

# Run-and-tumble motion and differential dynamic microscopy

Zhao Yongfeng

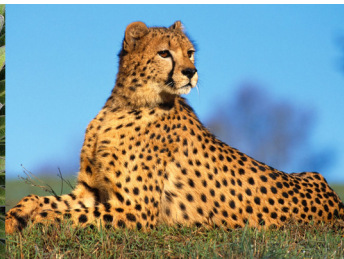
Department of Physics, The University of Hong Kong

October 24, 2016

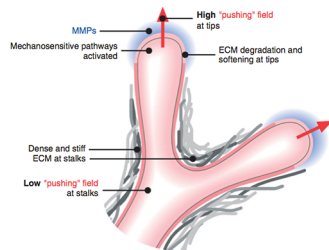
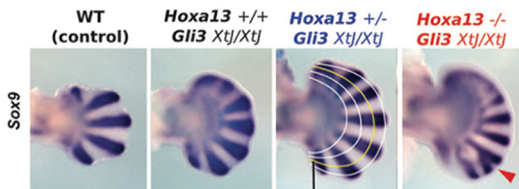
# Outline

- 1 Pattern formation in biology
- 2 Patterns from interactions of two species
- 3 Differential dynamic microscopy
- 4 Run-and-tumble motion with obstacles
- 5 Summary and future work

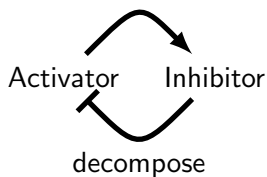
# Patterns



# Patterns

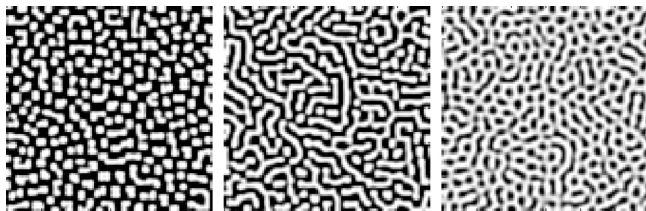


# Turing pattern (1952)



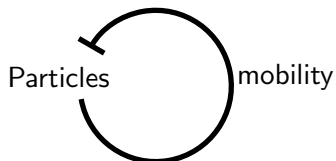
$$\frac{\partial A}{\partial t} = D_A \nabla^2 A + f(A, I)$$

$$\frac{\partial I}{\partial t} = D_I \nabla^2 I + g(A, I)$$

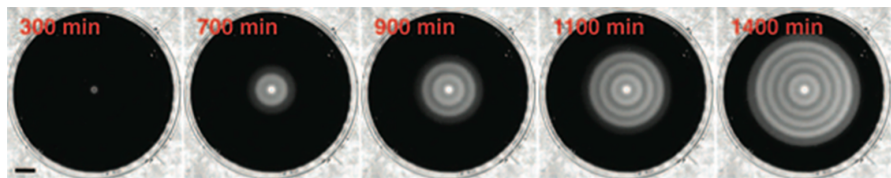


(*Wikipedia.org*)

## Density-dependent mobility induced pattern



$$\frac{\partial \rho}{\partial t} = \nabla [D(\rho) \nabla \rho]$$

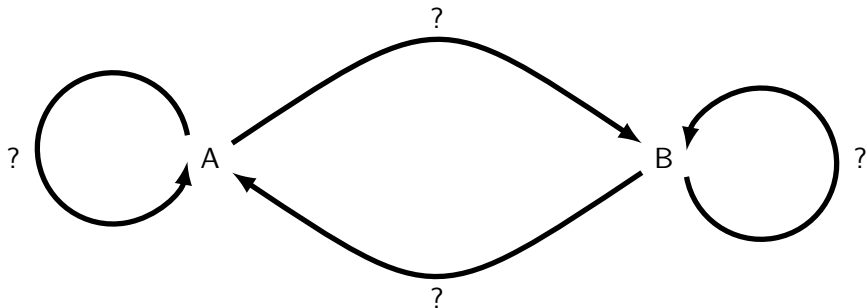


(2011, Chenli Liu, Xiongfei Fu, et al, Science)

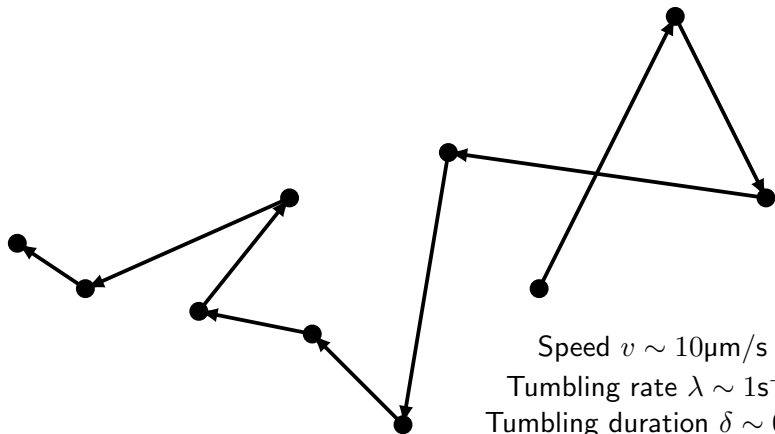
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## Interactions among two species





Run-and-tumble motion of *E. coli*

$$\frac{\partial \rho}{\partial t} = \nabla \cdot (D \nabla \rho) + \nabla \left[ \frac{v}{d\lambda} \nabla \left( \frac{v}{1 + \lambda \delta \rho} \right) \right].$$

# Linear stability analysis

$$\frac{\partial \rho_a}{\partial t} = \nabla \left[ \frac{v_a^2}{d\lambda_a(\rho_b)(1 + \lambda_a(\rho_b)\delta_a)} \nabla \rho_a - \frac{v_a^2 \delta_a \lambda'_a(\rho_b) \rho_a}{d\lambda_a(\rho_b)(1 + \lambda_a(\rho_b)\delta_a)^2} \nabla \rho_b \right],$$

$$\frac{\partial \rho_b}{\partial t} = \nabla \left[ \frac{v_b^2}{d\lambda_b(\rho_a)(1 + \lambda_b(\rho_a)\delta_b)} \nabla \rho_b - \frac{v_b^2 \delta_b \lambda'_b(\rho_a) \rho_b}{d\lambda_b(\rho_a)(1 + \lambda_b(\rho_a)\delta_b)^2} \nabla \rho_a \right].$$

## Bifurcation condition

$$\lambda'_a(\rho_{b0}) \lambda'_b(\rho_{a0}) > \frac{(1 + \lambda_a(\rho_{a0})\delta_a)(1 + \lambda_b(\rho_{b0})\delta_b)}{\delta_a \delta_b \rho_{a0} \rho_{b0}}.$$

## Eigenvector

$$\left( \frac{v_a^2}{d\lambda_a(\rho_{b0})(1 + \lambda_a(\rho_{b0})\delta_a)} + \eta \right) \delta \rho_a = \frac{v_a^2 \delta_a \lambda'_a(\rho_{b0}) \rho_{a0}}{d\lambda_a(\rho_{b0})(1 + \lambda_a(\rho_{b0})\delta_a)^2} \delta \rho_b.$$

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## Two general principles

$$\lambda'_a(\rho_{b0})\lambda'_b(\rho_{a0}) > \frac{(1 + \lambda_a(\rho_{a0})\delta_a)(1 + \lambda_b(\rho_{b0})\delta_b)}{\delta_a\delta_b\rho_{a0}\rho_{b0}} \implies$$

$$\lambda'_a(\rho_{b0}) > 0, \lambda'_b(\rho_{a0}) > 0 \text{ or } \lambda'_a(\rho_{b0}) < 0, \lambda'_b(\rho_{a0}) < 0.$$

- $\lambda'_a(\rho_{b0}) > 0, \lambda'_b(\rho_{a0}) > 0$ : **mutual inhibition**  
 $\delta\rho_a \propto \delta\rho_b$ : co-migrating pattern.
- $\lambda'_a(\rho_{b0}) < 0, \lambda'_b(\rho_{a0}) < 0$ : **mutual activation**  
 $\delta\rho_a \propto -\delta\rho_b$ : segregating pattern.

The similar conclusions hold for density dependent speed (from Curatolo) or tumbling duration.

## Two general principles

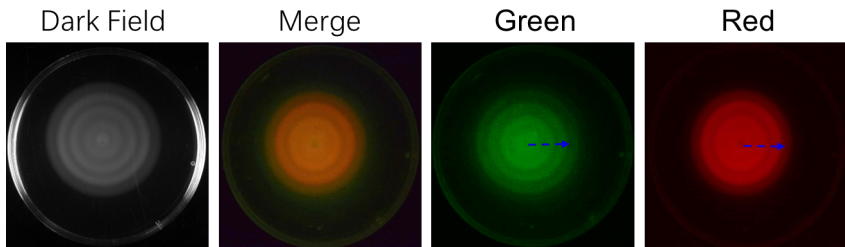
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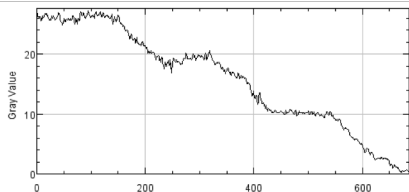
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# Experiments - mutual inhibition

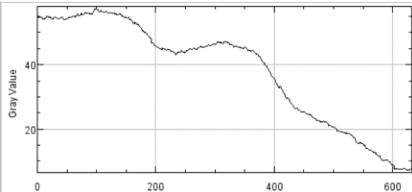


1 cm

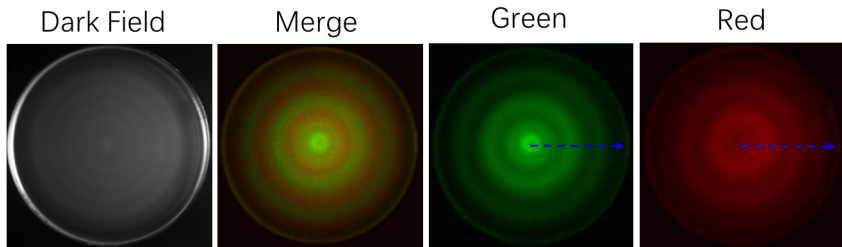
Green



Red

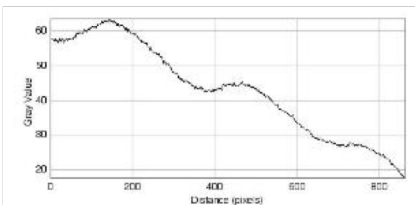
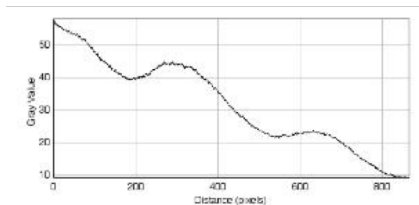


## Experiments - mutual activation



Green

Red



# A question

How do we know the designed system works as we expected?

⇒ How can we measure the speed/tumbling rate/tumbling duration of *E. coli* ?



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## Why not tracking?

- Special equipment for 3D measurement.
- Difficult to measure tumbling duration.
- Valid only for low density.
- Laborious.
- Poor statistics ( $\sim 10^2$  cells).

If I am telling you there is a method:

- Usual equipment automatically doing 3D measurement.
- Easier to measure tumbling duration.
- Valid for high density.
- Easy.
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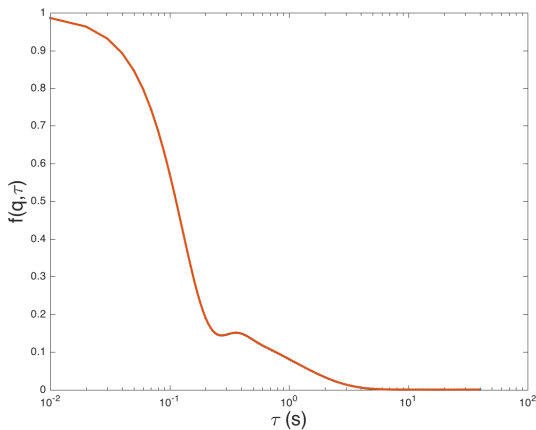
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## Intermediate scattering function (ISF)

$$f(q, \tau) = \frac{\langle \Delta\rho(q, t) \Delta\rho^*(q, t + \tau) \rangle_e}{\langle \Delta\rho(q, t) \Delta\rho^*(q, t) \rangle_e} .$$



# Differential dynamic microscopy

## The principle of differential dynamic microscopy

It can be proven for ergodic point particles that

$$f(q, \tau) = \frac{\langle \Delta\rho(q, t) \Delta\rho^*(q, t + \tau) \rangle_t}{\langle \Delta\rho(q, t) \Delta\rho^*(q, t) \rangle_t} = p(q, \tau),$$

which is the solution of corresponding master equation with initial condition to be  $p(x, t) = \delta(x)$ .

- $f(q, \tau)$  can be calculated from image intensity  $I(q, t)$ , via

$$g(q, \tau) = \langle |I(q, t + \tau) - I(q, t)|^2 \rangle_t = A(q)(1 - f(q, \tau)) + B(q).$$

- $p(q, \tau)$  can be obtained from solving the master equation.

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# Master equation of run-and-tumble particles

$$\frac{\partial p(\mathbf{x}, \mathbf{v}, t)}{\partial t} = D\nabla^2 p - \mathbf{v} \cdot \nabla p - \lambda p + \frac{\lambda}{\Omega} \int p(\mathbf{x}, \mathbf{v}', t) d\Omega'.$$

$$p(q, v, s) = \frac{\arctan(qv/(s + Dq^2 + \lambda))}{qv - \lambda \arctan(qv/(s + Dq^2 + \lambda))}.$$

Adding a distribution of  $v$  and a contribution of dead cells,

$$f(q, \tau) = (1 - \alpha)e^{-Dq^2\tau} + \alpha \int_0^\infty p(q, v, t) P(v) dv,$$

where

$$P(v) = \frac{v^Z}{\Gamma(Z + 1)} \left( \frac{Z + 1}{\bar{v}} \right)^{Z+1} e^{-(Z+1)v/\bar{v}}.$$

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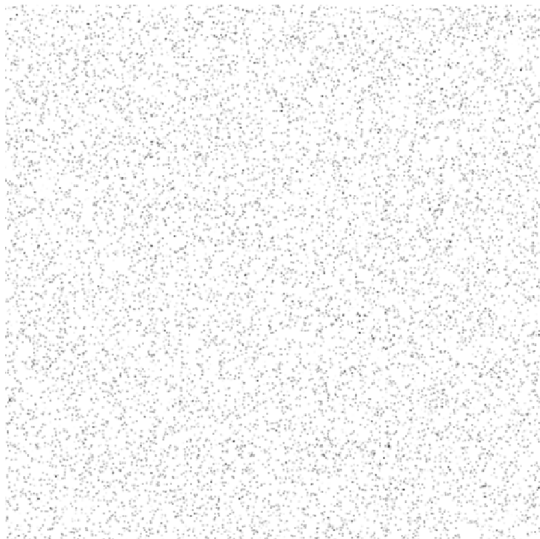
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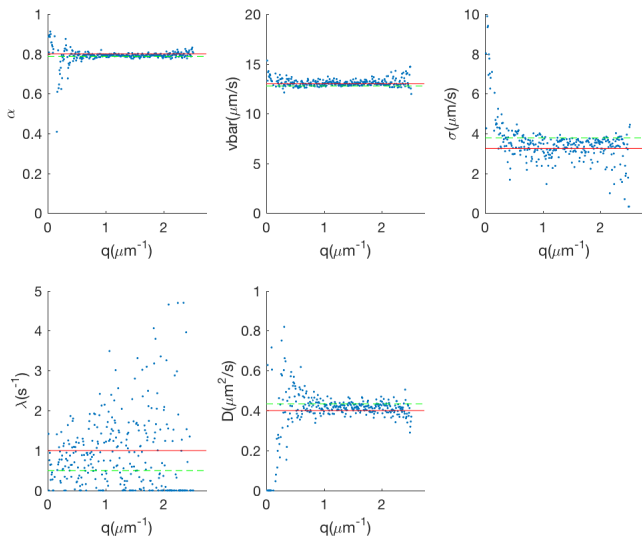


# Simulation

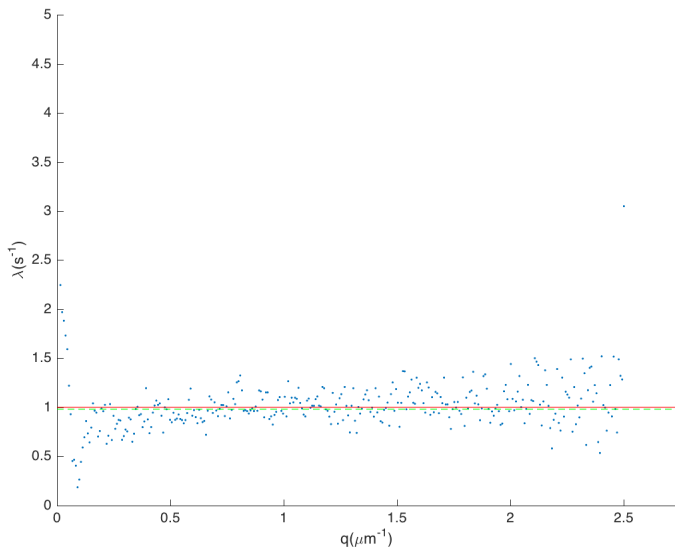


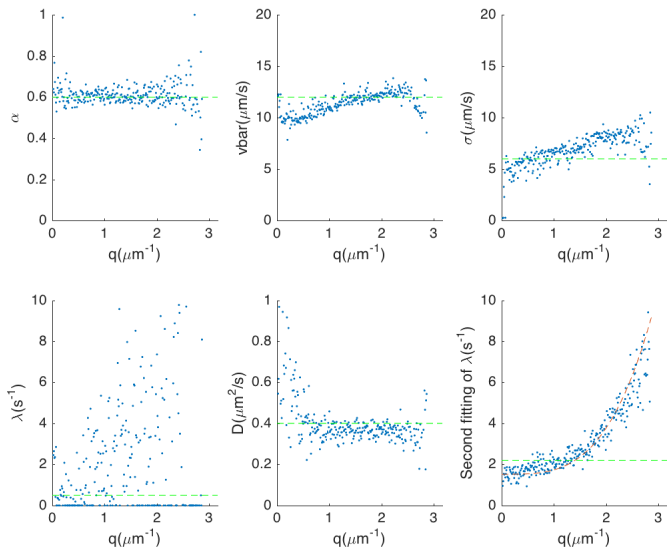
- $512 \times 512$  pixels.
- Pixel size corresponds to real microscopy systems.
- Depth of fields  $\sim 40 \mu\text{m}$ .
- Particle number  $\sim 10^4$ .

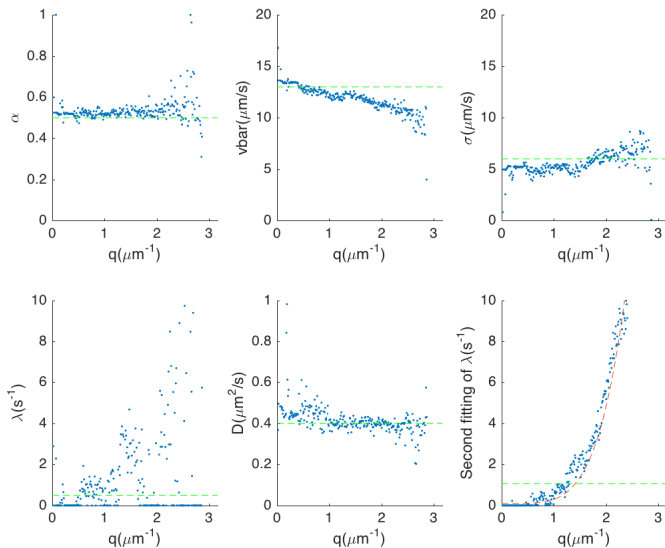
## Fitting result of simulation



# A second fitting with fixed parameters



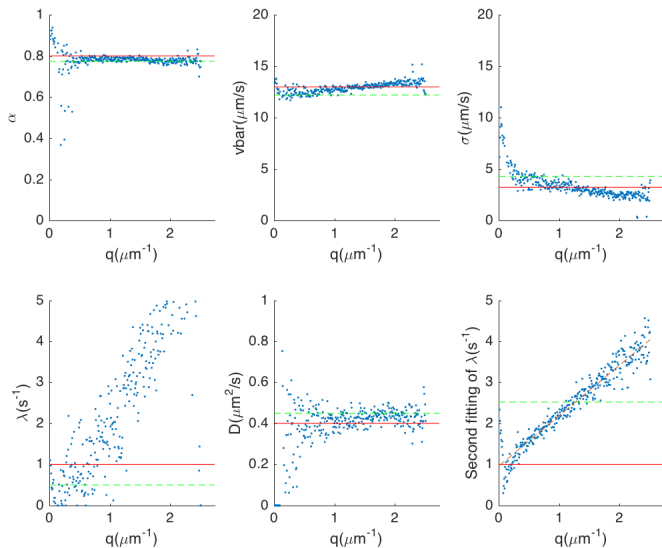
Fitting result of experiment of wild type *E. coli*

Fitting result of experiment of  $\Delta$ CheY *E. coli*

# What is missing?

- Finite tumbling duration.
- Rotational diffusion.
- Active rotational diffusion causing bias in tumbling.
- Lévy's walk (power law distribution in running time).

## Simulation with finite tumbling duration



# Finite tumbling duration

## Master equation

$$\frac{\partial p_r(\mathbf{x}, \mathbf{v}, \tau)}{\partial \tau} = D \nabla^2 p_r - \mathbf{v} \cdot \nabla p_r - \lambda p_r + \frac{p_t}{\delta \Omega},$$

$$\frac{\partial p_t(\mathbf{x}, \tau)}{\partial \tau} = D \nabla^2 p_t + \lambda \int p_r(\mathbf{x}, \mathbf{v}', \tau) d\Omega' - \frac{p_t}{\delta}.$$

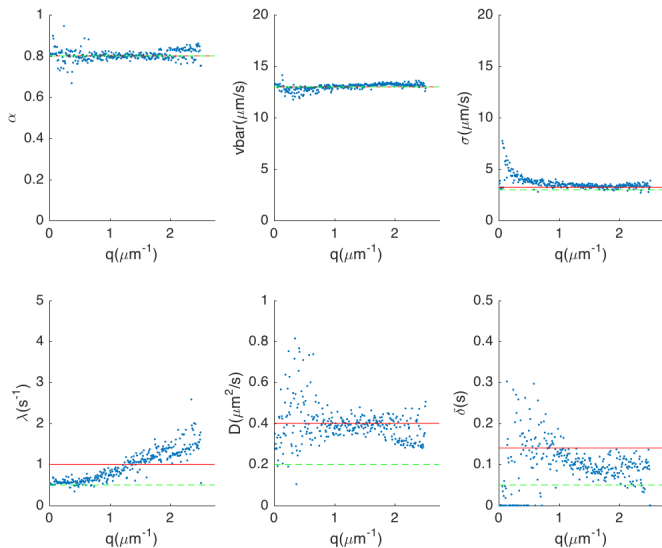
## Intermediate scattering function

$$p(q, v, s) = \frac{1}{(\delta(s + Dq^2) + 1)(\delta\lambda + 1)} \left( \frac{(\delta(s + \lambda + Dq^2) + 1)^2 \arctan(qv/(s + \lambda + Dq^2))}{qv(\delta(s + Dq^2) + 1) - \lambda \arctan(qv/(s + \lambda + Dq^2))} + \delta^2 \lambda \right).$$

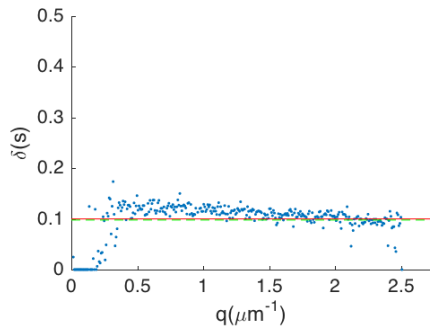
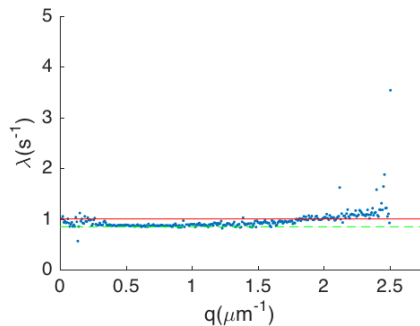
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## Fitting with tumbling duration



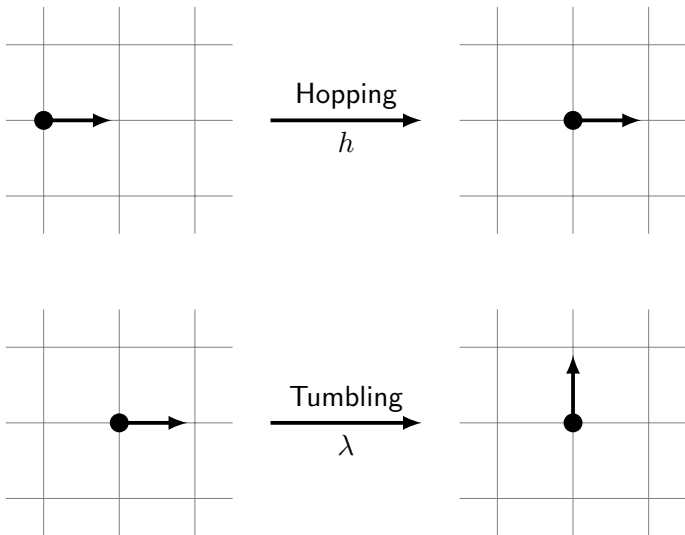
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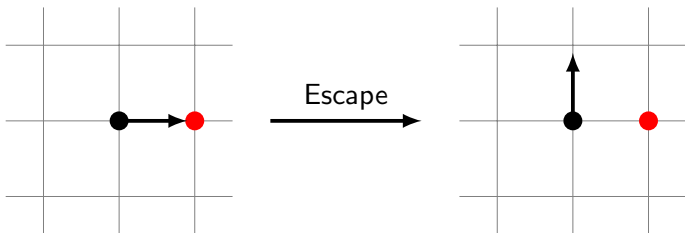
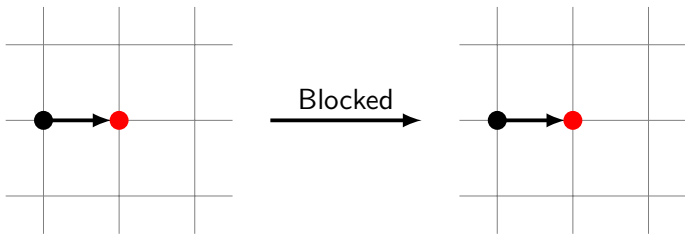
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## Lattice model



## Lattice model



# Mean field approximation

- $c$ : Concentration of obstacles.

## Master equation

$$\begin{aligned}\frac{\partial p_r(\mathbf{x}, \hat{\mathbf{v}}, t)}{\partial t} &= -\nabla \cdot (\hat{\mathbf{v}} h p_r) - \lambda p_r - \gamma_d(c) h c p_r + \frac{\lambda(1-c)}{\Omega} \rho_M, \\ \frac{\partial p_b(\mathbf{x}, \hat{\mathbf{v}}, t)}{\partial t} &= -\lambda p_b + \frac{\lambda c}{\Omega} \rho_M + \gamma_d(c) h c p_r, \\ \rho_M &= \int (p_r + p_b) d\Omega.\end{aligned}$$

## Effective diffusion coefficient

$$D_{\text{eff}} = \frac{h^2 \lambda (1-c)}{d [h c \gamma_d(c) + \lambda]^2}.$$

# Mean field approximation

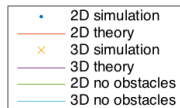
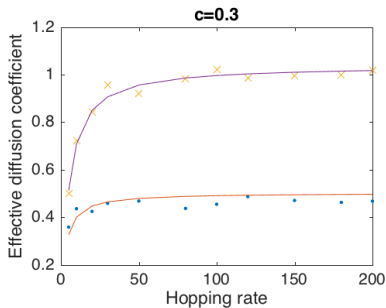
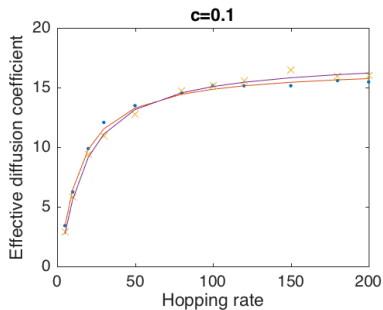
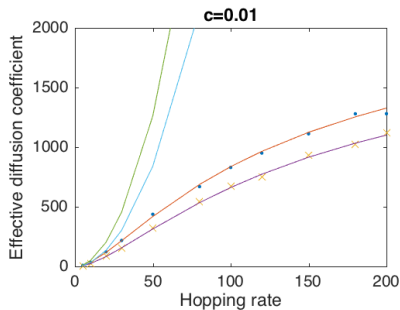
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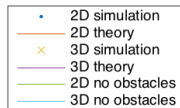
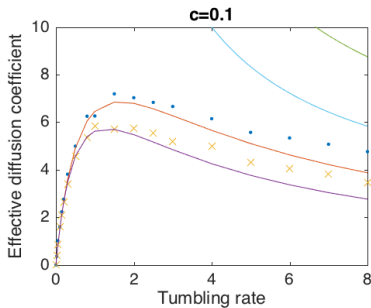
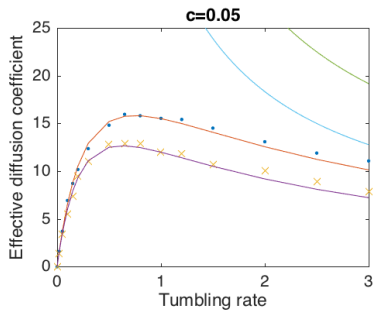
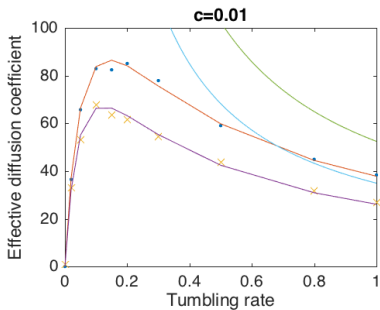
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# Summary

## New mechanism for pattern formation

- Mutual inhibition of mobility: co-migrating pattern.
- Mutual activation of mobility: segregating pattern.

## New development of differential dynamic microscopy

- Tumbling rate can be measured for run-and-tumble particles with instantaneous tumbling.
- Tumbling duration can be measured for run-and-tumble particles if the tumbling rate is known.
- The motion of *E. coli* may have some ingredients we haven't known.

## New attempt for *E. coli* motion with obstacles

- A valid lattice model.
- A mean field approximation.

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# Future work

## Pattern formation

- Experiments: tuning the pattern.
- Three-species, four-species, ...: more complex network motif.
- Growth, death, ...: more kinds of interactions.

## Differential dynamic microscopy

- Way to specify the tumbling rate of run-and-tumble particles with finite tumbling duration: multi-scale imaging?
- Measure rotational diffusivity.
- Effect of Levy's walk.

## *E. coli* moving in agar

- Existence of better continuous approximation: calculation of  $\gamma_d(c)$ .
- Possibility of DDM.

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- Effect of Levy's walk.

## *E. coli* moving in agar

- Existence of better continuous approximation: calculation of  $\gamma_d(c)$ .
- Possibility of DDM.

## Future work

### Pattern formation

- Experiments: tuning the pattern.
- Three-species, four-species, ...: more complex network motif.
- Growth, death, ...: more kinds of interactions.

### Differential dynamic microscopy

- Way to specify the tumbling rate of run-and-tumble particles with finite tumbling duration: multi-scale imaging?
- Measure rotational diffusivity.
- Effect of Levy's walk.

### *E. coli* moving in agar

- Existence of better continuous approximation: calculation of  $\gamma_d(c)$ .
- Possibility of DDM.



# What's more?

- Applying DDM to study the motion of other "particles": mammalian cells, fishes, birds, sheep, humans, ...
- Studying their collective behaviour.
- Finding principles in coordination and self-organization.
- Answering questions in organ development, morphogenesis, microbe infection, ...

# Acknowledgement

- Prof. Cheng, Kwong Sang
- Prof. Zhang, Fu-Chun
- Prof. Huang, Jian-Dong
- Dr. Julien Tailleur  
(University Paris Diderot)
- Dr. Vincent Martinez  
(The University of Edinburgh)
- Dr. Adrian Daerr  
(University Paris Diderot)
- Dr. Huang, Wei
- Prof. Peter Lenz
- Mr. Zhou, Nan
- Ms. Agnese Curatolo  
(University Paris Diderot)
- Dr. Alexandre Solon  
(MIT)
- Dr. Lina Hamouche  
(University Paris Diderot)

## Case no obstacle: compare with continuous model

### Master equation

$$\frac{\partial P(\mathbf{x}, \mathbf{e}_i, t)}{\partial t} = hP(\mathbf{x} - \mathbf{e}_i, \mathbf{e}_i, t) - hP - \lambda P + \frac{\lambda}{2d} \sum_i P(\mathbf{x}, \mathbf{e}_i, t).$$

### Mean square displacement - lattice model

$$\langle \Delta x^2(t) \rangle = \left( \frac{2h^2}{d\lambda} + \frac{h}{d} \right) t + \frac{2h^2}{d\lambda^2} (e^{-\lambda t} - 1).$$

### Mean square displacement - continuous model

$$\langle \Delta x^2(t) \rangle = \frac{2v^2}{d\lambda} t + \frac{2v^2}{d\lambda^2} (e^{-\lambda t} - 1).$$

- Necessary condition of lattice model to be valid:  $h \gg \lambda/2$ .

# Numerical inverse Laplace transformation - Week's method

$$\mathcal{L}\{f(t)\} = F(s).$$

- Möbius transformation:  $s = \sigma - b \frac{z+1}{z-1}$ .
- Expand the function:

$$(s - \sigma + b)F(s) = \frac{2b}{1-z} F\left(\sigma - b \frac{z+1}{z-1}\right) = \sum_{n=0}^{\infty} a_n z^n.$$

- Laplace transformation of Laguerre polynomial:  $\mathcal{L}[L_n(2bt)] = \frac{(s-2b)^n}{s^{n+1}}$ .
- $\mathcal{L}^{-1}[F(s)] = f(t) = \sum_{n=0}^{\infty} a_n e^{(\sigma-b)t} L_n(2bt)$ .

$$a_n = \frac{1}{2\pi} \int_0^{2\pi} e^{-in\theta} \frac{2b}{1-e^{i\theta}} F\left(\sigma - b \frac{e^{i\theta} + 1}{e^{i\theta} - 1}\right) d\theta.$$