so  $(R^T \dot{R})^T = \dot{R}^T R = -R^T \dot{R}$

$\Rightarrow R^T \dot{R}$  is antisymmetric

$$[R^T \dot{R} D]_{ii} = (R^T \dot{R})_{ik} D_{ki} = (R^T \dot{R})_{ii} D_{ii} = 0$$

(no sum)

$$\dot{D}_{ii} = D_{il} \tilde{A}_{li} + \tilde{A}_{li} D_{li} + 2\kappa$$

$$\dot{D}_{ii} = 2\tilde{A}_{ii} D_{ii} + 2\kappa$$


Write  $D_{ii} = e^{2p_i}$ , with  $p_1 \geq p_2 \geq \dots \geq p_d$ .

$$\dot{D}_{ii} = 2e^{2p_i} \dot{p}_i$$

$$\dot{p}_i = \tilde{A}_{ii} + \kappa e^{-2p_i}$$



Great equation:  $\tilde{A} = R^T A R \rightarrow$  rotated velocity gradient matrix.

$e^{-2p_i} \rightarrow$  negligible unless  $p_i < 0$  

compression

Moral: the directions of contraction or compression play an important role.

Now we need an equation for  $R$ : off-diagonal terms.

$$[R^T \dot{R} D]_{ij} = (R^T \dot{R})_{il} D_{lj} = (R^T \dot{R})_{ij} D_{jj}, \quad i \neq j$$

$$[D \dot{R}^T R]_{ij} = D_{il} (\dot{R}^T R)_{lj} = D_{ii} (\dot{R}^T R)_{ij} = - (R^T \dot{R})_{ij} D_{ii}$$

(no sum over  $i, j$ )

$$(D_{jj} - D_{ii})(R^T \dot{R})_{ij} = D_{ii} \tilde{A}_{ij} + \tilde{A}_{ji} D_{jj}$$

$$(R^T \dot{R})_{ij} = \Omega_{ij} \iff \dot{R} = R \Omega$$

$$\Omega_{ij} = \frac{e^{2p_i} \tilde{A}_{ij} + e^{2p_j} \tilde{A}_{ji}}{e^{2p_j} - e^{2p_i}}$$

Not completely obvious what this means...

(= 0 for  $i=j$ )

Almost always true for long time, esp. in 2D, 3D with  $p_1 + p_2 (+p_3) = 0$ . Usually a symmetry can break this, or fails locally.

Assume we have separation between the eigenvalues:  $e^{2p_i} \gg e^{2p_j}, i < j$

$$\Omega_{ij} \simeq \frac{e^{2p_i} \tilde{A}_{ij} + e^{2p_j} \tilde{A}_{ji}}{e^{2p_j} - e^{2p_i}} = -\tilde{A}_{ij}, \quad i < j$$

$$\Omega_{ij} \approx \begin{cases} -\tilde{A}_{ij}, & i < j \\ \tilde{A}_{ji}, & i > j \end{cases}$$

(large t)

Independent of eigenvalues!

Can solve:  $\dot{p}_i = \tilde{A}_{ii} p_i + \kappa e^{-2p_i}$  since  $\tilde{A}$  indep. of  $p_i$

$$p_i(t) = p_{i0} + A_i(t) + \frac{1}{2} \log \left[ 1 + 2\kappa e^{-2p_{i0}} \int_0^t \exp(-2A_i(t')) dt' \right]$$

where

$$A_i = \int_0^t \tilde{A}_{ii}(t') dt'$$

diffusion

When diffusion negligible:  $p_i(t) = p_{i0} + \int_0^t \tilde{A}_{ii}(t') dt'$

In fact, solving the equations for  $p_i$ ,  $R$ ,  $\kappa=0$ , is not a bad way of computing Lyapunov exponents:

$$\lambda_i = \lim_{t \rightarrow \infty} \frac{1}{t} p_i(t)$$

$$\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_d$$

(Some numerical issues regarding orthogonality of  $R$ .)

Convergence: famous Oseledec Multiplicative ergodic theorem

Now comes the stochastic part: could have formulated things in terms of an SDE. But we take a shortcut:

$$p_i(t) = p_{i0} + \sum_t \tilde{A}_{ii} \leftarrow \text{sum of uncorrelated random numbers (more later)}$$

What is PDF of  $p_i(t)$ ?

Recall: if  $x_i$  are i.i.d. and  $X = \sum_{i=1}^N x_i$       $\overline{x_i} = \xi$   
 $\overline{x_i^2} - \overline{x_i}^2 = \sigma^2$

What is PDF of  $X$ ? **CENTRAL LIMIT THEOREM**

$$P(X, N) \sim \frac{1}{\sqrt{2\pi N\sigma^2}} \exp\left(-\frac{(X - N\xi)^2}{2N\sigma^2}\right)$$

← mean of  $X$

Valid for: (i)  $N \gg 1$ ; (ii)  $X - N\xi < \sqrt{N}\sigma$

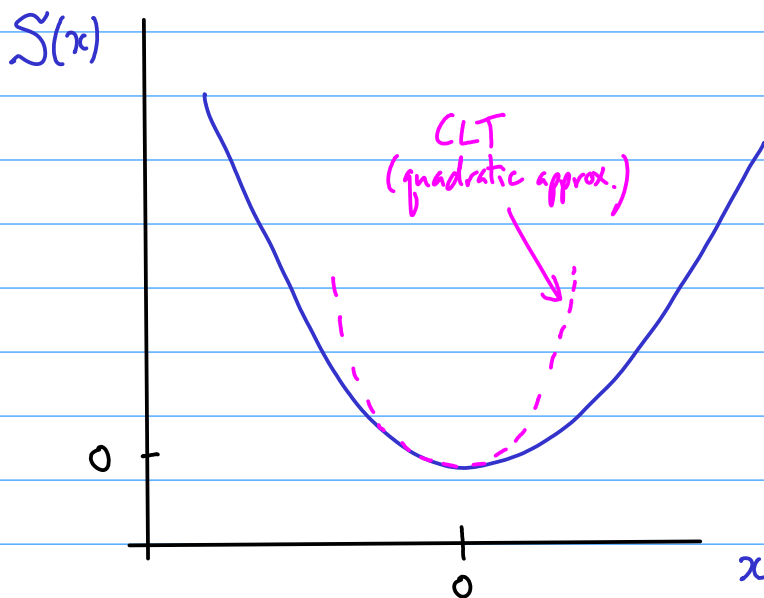
This second restriction is less commonly stated: it tells us that the CLT is not valid in the tails. The CLT tends to vastly underestimate the probability of rare events, or black swans as is trendy to call them these days. *These tails matter for mixing.*

More generally,

$$P(X, N) \sim \exp\left(-N S\left(\frac{X - N\xi}{N}\right)\right)$$

*Large deviation form*

$S(x)$  is a convex function with  $S(0) = S'(0) = 0$ .



$$S(x) = \overset{\circ}{S(0)} + \overset{\circ}{S'(0)}x + \frac{1}{2}S''(0)x^2 + \dots$$

$$S\left(\frac{X-N\xi}{N}\right) = \frac{1}{2}S''(0)\frac{(X-N\xi)^2}{N^2} + \dots$$

$$\exp\left(-NS\left(\frac{X}{N} - \xi\right)\right) \sim \exp\left(-S''(0)\frac{(X-N\xi)^2}{2N}\right)$$

Compare to CLT:  $S''(0) = \frac{1}{\sigma^2}$

Can also express in terms of mean:  $x = \frac{X}{N}$

$$P(x, N) \sim \exp(-NS(x - \xi))$$

Example: Binomial distribution for  $x_i$  (-1 or 1, mean 0)

$$p(x_i) = \frac{1}{2}\delta(x_i + 1) + \frac{1}{2}\delta(x_i - 1)$$

$$e^{-s(k)} = \int p(\xi) e^{-ik\xi} d\xi \quad \text{characteristic function}$$

$$= \frac{1}{2}(e^{ik} + e^{-ik}) = \cos k$$

For the mean  $x = \frac{1}{N} \sum x_i$ :

$$P(x, N) = \int p(x_1) \dots p(x_N) \delta\left(\frac{x_1 + \dots + x_N}{N} - x\right) dx_1 \dots dx_N$$

$$e^{-S(k)} = \int P(x, N) e^{-ikx} dx$$

$$= \int p(x_1) \dots p(x_N) e^{-ik(x_1 + \dots + x_N)/N} dx_1 \dots dx_N$$

$$= \prod_{i=1}^N \int p(x_i) e^{-ikx_i/N} dx_i = \left( \int p(\xi) e^{-ik\xi/N} d\xi \right)^N$$

Inverse Fourier  $\rightarrow$

$$= \left( e^{-s(k/N)} \right)^N = \cos^N\left(\frac{k}{N}\right)$$

$$P(x, N) = \frac{1}{2\pi} \int e^{-S(k)} e^{ikx} dk = \frac{1}{2\pi} \int \cos^N\left(\frac{k}{N}\right) e^{ikx} dk$$

$$= \frac{N}{2\pi} \int \cos^N K e^{iNKx} dK, \quad K = k/N.$$

$$= \frac{N}{2\pi} \int e^{N(\log \cos K + iKx)} dK$$

For  $N$  large, look for saddle (stationary) point:

$$\frac{d}{dK} \underbrace{(\log \cos K + iKx)}_{H(K, x)} = -\tan K + ix = 0 \quad \text{when } K = K_{sp}.$$
$$\tan K_{sp} = -ix$$

$$H(k, x) = H(k_{sp}, x) + H'(k_{sp}, x)(k - k_{sp}) + \frac{1}{2} H''(k_{sp}, x)(k - k_{sp})^2 + \dots$$

With this approximation the inverse transform is a Gaussian integral.

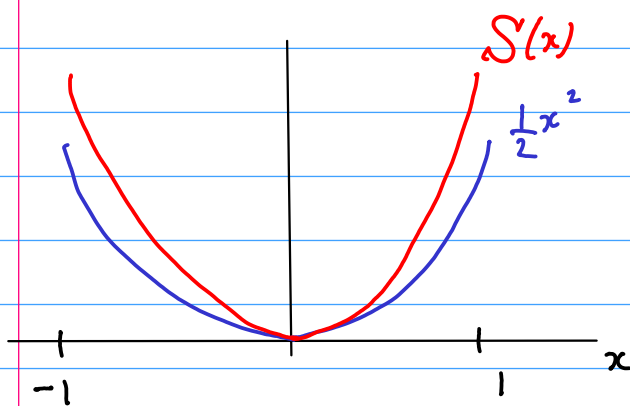
Get finally (skip some steps... see Aosta lecture notes)

$$P(x, N) = \sqrt{\frac{NS''(0)}{2\pi}} e^{-NS(x)}, \text{ with}$$

$$S(x) = -\frac{1}{2}(x+1) \log\left(\frac{1-x}{x+1}\right) + \log(1-x) \quad -1 \leq x \leq 1$$

Note  $S(0) = 0$ ,  $S'(x) = -\frac{1}{2} \log\left(\frac{1-x}{x+1}\right)$ , so  $S'(0) = 0$

$$S''(x) = \frac{1}{1-x^2}, \text{ so } S''(0) = 1$$



$S(x)$  is called the  
rate function  
Cramer function  
entropy function

For this case the Gaussian form overestimates the probability in the tails (not typical)

More refs:  
Falkovich et al. 2001  
Zeldovich et al. 1984

What this has to do with mixing?

For  $\kappa=0$ , we argued that if  $A_{ii}$  is a random var., then  $\rho_i$  are distributed according to large deviation form (for large  $t$ ).

$$P(\rho_1, \rho_2, t) \sim \exp\left(-t S\left(\frac{\rho_1 - \lambda_1 t}{t}\right)\right) \Theta(\rho_1) \delta(\rho_1 + \rho_2)$$

in 2D ( $d=2$ ). (return 3D later)

ordering  $\rho_1 \geq \rho_2$       incompressibility

$$\lambda_1 = \lim_{t \rightarrow \infty} \frac{\rho_1}{t} = \text{Lyapunov exp.} \geq 0 \quad (\text{for chaotic flows})$$

$\Theta(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases}$  step function

What happens with diffusion? Recall "filament":  
The contracting direction "stabilizes" near the Batchelor width  $\sqrt{\frac{\kappa}{\lambda_1}}$ .



or "freezes"

Shraiman & Siggia 1994

Chertkov et al. 1997

Balkovsky & Fouxon 1999

$$P(\rho_1, \rho_2, t) \sim \exp\left(-t S\left(\frac{\rho_1 - \lambda_1 t}{t}\right)\right) P_{\text{stab}}(\rho_2)$$

stationary distribution.

If we assume, say, an initial Gaussian "patch" of passive scalar, then the concentration at a point scales as

$$\Theta(\underline{x}, t) \sim \frac{\text{total concentration}}{\text{volume}} \sim (\det M)^{-1/2} = \exp\left(-\sum \rho_i\right)$$

indep. of  $\underline{x}$

Expected value:

$$\langle \theta^\alpha \rangle(t) \sim \int e^{-\alpha Z p_i} \exp\left(-t S\left(\frac{p_i - \lambda_i}{t}\right)\right) P_{\text{stab}}(p_2) dp_1 dp_2$$

Non-exponential  
function of  $t$   
(neglect)

$$\sim \int e^{-\alpha p_i} \exp\left(-t S\left(\frac{p_i - \lambda_i}{t}\right)\right) dp_i \leftarrow \text{Do the } p_2 \text{ integral}$$

Use  $h_i = p_i/t$  as variable:

$$\langle \theta^\alpha \rangle(t) \sim \int e^{-\alpha h_i t} e^{-t S(h_i - \lambda_i)} dh_i$$

$$\langle \theta^\alpha \rangle(t) \sim \int e^{-t(\alpha h + S(h - \lambda))} dh$$

$h_i \rightarrow h$   
 $\lambda_i \rightarrow \lambda$

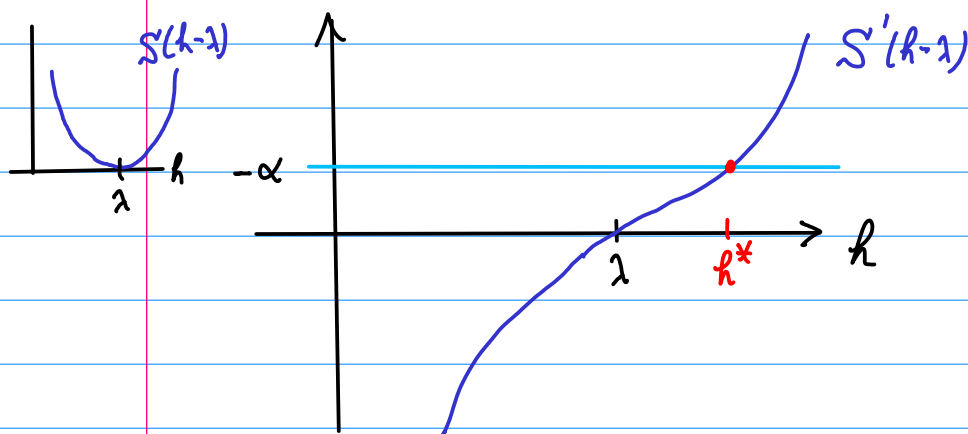
expected  
value,  
not  
integral



$$\text{Let } H(h) = \alpha h + S(h-1).$$

For large time, the integral is dominated by saddle point  $h^*$ :

$$H'(h^*) = 0 = \alpha + S'(h^*-1)$$



Because of convexity of  $S$ ,  $h^*$  is unique.

$$\text{We then have } H(h) = H(h^*) + \frac{1}{2} H''(h^*) (h-h^*)^2 + \dots$$

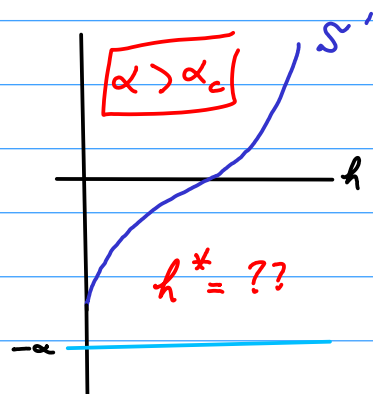
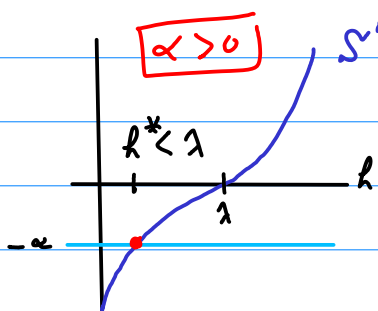
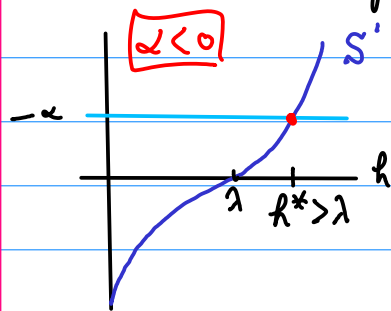
which we use to evaluate the integral. Find:

$$\langle \theta^\alpha \rangle (t) \sim e^{-\sigma_\alpha t}, \text{ where } \sigma_\alpha = H(h^*)$$

Note that we do not have  $\langle \theta^\alpha \rangle \sim e^{-\alpha t}$ , which would be the case if  $\theta$  decayed the same pointwise everywhere.

$$\text{Kurtosis} \sim \frac{\langle \theta^\alpha \rangle}{\langle \theta \rangle^\alpha} \sim e^{-\sigma_\alpha t}$$

So how do we expect  $\sigma_\alpha$  to behave?

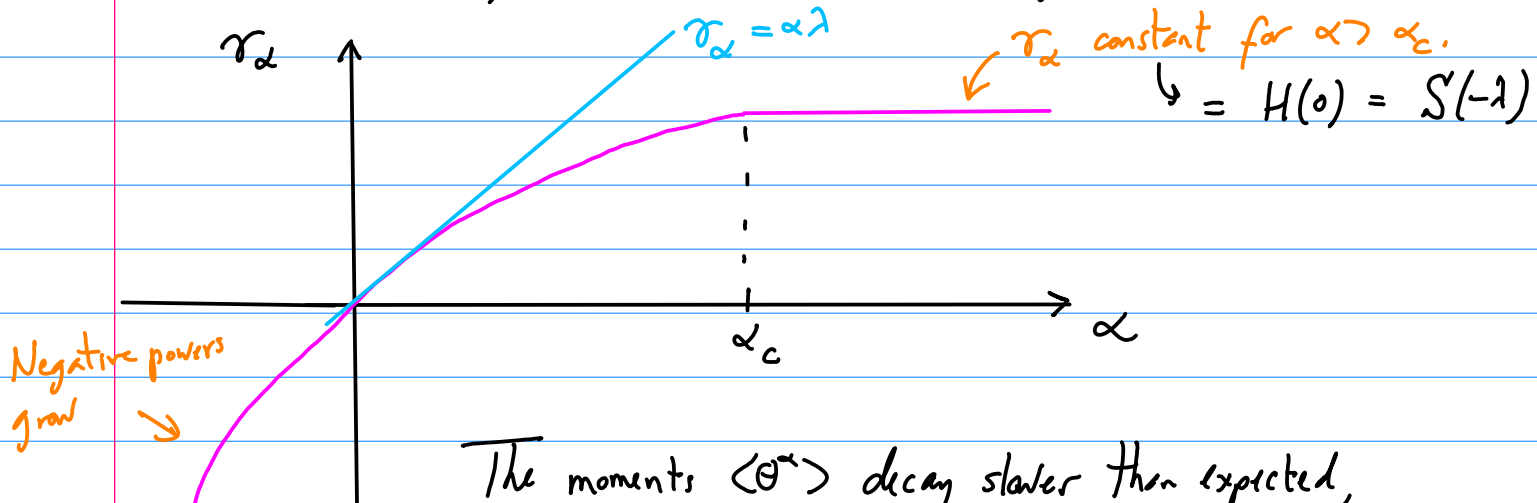


We have  $\tau_0 = 0$ , since  $S'(h-1) = 0$  at  $h=1$ , and  $S(0) = 0$ .

$\hookrightarrow \langle \theta^0 \rangle = 0$  ok!

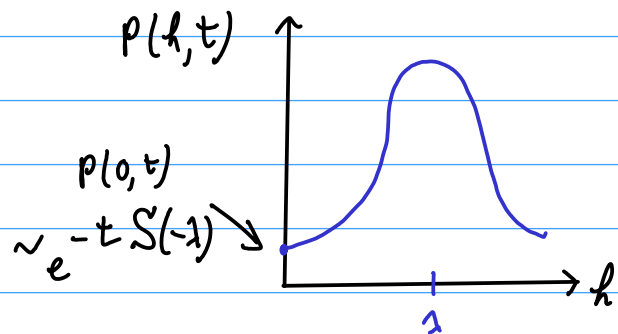
Hence,  $\tau_\alpha$  changes sign at  $\alpha = 0$ .

What happens for  $\alpha > \alpha_c$ ? No saddle point, since would require  $h^* < 0$  (not allowed). Hence, take  $h^* = 0$  (slowest decay)



The moments  $\langle \theta^\alpha \rangle$  decay slower than expected, all the more so for larger  $\alpha$ : INTERMITTENCY

Why the leveling-off? For large  $\alpha$ ,  $\langle \theta^\alpha \rangle$  is dominated by realizations with large  $\theta$ , that is, having experienced little stretching. For  $\alpha > \alpha_c$ , these are all that matter, so  $\tau_\alpha$  is the rate of decay of realizations with no stretching,



All this was for realizations of just one blob, but can scale up to many blobs. (See papers quoted) Validity of theory still controversial, but should work for times that are not too long, scales not too large.

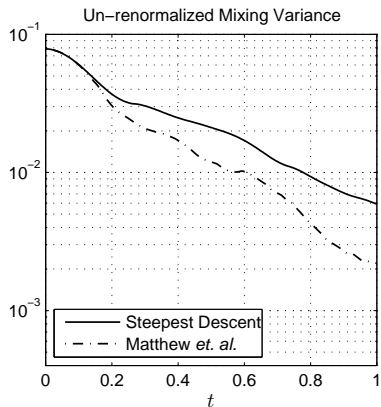
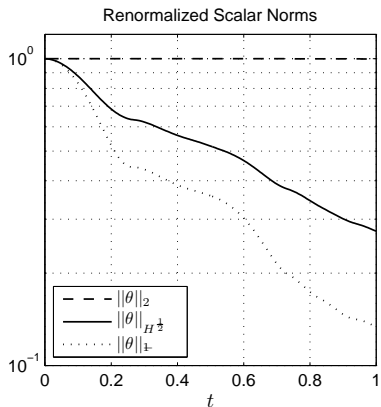
# Lecture 4: Mixing in the presence of sources and sinks

Jean-Luc Thiffeault

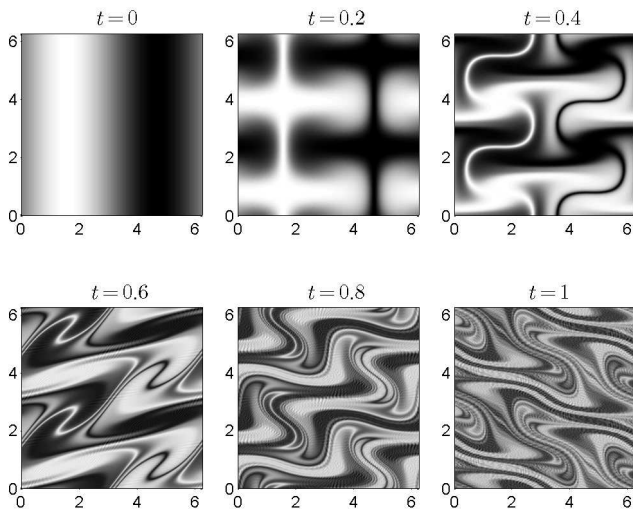
Department of Mathematics  
University of Wisconsin – Madison

Summer Program in Geophysical Fluid Dynamics, Woods Hole  
28 June 2010

# Optimal control vs steepest descent

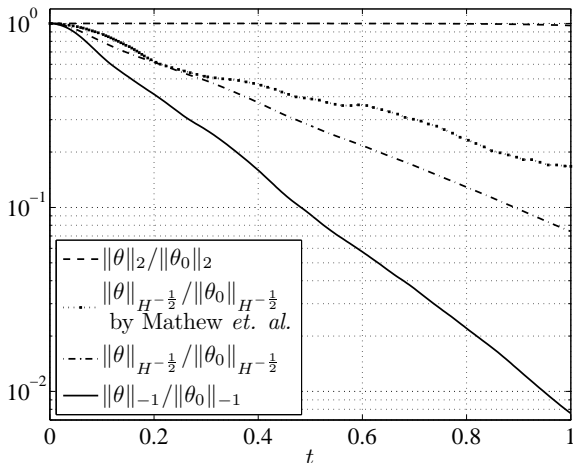


(from Lin, Thiffeault, Doering.)

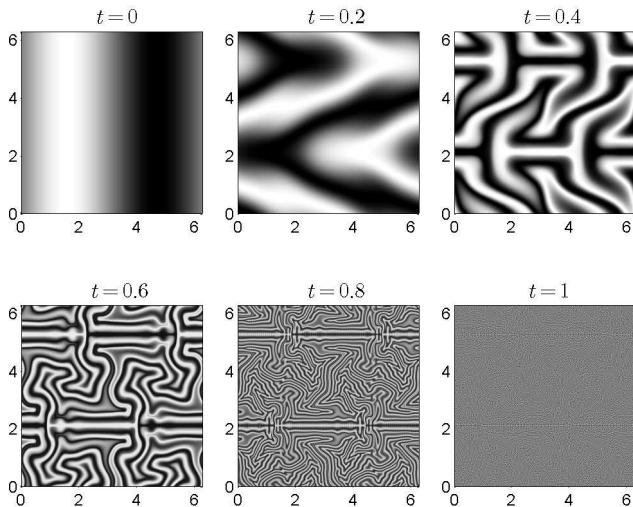
Steepest descent of  $\dot{H}^{-1}$ 

(from Lin, Thiffeault, Doering.)

# Optimal control vs steepest descent: any flow

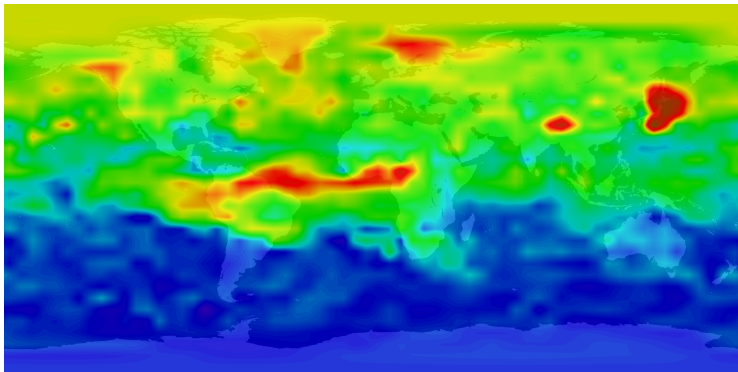


(from Lin, Thiffeault, Doering.)

Steepest descent of  $\dot{H}^{-1}$ : any flow

(from Lin, Thiffeault, Doering.)

## Sources and sinks: CO in the atmosphere



Red corresponds to high levels of CO (450 parts per billion) and blue to low levels (50 ppb). Note the immense clouds due to grassland and forest fires in Africa and South America. (Photo NASA/NCAR/CSA.)



# Matlab code: Minimize norm with fmincon

```
function [psi, Effq] = velopt(psi0, src, kappa, q, L, scalefac)

% Problem parameters for Matlab's optimizer fmincon.
psi0 = psi0(:); problem.x0 = psi0(2:end);
problem.objective = @(x) normHq2(x, src, kappa, q, L, scalefac);
problem.nonlcon = @(x) nonlcon(x, src, kappa, q, L, scalefac);
problem.solver = 'fmincon';
problem.options = optimset('Display', 'iter', 'TolFun', 1e-10, ...
    'GradObj', 'on', 'GradConstr', 'on', ...
    'algorithm', 'interior-point');

[psi, Hq2] = fmincon(problem);

% Mixing efficiency: call normHq2 with no flow to get pure-conduction solution.
Effq = sqrt(normHq2(zeros(size(psi)), src, kappa, q, L, scalefac) / Hq2);

psi = reshape([0; psi], size(src)); % Convert psi back into a square grid
```

## Matlab code: Right-hand side function

```
function [varargout] = normHq2(psi,src,kappa,q,L,scalefac)

N = size(src,1); src = src(:);

% 2D Differentiation matrices and negative-Laplacian
[Dx,Dy,Dxx,Dyy] = Diffmat2(N,L); mlap = -(Dxx+Dyy);
if q ~= 0 && q ~= -1, error('This code only supports q = 0 or -1.');
```

```
end

psi = [0;psi]; ux = Dy*psi; uy = -Dx*psi;
ugradop = diag(sparse(ux))*Dx + diag(sparse(uy))*Dy;

if q == 0
    Aop2 = (-ugradop + kappa*mlap);
elseif q == -1
    Aop2 = mlap*(-ugradop + kappa*mlap);
end
Aop1 = (ugradop + kappa*mlap)*Aop2;
% Solve for chi, dropping corner point to fix normalisation.
chi = [0; Aop1(2:end,2:end) \ src(2:end)];
theta = Aop2*chi;

% The squared H^q norm of theta.
varargout{1} = L^2*sum(theta.^2)/N^2 * scalefac;

if nargin > 1
    % Gradient of squared-norm Hq2.
    gradHq2 = 2*((Dx*theta).*(Dy*chi) - (Dy*theta).*(Dx*chi));
    varargout{2} = gradHq2(2:end) / N^2 * scalefac;
end
```

# Matlab code: Constraints

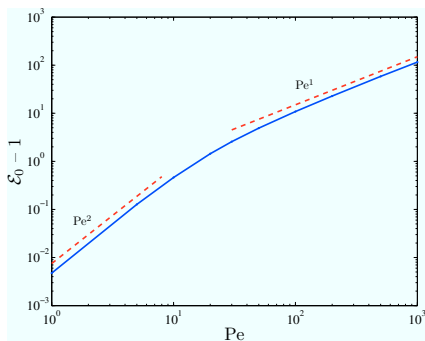
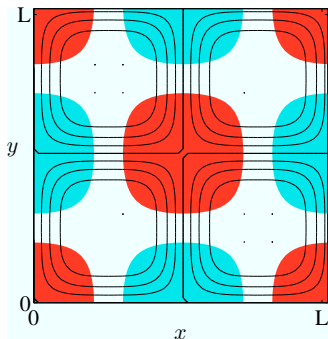
```
function [c,ceq,gc,gceq] = nonlcon(psi,src,kappa,q,L,scalefac)

psi = [0;psi]; N = size(src,1);
c = []; gc = [];

[Dx,Dy,Dxx,Dyy] = Diffmat2(N,L); % 2D Differentiation matrices
U2 = L^2*(sum((Dx*psi).^2 + (Dy*psi).^2)/N^2);
ceq(1) = (U2-1) * scalefac;

if nargin > 2
    % Gradient of constraints
    mlappsi = -(Dxx+Dyy)*psi;
    gceq(:,1) = 2*mlappsi(2:end) / N^2 * scalefac;
end
```

# Optimal stirring flow



Left: Optimal stirring velocity field (streamlines) for the source  $\sin x \sin y$ , for  $Pe = 10$ . Right: Dependence on Péclet number of the optimal mixing efficiency  $\varepsilon_0$ . For small  $Pe$  the optimal streamfunction  $\rightarrow (\sqrt{2\pi})^{-1} \cos x \cos y$ .

- DOERING, C. R. & THIFFEAULT, J.-L. 2006 Multiscale mixing efficiencies for steady sources. *Phys. Rev. E* **74** (2), 025301(R).
- LIN, Z., THIFFEAULT, J.-L., AND DOERING, C. R. 2010 Optimal stirring strategies for passive scalar mixing. Preprint.
- MATHEW, G., MEZIĆ, I., GRIVOPOULOS, S., VAIDYA, U. & PETZOLD, L. 2007 Optimal control of mixing in Stokes fluid flows. *J. Fluid Mech.* **580**, 261–281.
- MATHEW, G., MEZIĆ, I. & PETZOLD, L. 2005 A multiscale measure for mixing. *Physica D* **211** (1-2), 23–46.
- OKABE, T., ECKHARDT, B., THIFFEAULT, J.-L. & DOERING, C. R. 2008 Mixing effectiveness depends on the source–sink structure: Simulation results. *Journal of Statistical Mechanics: Theory and Experiment* **2008** (7), P07018.
- PLASTING, S. & YOUNG, W. R. 2006 A bound on scalar variance for the advection–diffusion equation. *J. Fluid Mech.* **552**, 289–298.
- SHAW, T. A., THIFFEAULT, J.-L. & DOERING, C. R. 2007 Stirring up trouble: Multi-scale mixing measures for steady scalar sources. *Physica D* **231** (2), 143–164.
- THIFFEAULT, J.-L., DOERING, C. R. & GIBBON, J. D. 2004 A bound on mixing efficiency for the advection–diffusion equation. *J. Fluid Mech.* **521**, 105–114.

Lecture 4: Mixing in the Presence of Sources and Sinks

Part 1: Norms

$$\partial_t \theta + \underline{u} \cdot \nabla \theta = \kappa \nabla^2 \theta, \quad \nabla \cdot \underline{u} = 0 \quad (AD)$$

in  $\Omega$  a  $\begin{cases} \cdot \text{bounded domain with zero-flux conditions} \\ \text{or} \\ \cdot \text{periodic domain} \end{cases}$

Assume  $\int_{\Omega} \theta \, d\Omega = 0$ . Let  $\|\theta\|_2^2 = \int_{\Omega} \theta^2 \, d\Omega$   $L^2$ -norm  
Also VARIANCE

Recall:  $\frac{d}{dt} \|\theta\|_2^2 = -2\kappa \|\nabla \theta\|_2^2$  Equation of variance decay.

Variance ( $L^2$ -norm) would seem a good measure of mixing. But it requires knowledge of small-scales in  $\theta$ , which we may not care about. Wouldn't it be better to blindly solve:

$$(A) \quad \frac{\partial \theta}{\partial t} + \underline{u} \cdot \nabla \theta = 0 \quad ? \quad \text{since often we don't care how something is homogenized}$$

But then:  $\frac{d}{dt} \|\theta\|_2^2 = 0$ , so can't use variance.

The advection equation (A) takes us closer to the ergodic theory sense of mixing.

In ergodic theory, we think of an operator  $S^t: \Omega \rightarrow \Omega$ , which is obtained from the solution of (A).  $S^t$  "moves forward" a patch of dye  $\theta_0(x)$  to  $\theta(x, t)$ .

For a patch  $A$ ,  $\text{Vol}(A)$  (or  $\text{Area}(A)$ ) is the Lebesgue measure of  $A$ .  
 $\theta(x, t)$  only 0 or 1, say

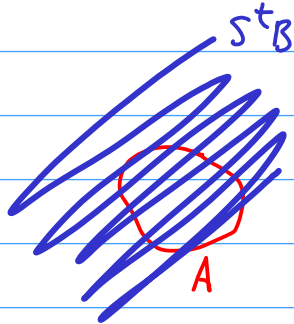
Because of incompressibility,  $S^t A$  has the same volume as  $A$ .  
 $S^t$  is measure-preserving.

Now for the definition of MIXING (in the sense of ergodic theory):

$$\lim_{t \rightarrow \infty} \text{Vol}(A \cap S^t(B)) = \text{Vol}(A) \text{Vol}(B) \quad \text{for all patches } A, B \text{ in } \Omega.$$

↑ usual def'n has  $-t$ , but  $S$  invertible here so it's the same.

What does this mean?



Imagine  $B$  has been mixed:

Recall  $S^t B$  has the same volume as  $B$ . So if it "fills the space"  $\Omega$  as best as it can, its intersection with  $A$  can only be as large as  $\text{Vol}(B)$ , but also  $\text{Vol}(A)$ . This is true for any  $A, B$ , so every blob must spread everywhere.

This is actually called STRONG MIXING. It implies ergodicity, but not the other way around!

Notice that this follows our intuition for what "good mixing" is, but no diffusion is needed.

In fact, the arbitrary "reference patch"  $A$  is a bit like a function that we project on. This suggests another def'n, which is more "analytic":

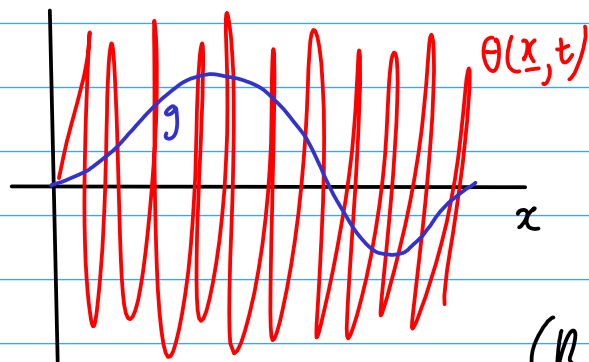
Weak convergence:

$$\lim_{t \rightarrow \infty} \langle \theta(x, t), g \rangle = 0 \quad (\theta \text{ converges to zero weakly})$$

for all functions  $g(x)$  in  $L^2(\Omega)$

Here:  $\langle f, g \rangle = \int_{\Omega} f(x) g(x) d\Omega$ , and a function  $f$  is in  $L^2(\Omega)$  if  $\int_{\Omega} |f|^2 d\Omega < \infty$  (for example,  $\delta$ -functions are not)

Weak convergence is equivalent to mixing. Why?



$\theta$  is not vanishing, but it is getting wigglier, so  $\int \theta g dx \rightarrow 0$

(Riemann-Lebesgue lemma)

But neither the def'n of mixing and weak convergence are that useful in practice: hard to compute something over all functions  $g(x)$ !



But there is a simpler way: **Matthew, Mezic, & Petzold** introduced the mix-norm, which is basically a negative Sobolev norm:

The "dot" is because we assume  $\int \theta = 0$

$$\|\theta\|_{\dot{H}^g} := \|\nabla^g \theta\|_2$$

Sobolev norm for  $H^g(\mathbb{T})$   
( $g=0$  is  $L^2$  norm)

We can interpret this norm for  $g < 0$  as well! This is easiest on a periodic domain.

$$\|\theta\|_{\dot{H}^g}^2 = \sum_{\underline{k}} |\underline{k}|^{2g} |\hat{\theta}_{\underline{k}}|^2$$

Note  $\hat{\theta}_0 = 0$   
(mean)

For  $g < 0$ ,  $\|\theta\|_{\dot{H}^g}$  smooths  $\theta$  before taking the  $L^2$  norm.

Theorem (Matthew-Mezic-Petzold, Doering-Lin-T)

$$\lim_{t \rightarrow \infty} \|\theta\|_{\dot{H}^g} = 0, \quad g < 0 \iff \theta \text{ converges weakly to } 0.$$

(proof is short, but a bit technical.)

Upshot: we can track any of these norms to determine if a system is mixing.  $g$  controls how much smoothing is imposed.

This makes optimization easier, for instance.

Time-evolution of  $H^g$ -norms: (w/o diffusion)

$$\nabla^{-1} \sim \frac{-ik}{|k|^2}$$

$$\frac{d}{dt} \|\theta\|_{\dot{H}^{-1}}^2 = \langle \nabla^{-1} \theta \cdot \nabla u \cdot \nabla^{-1} \theta \rangle$$

NOT conserved even in the absence of diffusion.

$$\frac{d}{dt} \|\theta\|_{\dot{H}^1}^2 = - \langle \nabla \theta \cdot \nabla u \cdot \nabla \theta \rangle$$

(other norms are uglier)

Matthew, Mezić, Griropoulos, Vaidya, Petzold: use optimal control  
to optimize decay of  $\|\theta\|_H^2$  (nonlocal in time)

Lin, Doering, T: maximize instantaneous decay rate of  $\|\theta\|_H^2$   
(local in time, easier, almost as good)

SLIDES pages 2-5

## PART 2: SOURCES AND SINKS

$$\partial_t \theta + \underline{u} \cdot \nabla \theta = \kappa \nabla^2 \theta + s(\underline{x}, t) \quad (\text{AD5})$$

$$(\nabla \cdot \underline{u} = 0)$$

sources/sinks  
 $> 0$     $< 0$

(SLIDE p. 6)

Assume:  $\int_{\Omega} s(\underline{x}, t) d\Omega = 0$  (otherwise subtract the mean)

More convenient to think of hot/cold  
sources sinks

For simplicity, restrict to time-independent  $s(\underline{x})$ .

Then system achieves a steady-state: (unlike decaying problem)

$$\underline{u} \cdot \nabla \theta = \kappa \nabla^2 \theta + s \quad \text{let } \mathcal{L} \equiv \underline{u} \cdot \nabla - \kappa \nabla^2$$

$$\hookrightarrow \mathcal{L} \theta = s \quad \text{or} \quad s = \mathcal{L}^{-1} \theta$$

integral operator

Note that  $\kappa \neq 0$  is needed to reach steady-state.

So, assuming the system has reached a steady-state, how do we measure the "quality of mixing"?

Can look at norms  $\|\theta\|_{H^2}$  ( $g=0$  is standard deviation)

But what do we compare to?

One possibility:  $\frac{\|\theta\|_{H^2}}{\|s\|_{H^2}}$  Pretty good, but has units of inverse time.

Prefer mixing enhancement factors:

$$\mathcal{E}_g = \frac{\|\tilde{\theta}\|_{H^g}}{\|\theta\|_{H^g}}$$

$$\begin{aligned}\tilde{\mathcal{L}} &= -\kappa \nabla^2 \\ \tilde{\mathcal{L}}\tilde{\theta} &= s\end{aligned}$$

$\tilde{\theta}$  is the solution in the absence of stirring. (purely diffusive)

Since  $\|\theta\|_{H^g}$  is usually decreased by stirring,  $\mathcal{E}_g$  measures the enhancement over the pure-diffusion state.

Several properties given in Doering & T, Shaw, Doering, & T.

For instance, can we have  $\mathcal{E}_g < 1$ , i.e., can stirring ever be worse than not stirring?

Consider  $\mathcal{E}_1 = \frac{\|\nabla\tilde{\theta}\|_2}{\|\nabla\theta\|_2}$ .

$$\tilde{\theta} = \tilde{\mathcal{L}}^{-1}s = (-\kappa \nabla^2)^{-1}s = -\kappa^{-1} \nabla^{-2}s \Rightarrow \nabla\tilde{\theta} = -\kappa^{-1} \nabla^{-1}s.$$

Also:  $\mathcal{L}\theta = s \Rightarrow \langle \theta \mathcal{L}\theta \rangle = \langle s\theta \rangle$   $\langle \cdot \rangle = \int_{\Omega} \cdot d\Omega$

$$\begin{aligned}\langle \theta \nabla \cdot \nabla \theta \rangle - \kappa \langle \theta \nabla^2 \theta \rangle &= \langle s\theta \rangle \\ = \langle \nabla \cdot (\kappa \theta^2/2) \rangle &= 0 \quad \kappa \langle |\nabla\theta|^2 \rangle = \langle s\theta \rangle = \langle \theta \nabla \cdot \nabla^{-1}s \rangle \\ \kappa \|\theta\|_{H^1}^2 &= -\langle \nabla\theta \cdot \nabla^{-1}s \rangle = \kappa \langle \nabla\theta \cdot \nabla\tilde{\theta} \rangle\end{aligned}$$

$$\|\theta\|_{H^1}^2 = \langle \nabla\theta \cdot \nabla\tilde{\theta} \rangle \leq \underbrace{\|\nabla\theta\|_2}_{\|\theta\|_{H^1}} \underbrace{\|\nabla\tilde{\theta}\|_2}_{\|\tilde{\theta}\|_{H^1}} \quad \text{Cauchy-Schwartz inequality}$$

$$\therefore \|\theta\|_{\dot{H}^1} \leq \|\tilde{\theta}\|_{\dot{H}^1} \iff \boxed{\varepsilon_1 \geq 1}$$

This is somewhat counter-intuitive: gradients are usually increased by stirring! However, here we're talking about gradients in a steady-state, affected by diffusion.

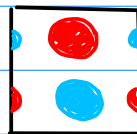
What about the other ones,  $\varepsilon_q$ ,  $q \neq 1$ ? Do we have  $\varepsilon_q \geq 1$ ?

We tried and failed to prove this, because it isn't true. Following a challenge by Charlie Doering, Jeff Weiss came up with something like:

$$\underline{u} = (2 \sin x \cos 2y, -\cos x \sin 2y)$$

0	0
0	0
0	0
0	0

$$s = (\cos x - \frac{1}{2}) \sin y$$



(Péclet = 4)

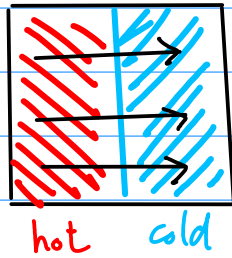
This manages to "concentrate" the source-sink distribution more than under pure diffusion, and

$$\varepsilon_0 \approx .978, \quad \varepsilon_{-1} \approx .945$$

Slightly less than 1! Not a dramatic effect, but it's there!  
(more later)

OPTIMIZATION: What kinds of flow give the largest  $E_q$ , given source/sink distribution  $s(x)$ ? (FIXED ENERGY)

Surprising example:  $s(x) = \sin x$  (periodic B.C.)



Optimal:  $\underline{u} = U \hat{x}$  Constant flow!

(see Shaw-T-Doering, Plastina-Yang)

This example demonstrates that with body sources the best stirring has more to do with transport than with creation of small scales.

SOLVE NUMERICALLY for more complicated sources. (SLIDE p.7, Matlab)