

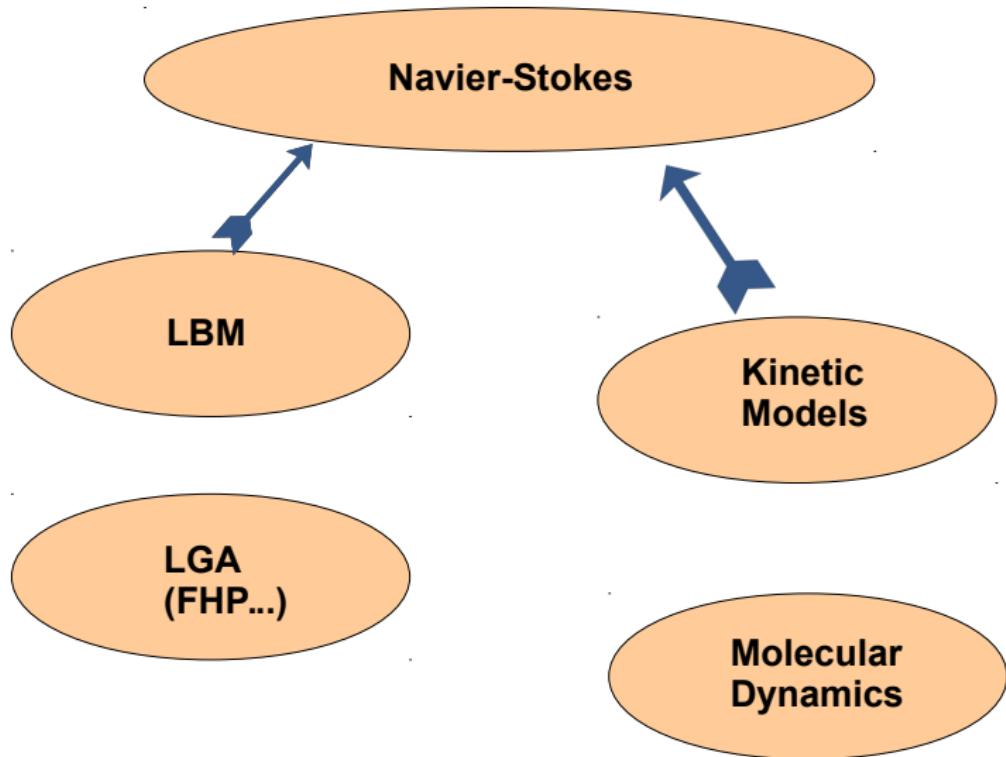
Familles de modèles : des fluides au transport routier, piétonnier, ou intracellulaire

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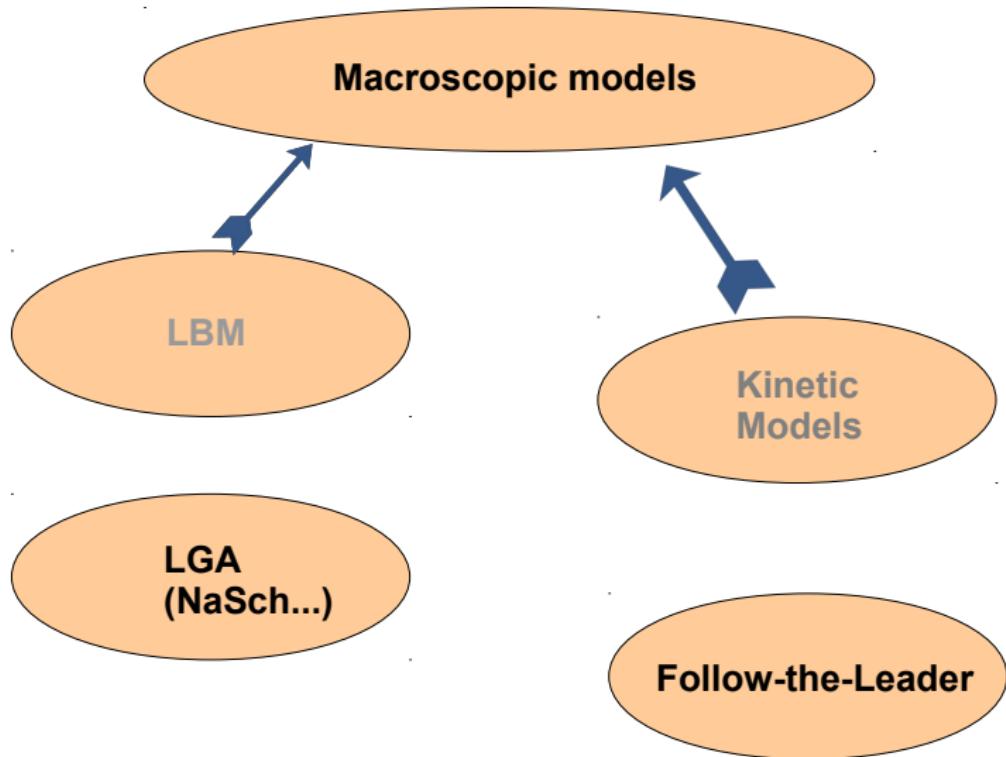
- Introduction : model families
- Road Traffic
 - Cellular automata
 - Macroscopic models
 - Follow-the-leader models and Micro-Macro derivation
 - Kinetic model of a bidirectional road
- Pedestrians
 - Microscopic models
 - Micro-Macro derivation
 - Macroscopic models
 - Ped-following model
 - Cellular automaton for flow crossing and pattern formation
- Intracellular transport
 - Dynamics of cargo-motor complexes
 - Dynamics of the network

Modèles pour les fluides



ROAD TRAFFIC

Modèles pour le traffic routier



Cellular automata simulations

Road = divided into cells

Particle = vehicle

State = speed (between 0 and v_{MAX})

Evolution rules = acceleration and deceleration + propagation

- Pionnering work [Nagel & Schreckenberg (1992)]
- Model by [Knospe et al (2000)]
 - finite braking capacity
 - anticipation
 - slow-to-start rule -> metastability

Configuration at time t :



a) Acceleration:



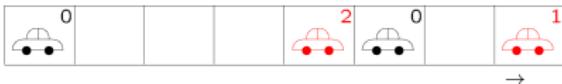
b) Braking:



c) Randomization ($p = 1/3$):

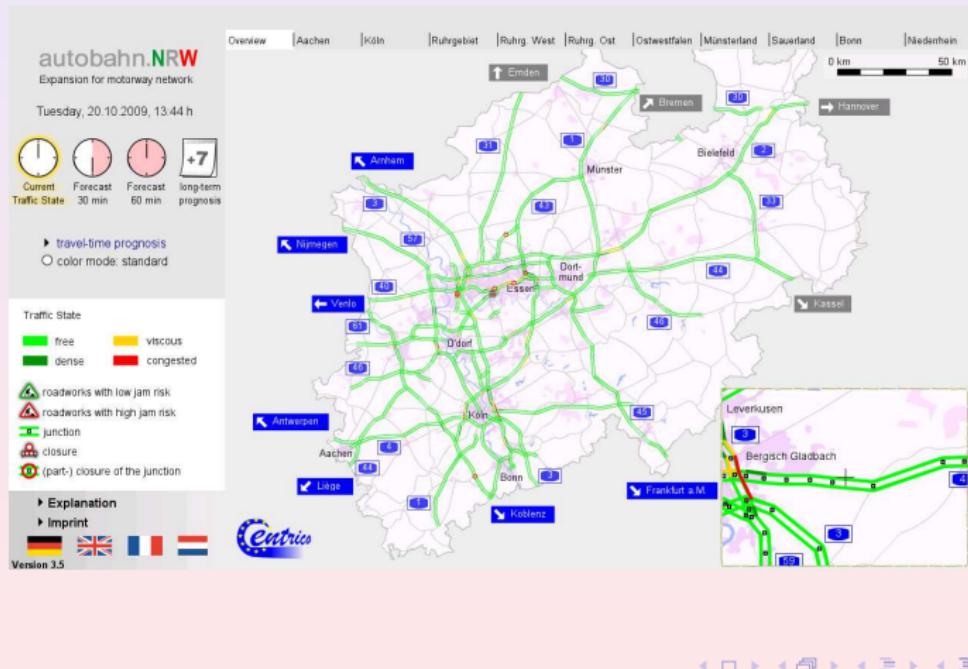


d) Driving (= configuration at time $t + 1$):

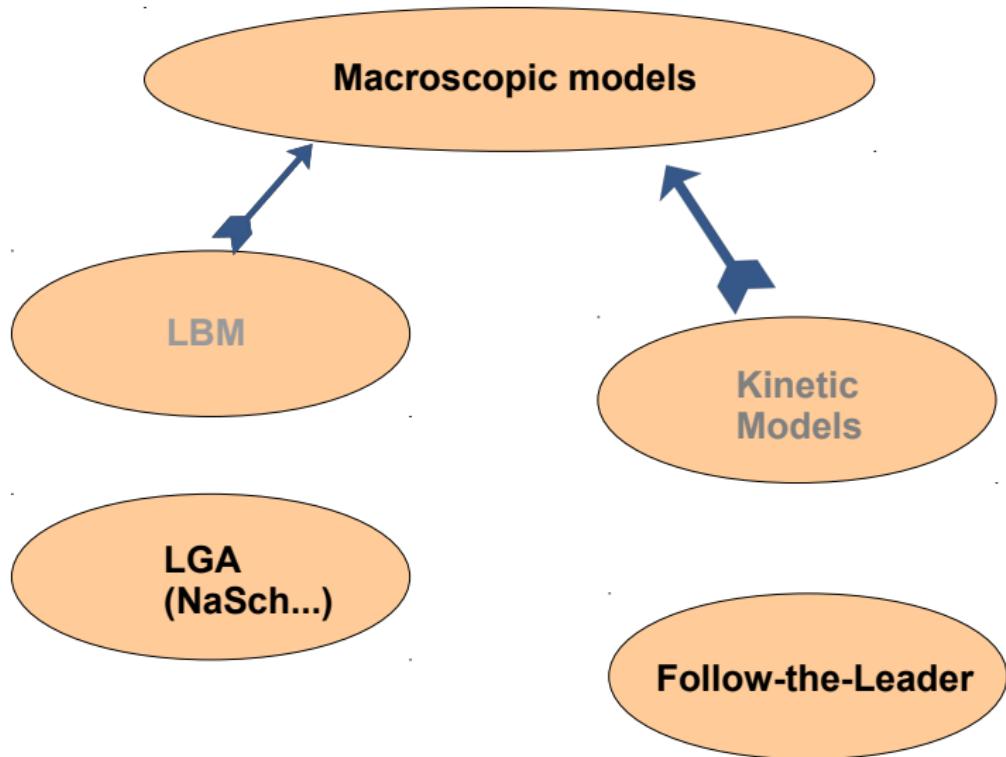


Road traffic by cellular automata

Many improvements, real life applications



Modèles pour le traffic routier

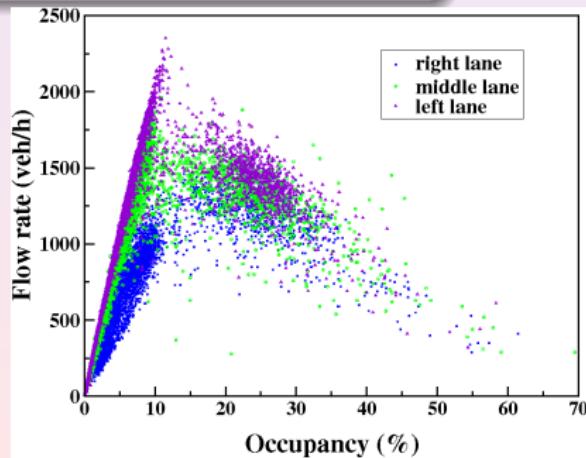


Macroscopic model for car traffic

Mass conservation

Model LWR (1955-1956)

$$\begin{aligned}\partial_t \rho + \partial_x (\rho u) &= 0 \\ u &= V(\rho)\end{aligned}$$



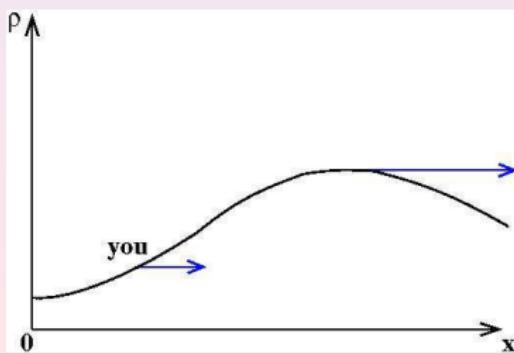
Macroscopic model for car traffic

Mass conservation

Payne-Whitham model (1971)

$$\partial_t \rho + \partial_x (\rho u) = 0$$

$$\partial_t u + u \partial_x u = -\frac{1}{\rho} \rho'(\rho) \partial_x \rho + \frac{1}{\tau} (V(\rho) - u)$$



Macroscopic model for car traffic

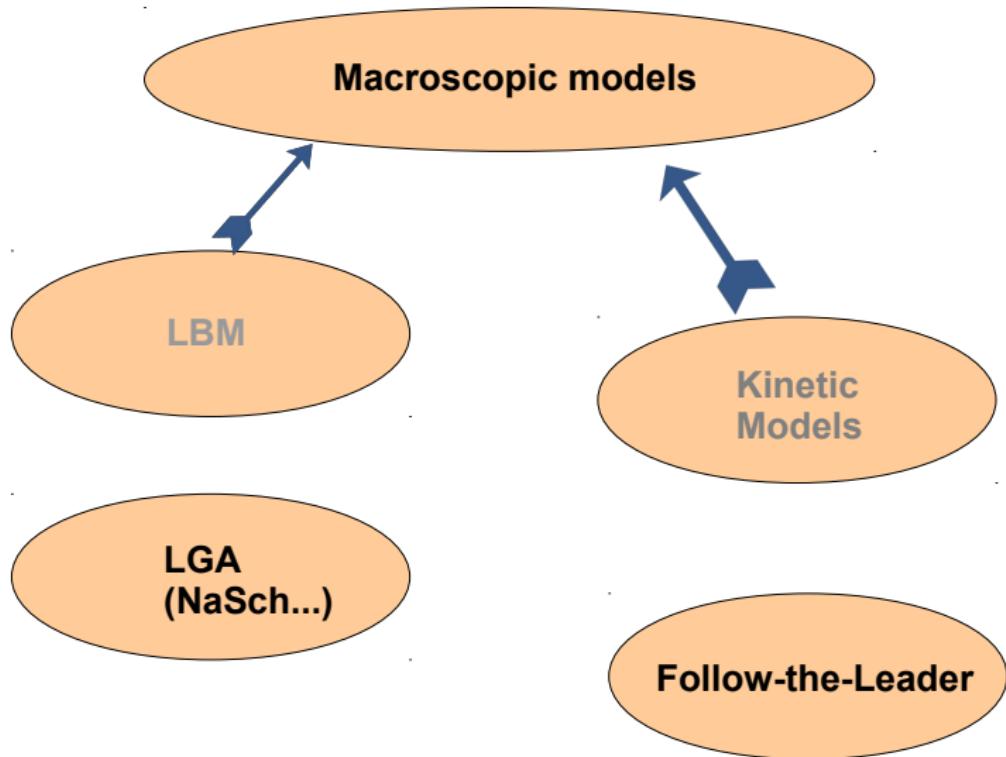
Aw-Rascle model (2000)

$$\begin{aligned}\partial_t \rho + \partial_x(\rho u) &= 0 \\ \partial_t(\rho u) + \partial_x(\rho uu) &= -\rho \frac{dp}{dt} + \frac{1}{\tau} (V(\rho) - u)\end{aligned}$$

where

$$d/dt = \partial_t + u \partial_x \quad (1)$$

Modèles pour le traffic routier



Follow-the-leader Model

Un exemple :

[Aw et al (2000)]

$$\begin{aligned}\dot{x}_i &= v_i \\ \dot{v}_i &= C_\gamma \frac{(v_{i+1} - v_i)}{(x_{i+1} - x_i)^{\gamma+1}} + A \frac{1}{T_r} (V(\rho_i) - v_i)\end{aligned}$$

where

$$\rho_i = \frac{l}{(x_{i+1} - x_i)}$$

Pas de chaos moléculaire

Systèmes homogènes

$$\rho_i = \frac{1}{(x_{i+1} - x_i)}$$

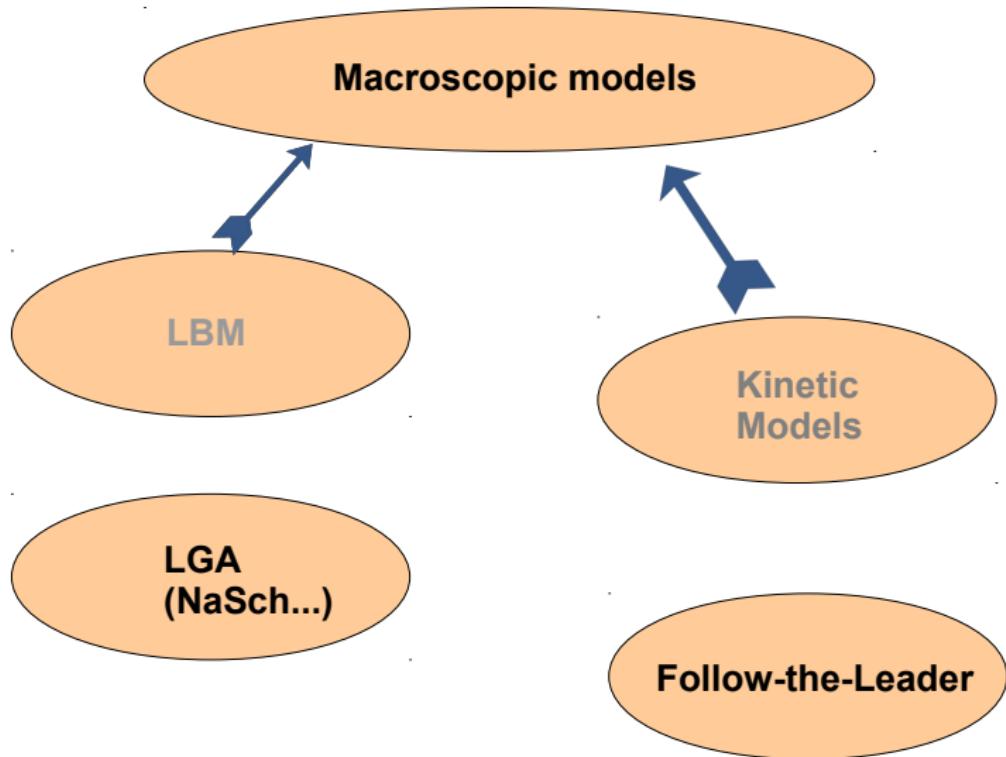
[Berg, Mason, Woods, PRE (2000)]

Systèmes inhomogènes

$$\int_0^{x_{i+1} - x_i} \rho(x + y) dy = 1$$

Expansion in powers of y

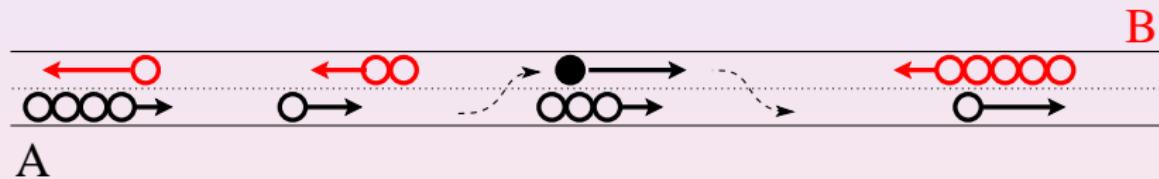
Modèles pour le traffic routier



Bidirectional road

[C. Appert-Rolland, H.J. Hilhorst and G. Schehr : *Spontaneous symmetry breaking in a two-lane model for bidirectional overtaking traffic*, J. Stat. Mech. (2010) P08024]

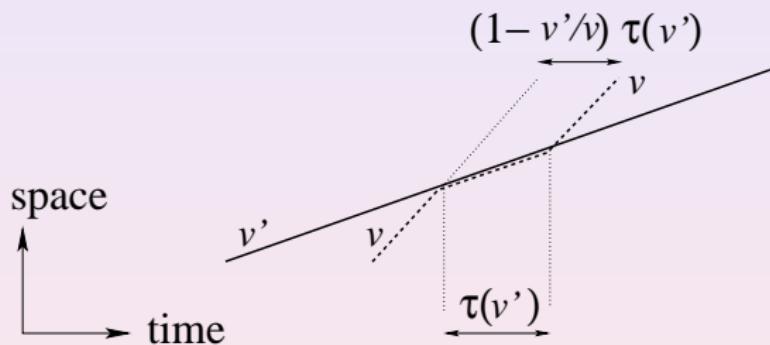
- Continuous space and time



- Distribution of desired velocities $P(v)$
(Minimum v_0)
- Need a delay τ_0 to take over

For a given lane...

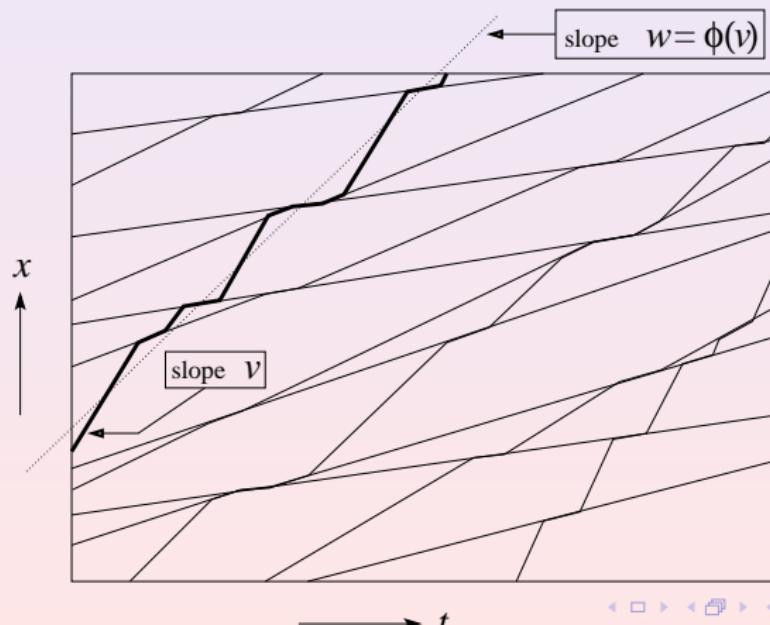
A vehicle with desired velocity v has to wait for a queuing time $\tau(v')$ to take over a vehicle of velocity $v' < v$.



For a given lane...

A vehicle with desired velocity v has to wait for a queuing time $\tau(v')$ to take over a vehicle of velocity $v' < v$.

→ possible to compute the effective velocity $\phi(v)$ of each vehicle having a desired velocity v



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→ possible to compute the effective velocity $\phi(v)$ of each vehicle having a desired velocity v

- Open boundary conditions

Injection with rate $\bar{\omega}$

$$\frac{1}{\phi(v)} = \frac{1}{v_0} - \int_{v_0}^v dv' \left[v' + \int_{v_0}^{v'} dv'' (v' - v'') \bar{\omega} P(v'') \tau(v'') \right]^{-2}.$$

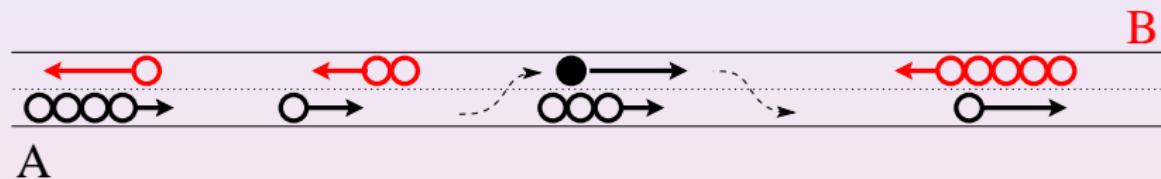
→ In particular $\phi(v_0) = v_0$

- Similar expressions for periodic boundary conditions
- Density of platoons of a certain length
- Density of free vehicles, etc ...

Mean-field coupling between 2 lanes

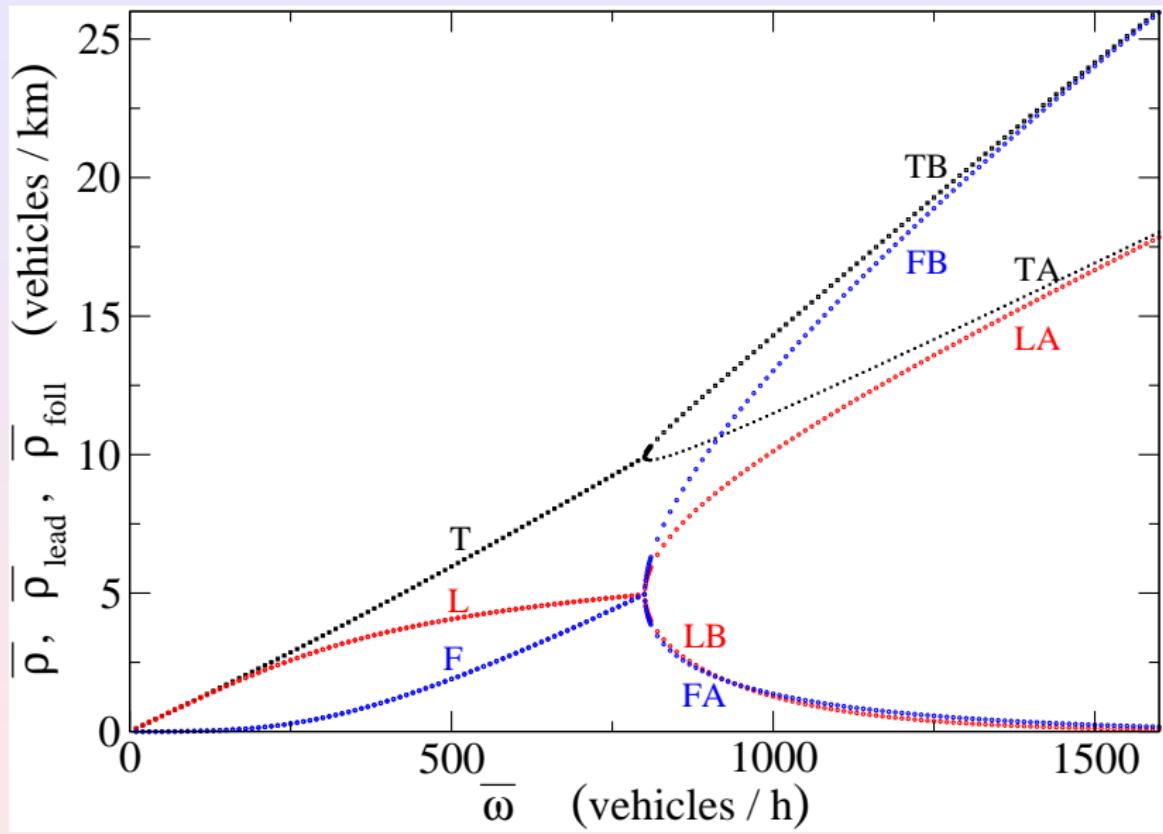
The waiting time $\tau(v_{slow})$ is computed from the configuration on the other lane (distribution of holes).

How long does it take to meet in the opposite lane a hole of duration greater than τ_0 ?



- Mean-field coupling between the lanes
- Two coupled equations to solve numerically

Mean-field coupling between 2 lanes

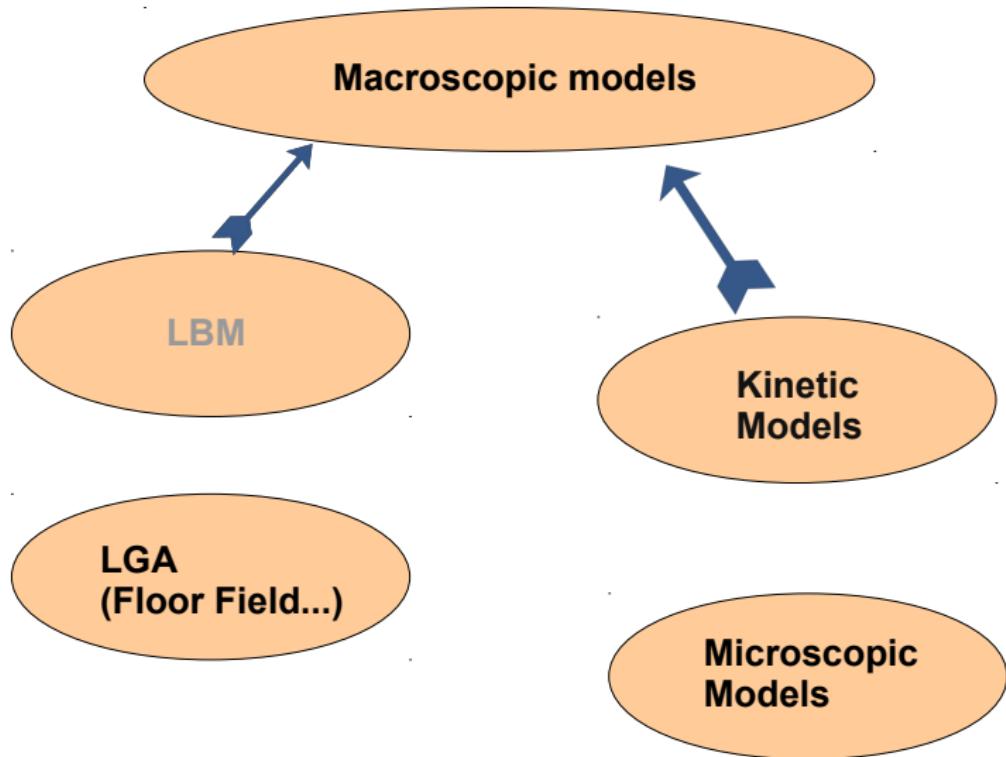


Modèle microscopique de route bidirectionnelle

- Spontaneous symmetry breaking in a mean-field description of a bidirectional road
- Microscopic model: asymmetry also observed between the lanes
- Size of the vehicles negligible if $\bar{\rho} \ll 40$ veh/km;
 - Transition around $\bar{\rho} = 5$ veh/km, observable on real data?

PEDESTRIANS

Modèles pour le traffic piétonnier



Modèles pour le traffic piétonnier

- Mass conservation
- Transport in 2D space
- Destination for each pedestrian
- Less inertial effects

First Generation Models

- Boids
- Rule models
- Force models

Boids

[Craig W. Reynolds, Computer Graphics (1987)]

- Flocks, Herds, and Schools

Pedestrians : Microscopic Models

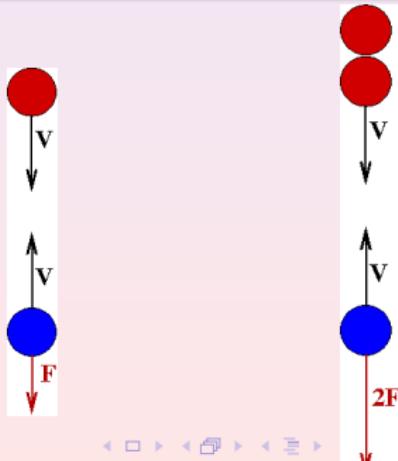
First Generation Models

- Boids
- Rule models
- Force models

Social force model

[D. Helbing & P. Molnár, PRE (1995)]

- Position Based Model
- Multiple interactions: Sum of forces



Pedestrians : Microscopic Models

First Generation Models

- Boids
- Rule models
- Force models

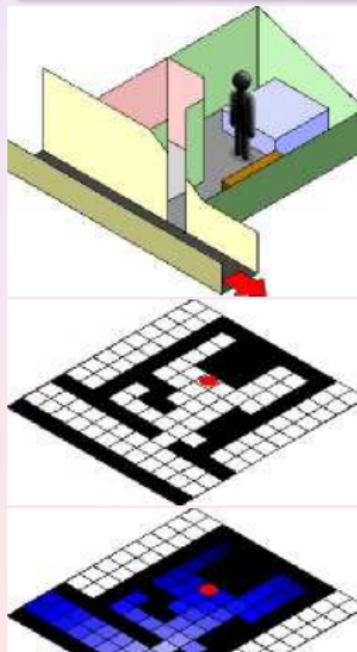
Cellular automata model

- Floor field model

→ isotropy pbl

[C. Burstedde et al, Physica A 295 (2001) 507-525]

- PEDGO Software

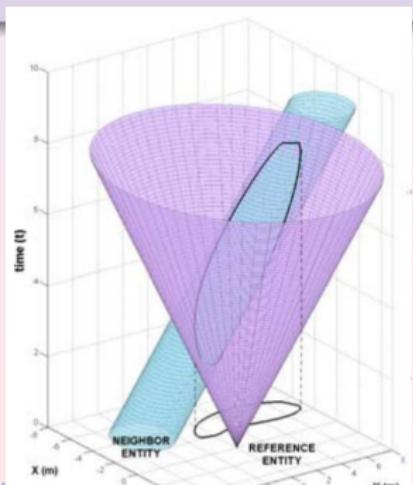


Pedestrians : Microscopic Models

Velocity based models

- [Paris, Pettré, Donikian (2007)]
- [RVO (2008)]
- [Pettré *et al* (2009)]
- [Ondrej et al (2010), Moussaïd et al (2011)]

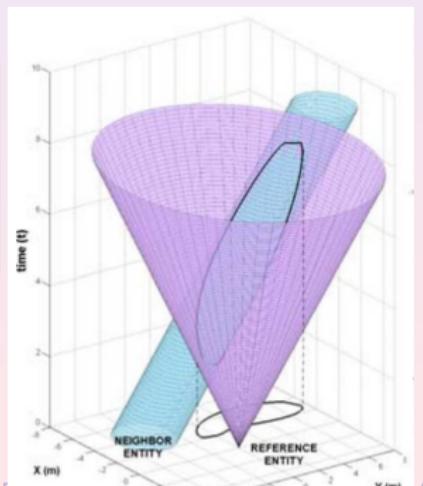
- Determination of admissible velocities (to avoid collision in the next few seconds)
- Optimal choice among this set of velocity



Pedestrians : Microscopic Models

- [Paris, Pettré, Donikian (2007)]
- [RVO (2008)]
- [Pettré *et al* (2009)] ➔ Velocities are gradually evaluated
- [Ondrej et al (2010), Moussaïd et al (2011)] ➔ Decoupling of velocity modulus and angle

- Determination of admissible velocities (to avoid collision in the next few seconds)
- Optimal choice among this set of velocity
- Automatic composition of interactions



[Paris *et al.* (2007)]

Pedestrians : Microscopic Models

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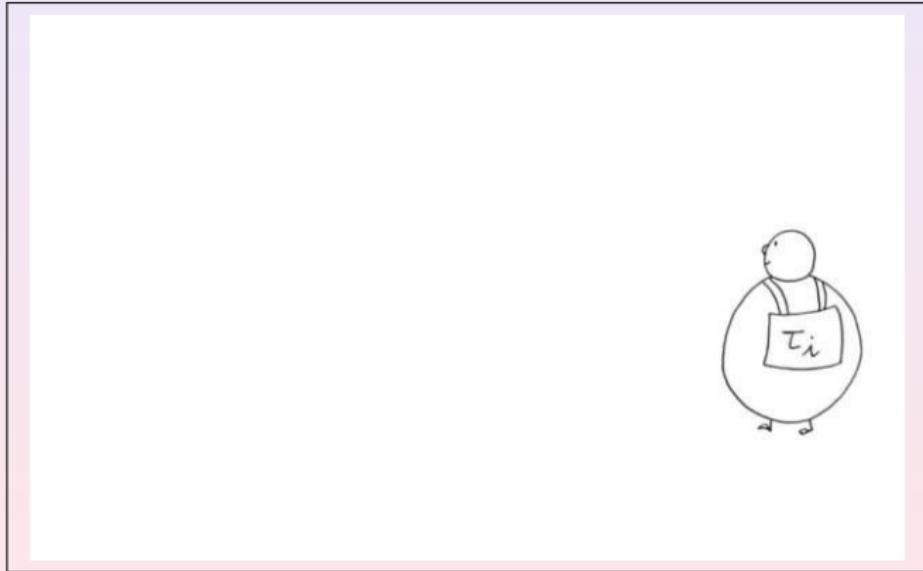
- Determination of velocities ?
 - visual information
 - cognitive process

- Vision based model [Ondrej et al, SIGGRAPH 2010]

Vision based model

[Ondrej et al, SIGGRAPH 2010]
[Cutting et al, 1995]

- Movement



Vision based model

[Ondrej et al, SIGGRAPH 2010]
[Cutting et al, 1995]

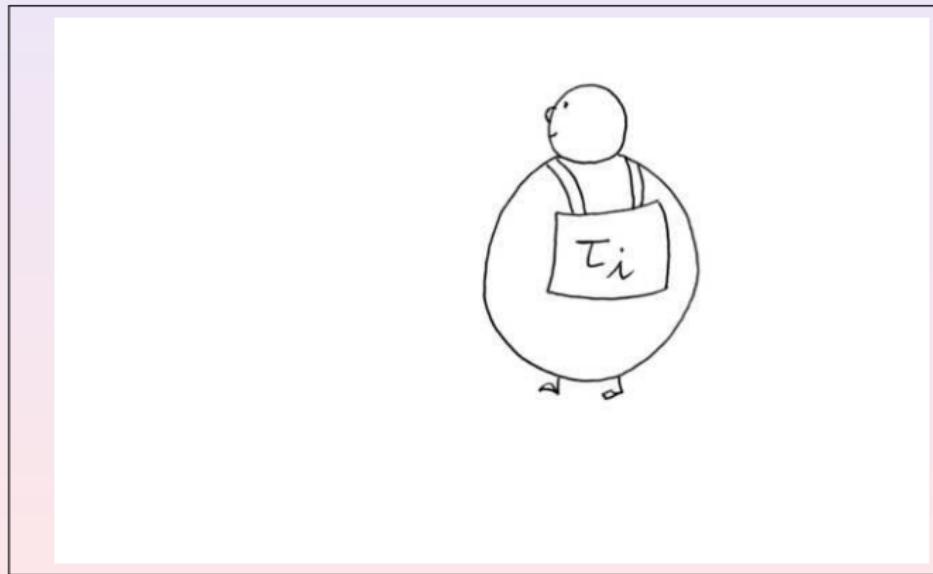
- Movement
- Size



Vision based model

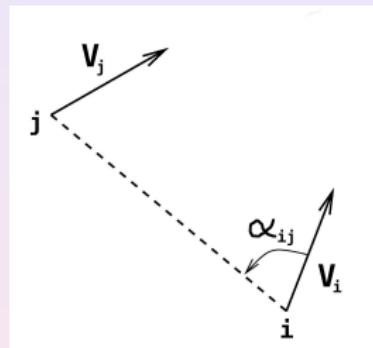
[Ondrej et al, SIGGRAPH 2010]
[Cutting et al, 1995]

- Movement
- Size



Vision based model: Perception

- Movement
- ▶ time Derivative of the Bearing Angle (DBA) $\dot{\alpha}_{ij}$
 - ☆ Future collision if $\dot{\alpha}_{ij} = 0$
- Size
- ▶ time to interaction (tti) τ_{ij}
 - ☆ Soon if τ_{ij} small

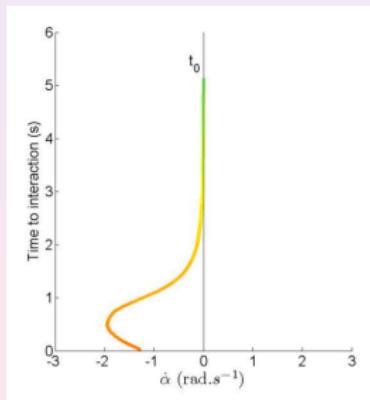


Vision based model: Reaction

[Ondrej et al, SIGGRAPH 2010]

Velocity can change in

- modulus
- direction

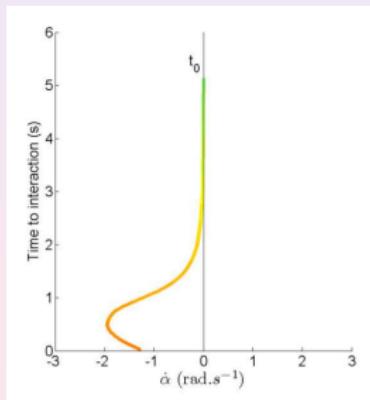


Vision based model: Reaction

[Ondrej et al, SIGGRAPH 2010]

Velocity can change in

- modulus
- direction ✓



Vision based model: Reaction

[Degond, A-R, Pettré, Theraulaz (2013) Kinetic and Related Models]

How threatening is the collision?

$$\Phi(|\dot{\alpha}_{ij}|, |\tau_{ij}|) = \Phi_0 \max\{\sigma - |\dot{\alpha}_{ij}|, 0\} \quad \text{with} \quad \sigma = a + \frac{b}{(|\tau_{ij}| + \tau_0)^c}$$

- Parameters a , b , and c can be evaluated from experiments
- τ_0 will bound the angular speed of pedestrians

Vision based model: Reaction

[Degond, A-R, Pettré, Theraulaz (2013) Kinetic and Related Models]

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$$\Phi(|\dot{\alpha}_{ij}|, |\tau_{ij}|) = \Phi_0 \max\{\sigma - |\dot{\alpha}_{ij}|, 0\} \quad \text{with} \quad \sigma = a + \frac{b}{(|\tau_{ij}| + \tau_0)^c}$$

- One pair interaction: Φ = angular velocity
 - In general:
 - Multiple interactions
 - Target ξ
- $\Phi_c(\mathbf{x}, \mathbf{u}, \xi)$ = cost function of most threatening collision = $\max_j \Phi$
- $\Phi_t(\mathbf{x}, \mathbf{u}, \xi)$ = cost function for deviating from the target
 $\min(\Phi_c + \Phi_t) \Rightarrow$ optimal velocity $\mathbf{u}_i(t)$ ($\|\mathbf{u}_i\| = 1$)

Mean-field kinetic model

Probability distribution $f(\mathbf{x}, \mathbf{u}, \xi, t)$

$$\partial_t f + c\mathbf{u} \cdot \nabla_{\mathbf{x}} f + \nabla_{\mathbf{u}} \cdot (\omega_f \mathbf{u}^\perp f) = d\Delta_{\mathbf{u}} f.$$

Determination of $\omega_f(\mathbf{x}, \mathbf{u}, \xi, t)$:

Extremum of cost function is ill-defined when a probability distribution is considered

- ➡ $\Phi_c(\mathbf{x}, \mathbf{u}, t)$ = weighted average of the cost functions Φ
- ➡ $\Phi_t(\mathbf{x}, \mathbf{u}, \xi, t)$ is the same as for the IBM

$$\Rightarrow \omega_f(\mathbf{x}, \mathbf{u}, \xi, t)\mathbf{u}^\perp = -\nabla_{\mathbf{u}} [\Phi_c(\mathbf{x}, \mathbf{u}, \xi, t) + \Phi_t(\mathbf{x}, \mathbf{u}, \xi, t)]$$

Macroscopic model

$$\rho(\mathbf{x}, \xi, t) = \int_{\mathbf{u} \in \mathbb{S}^1} f(\mathbf{x}, \mathbf{u}, \xi, t) d\mathbf{u},$$

$$\mathbf{U}(\mathbf{x}, \xi, t) = \frac{1}{\rho(\mathbf{x}, \xi, t)} \int_{\mathbf{u} \in \mathbb{S}^1} f(\mathbf{x}, \mathbf{u}, \xi, t) \mathbf{u} d\mathbf{u}$$

Moment method

Multiply the kinetic equation by the moments of \mathbf{u} : $(1, \mathbf{u}, \dots)$
Integrate over \mathbf{u}

→ Closure problem → Need for a closure relation

Macroscopic model: Closure relations

Monokinetic closure

$$f(\mathbf{x}, \mathbf{u}, \xi, t) = \rho(\mathbf{x}, \xi, t) \delta_{\mathbf{U}(\mathbf{x}, \xi, t)}(\mathbf{u}).$$

(no noise)

$$\partial_t \mathbf{U} + c \mathbf{U} \cdot \nabla_{\mathbf{x}} \mathbf{U} = \omega_{\rho \delta_U}(\mathbf{x}, \mathbf{U}(\mathbf{x}, \xi, t), \xi, t) \mathbf{U}^\perp(\mathbf{x}, \xi, t)$$

where again $\omega_{\rho \delta_U}$ is determined from a cost function.

Other closure relations are possible

Macroscopic model

Hydrodynamic limit

Force and diffusion dominate \rightarrow Development around a Local Thermodynamical Equilibrium solution f^0

$$\nabla_u \cdot (\omega_f^0 \mathbf{u}^\perp f^0) = d\Delta_u f^0.$$

First order macroscopic model

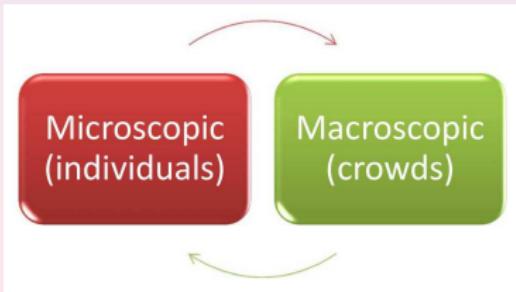
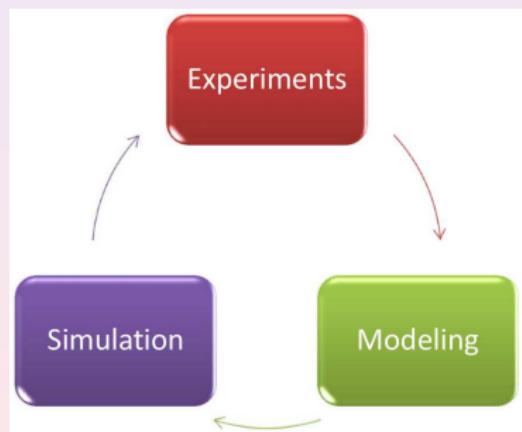
$$\partial_t \rho_{(x,t)}(\xi) + \nabla_x \cdot (c \rho_{(x,t)}(\xi) U_{x,[\rho_{(x,t)}]}(\xi)) = 0$$

supplemented by a relation giving $U_{x,[\rho_{(x,t)}]}(\xi)$

- Compare macroscopic models
- Can macroscopic model reproduce pattern formation?

PEDIGREE Project

PEDIGREE = PEDestrian GRoups: EmErgence of collective behavior through experiments, modelling and simulation



PEDIGREE Project

IMT, Toulouse

P. Degond



J. Fehrenbach

J. Hua

S. Motsch

J. Narski

L. Navoret



INRIA-Rennes

J. Pettré



S. Lemercier



S. Donikian

CRCA, Toulouse

G. Théraulaz



M. Moussaïd



M. Moreau

LPT, Paris-Sud

C. Appert-Rolland



A. Jelic



J. Cividini



Experiments

Aim:

- Well-controlled experiments
- Reference data
- Multi-scale data

High precision motion capture:
VICON system



Experiments with pedestrians

Two experimental campaigns (250 persons),
with the help from M2S (Univ. Rennes 2)

Ring corridor

Mono- or bi-directional flow

- ➔ lane formation, jamming



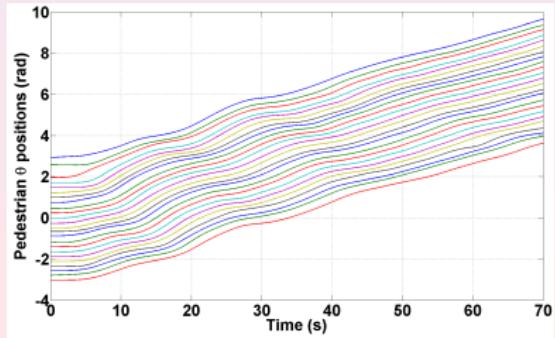
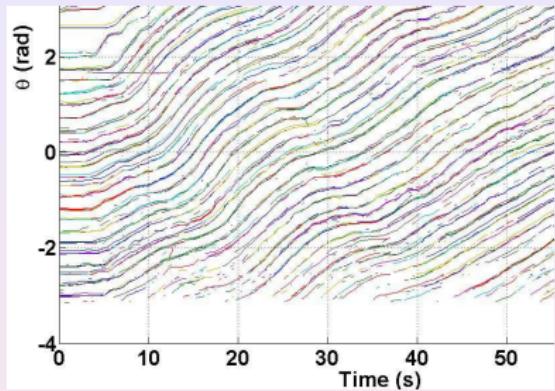
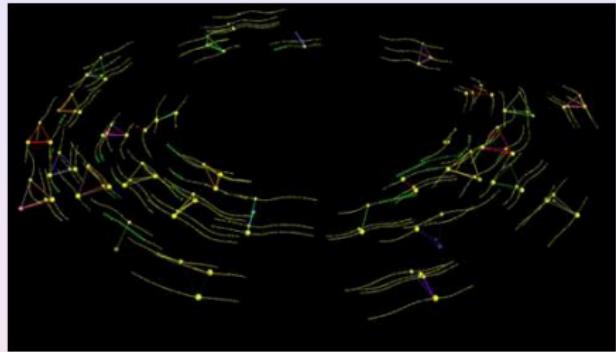
One-dimensional circle

No passing

- ➔ longitudinal interactions

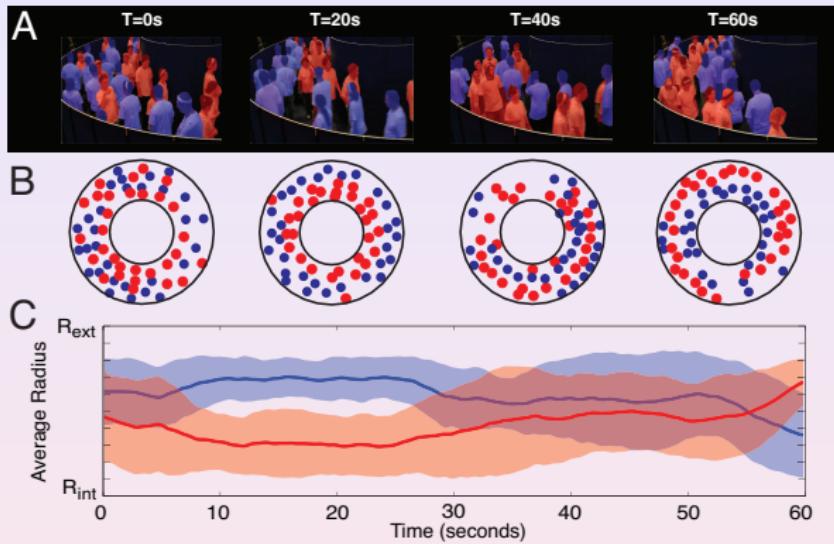


Reconstruction of trajectories



- From raw data to 3D markers' trajectories
- From markers to pedestrians
- Interpolating for missing data

Ring



[M. Moussaïd, E. Guillot, M. Moreau, J. Fehrenbach, O. Chabiron, S. Lemercier, J. Pettré, C. Appert-Rolland, P. Degond and G. Theraulaz, *Traffic Instabilities in Self-organized Pedestrian Crowds*, PLoS Computational Biology (2012)]

Macroscopic model for pedestrians in a corridor

$$\partial_t \rho_+ + \partial_x (\rho_+ u_+) = 0,$$

$$\partial_t \rho_- + \partial_x (\rho_- u_-) = 0,$$

$$\partial_t (\rho_+ u_+) + \partial_x (\rho_+ u_+ u_+) = -\rho_+ \left(\frac{d}{dt} \right)_+ [p(\rho_+, \rho_-)],$$

$$\partial_t (\rho_- u_-) + \partial_x (\rho_- u_- u_-) = \rho_- \left(\frac{d}{dt} \right)_- [p(\rho_-, \rho_+)],$$

where

$$(d/dt)_{\pm} = \partial_t + u_{\pm} \partial_x$$

[C. A-R, P. Degond, and S. Motsch. *Two-way multi-lane traffic model for pedestrians in corridors*. Networks and Heterogeneous Media, 6:351, (2011).]

Macroscopic model for pedestrians in a corridor

$$\begin{aligned} u_+ &= w_+ - p(\rho_+, \rho_-) \\ -u_- &= w_- - p(\rho_-, \rho_+) \end{aligned}$$

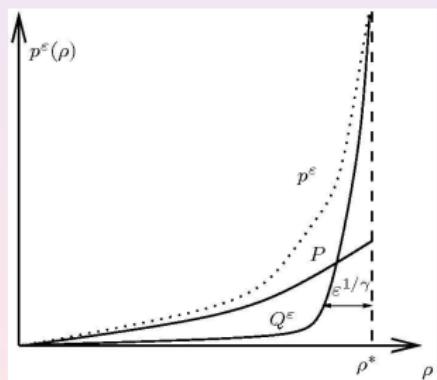
where w is a Riemann invariant

$$\begin{aligned} \partial_t w_+ + u_+ \partial_x w_+ &= 0 \\ \partial_t w_- + u_- \partial_x w_- &= 0 \end{aligned}$$

$$p(\rho_+, \rho_-) = P(\rho) + Q^\varepsilon(\rho_+, \rho_-), \quad \text{with} \quad \rho = \rho_+ + \rho_-$$

$$P(\rho) = M\rho^m, \quad m \geq 1,$$

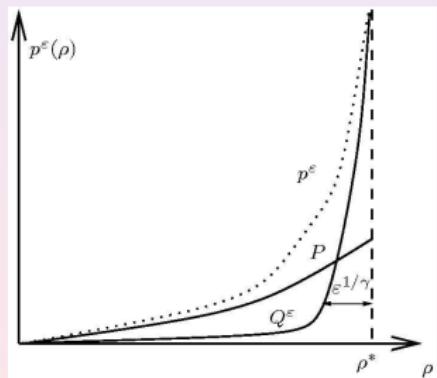
$$Q^\varepsilon(\rho_+, \rho_-) = \frac{\varepsilon}{q(\rho_+) \left(\frac{1}{\rho} - \frac{1}{\rho^*} \right)^\gamma}, \quad \gamma > 1.$$



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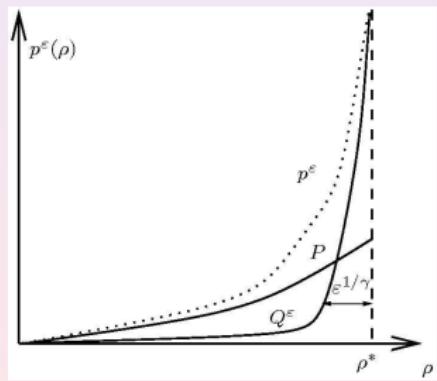


Ring

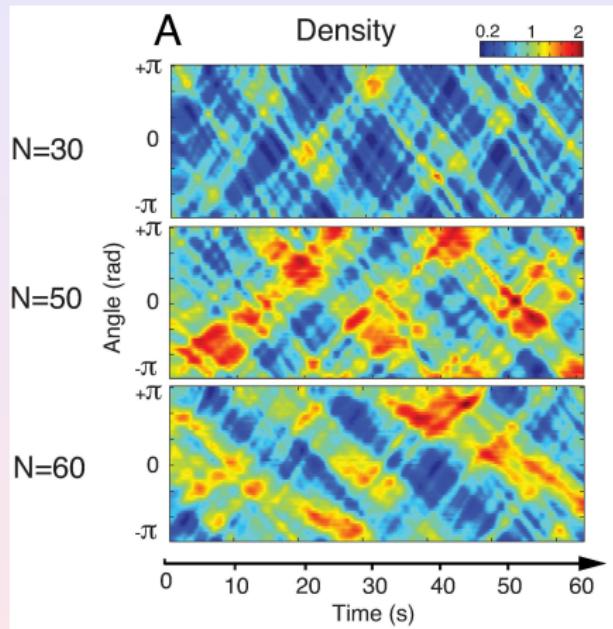
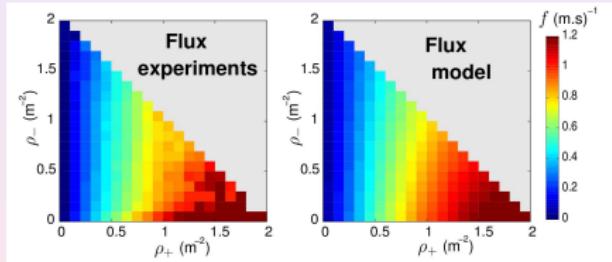
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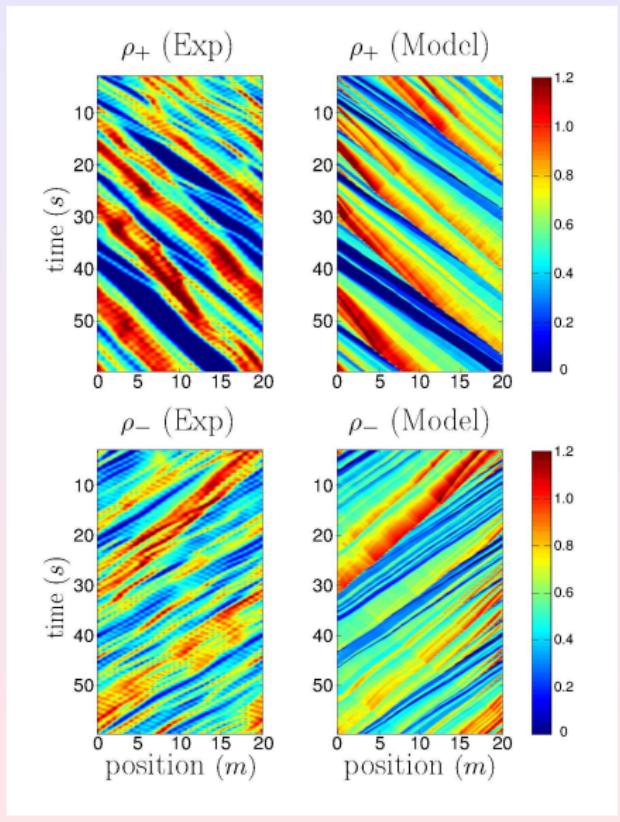
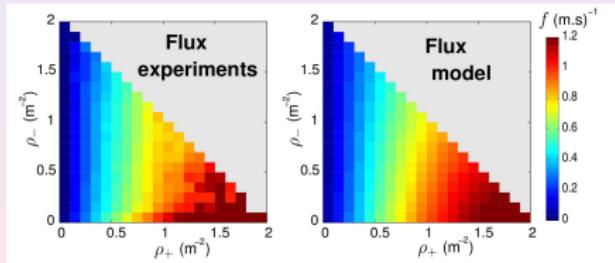
$$Q^\varepsilon(\rho_+, \rho_-) = \frac{\varepsilon}{q(\rho_+) \left(\frac{1}{\rho} - \frac{1}{\rho^*} \right)^\gamma}, \quad \gamma > 1.$$



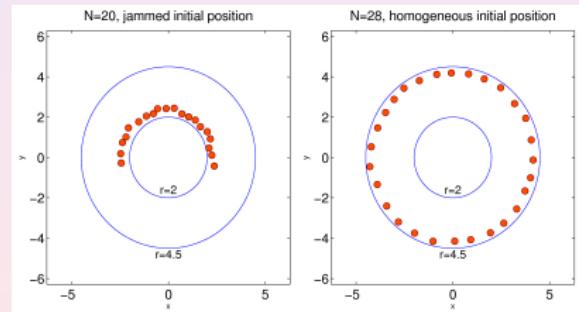
Ring



Ring



1D Circle

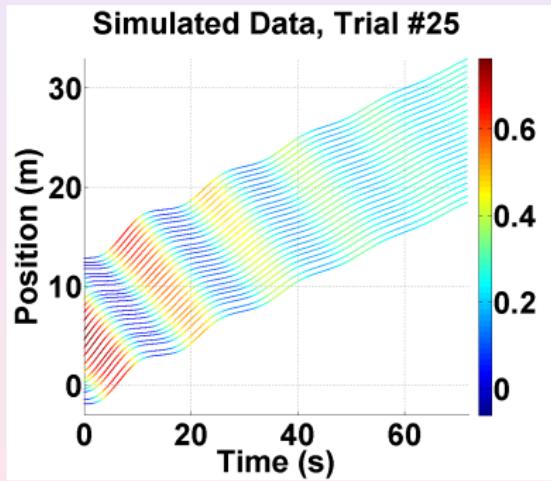
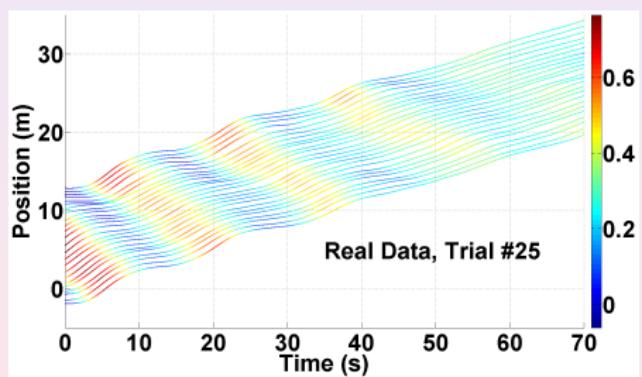


Density varying from 0.31 to 1.86 ped/m.

1D Circle

$$a(t) = C \frac{\Delta v(t - \tau)}{[\Delta x(t)]^\gamma}$$

Ex: $\rho = 1.59 \text{ ped/m}$

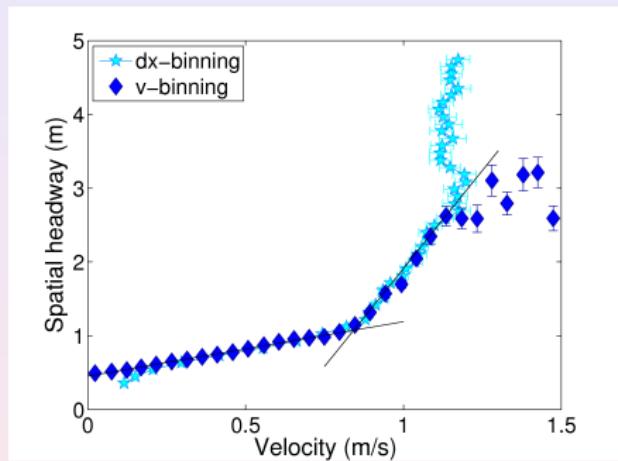


[S. Lemercier et al, *A realistic model of following behavior for crowd simulation*, EUROGRAPHICS (2012)]

1D Circle

1D Circle

1D Circle



Several regimes

- Free
- Weakly constrained
 - ➡ $t_{adaptation} = 5.32$ s
- Strongly constrained
 - ➡ $t_{adaptation} = 0.74$ s

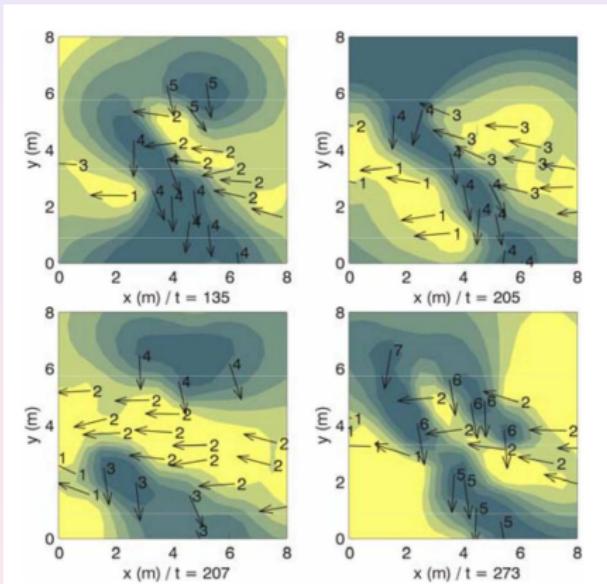
[A. Jelić, C. A-R, S. Lemercier, J. Pettré,
Properties of pedestrians walking in line – Fundamental diagrams,
Phys. Rev. E, **85** (2012) 036111]

Intersection of two perpendicular pedestrian flows

Diagonal instability: • observed in experiments

in

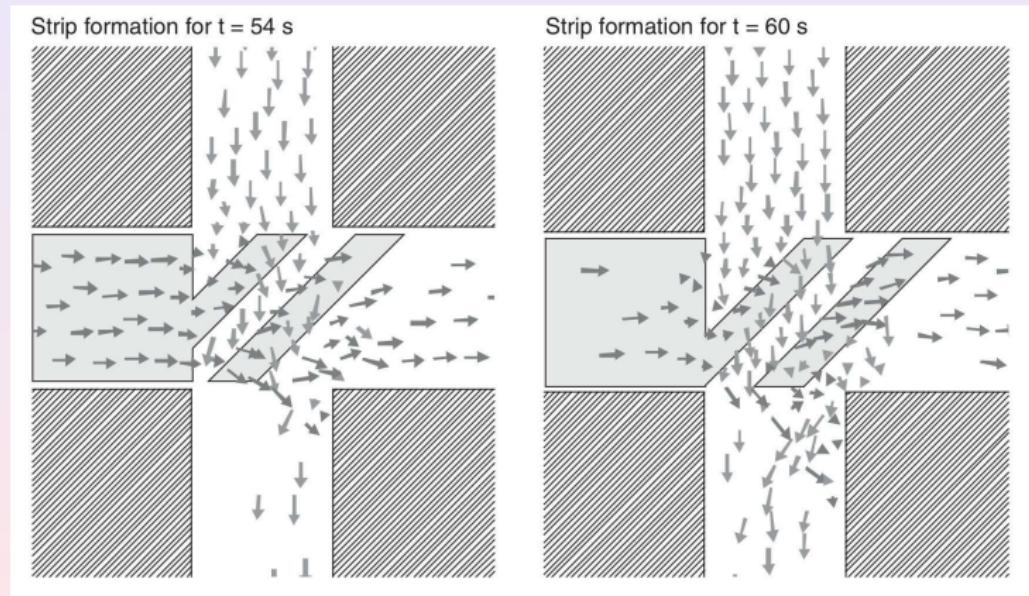
[Hoogendoorn & Daamen,
TGF'03 (Springer) 2005,
pp. 121]



Intersection of two perpendicular pedestrian flows

Diagonal instability:

- observed in simulations

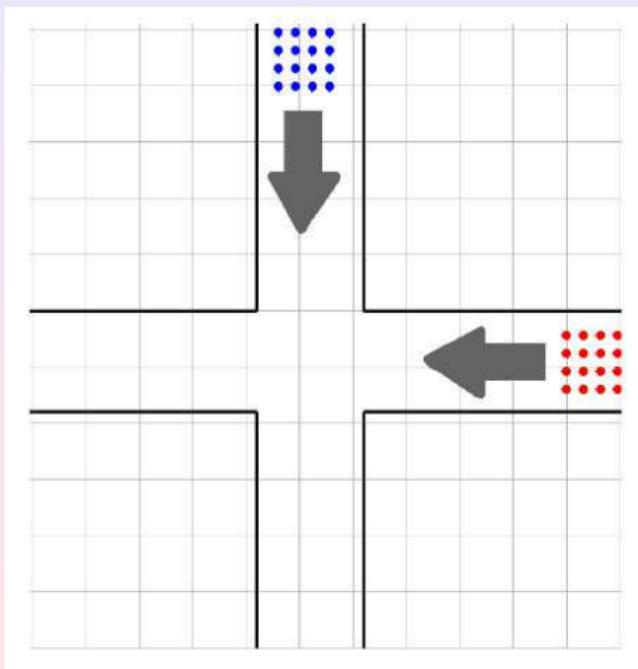


[Hoogendoorn & Bovy, Optim. Control Appl. Meth., 24 (2003) 153]

Intersection of two perpendicular pedestrian flows

Diagonal instability:

- observed in simulations

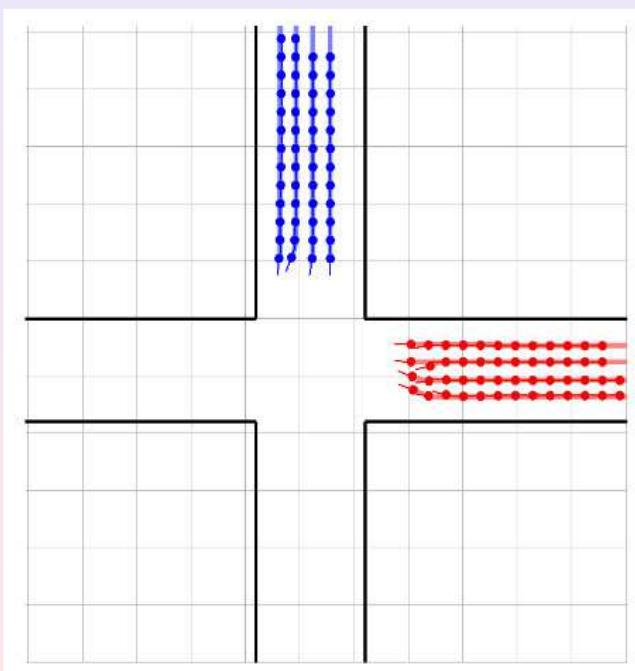


[Ondrej et al, SIGGRAPH 2010]

Intersection of two perpendicular pedestrian flows

Diagonal instability:

- observed in simulations

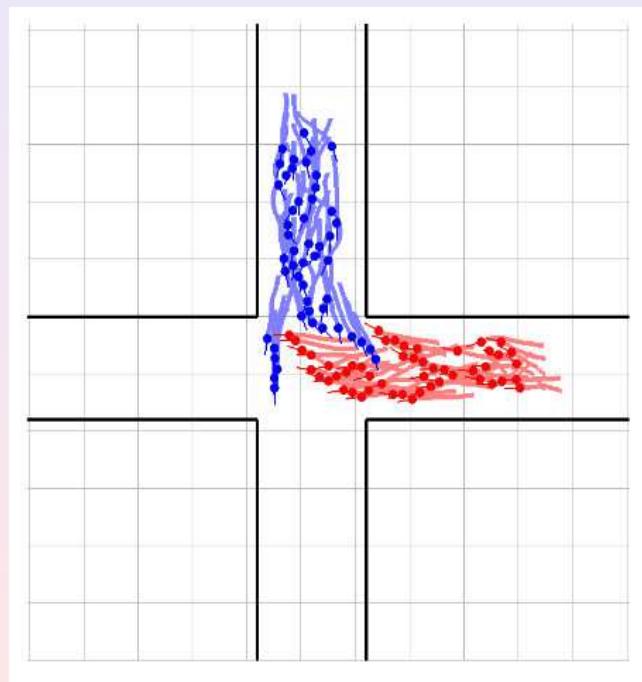


[Ondrej et al, SIGGRAPH 2010]

Intersection of two perpendicular pedestrian flows

Diagonal instability:

- observed in simulations

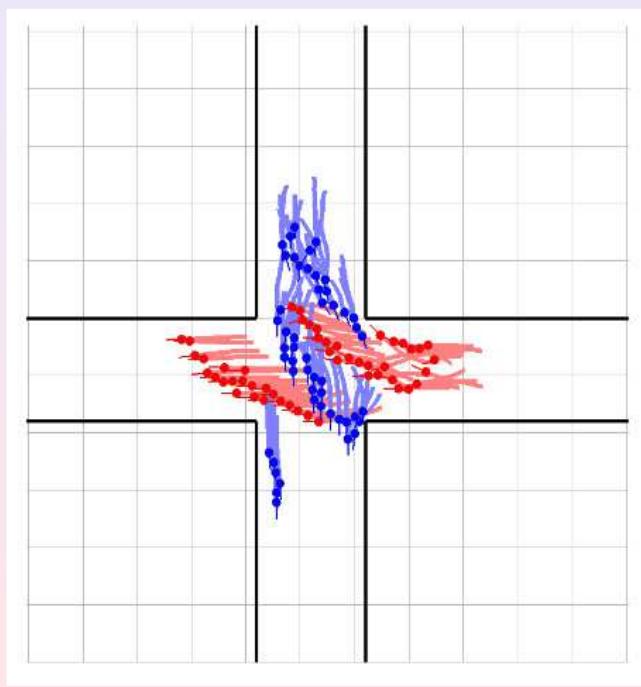


[Ondrej et al, SIGGRAPH 2010]

Intersection of two perpendicular pedestrian flows

Diagonal instability:

- observed in simulations

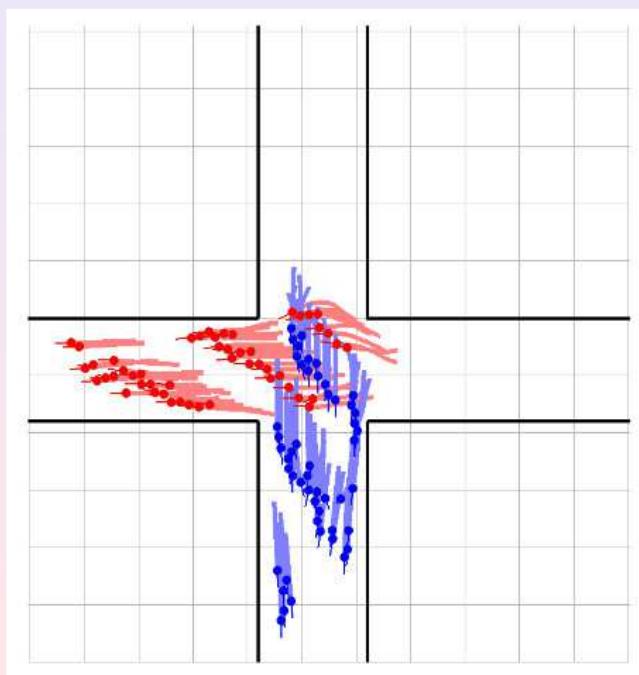


[Ondrej et al, SIGGRAPH 2010]

Intersection of two perpendicular pedestrian flows

Diagonal instability:

- observed in simulations

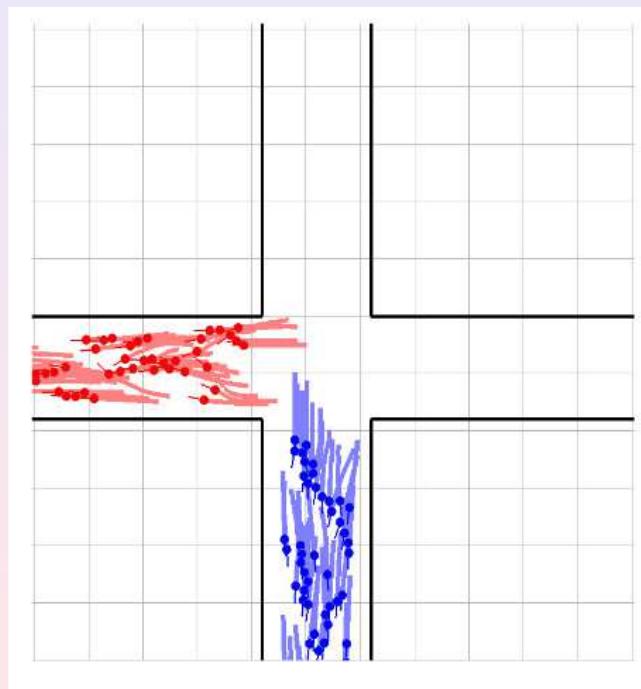


[Ondrej et al, SIGGRAPH 2010]

Intersection of two perpendicular pedestrian flows

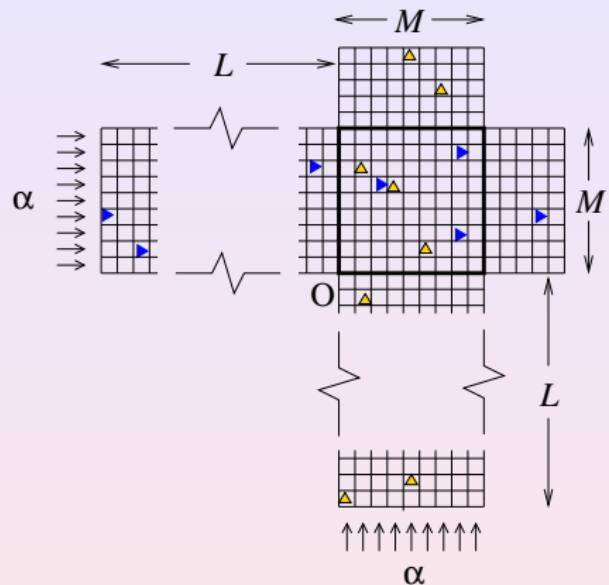
Diagonal instability:

- observed in simulations



[Ondrei et al., SIGGRAPH 2010]

Intersection of two perpendicular pedestrian flows



- \mathcal{E} = Eastbound particles
- \mathcal{N} = Northbound particles

$n^{\mathcal{E}}(\mathbf{r}), n^{\mathcal{N}}(\mathbf{r})$ = boolean occupation variables

- As α increases: jamming transition
[H. J. Hilhorst, C. A-R, J. Stat. Mech. (2012) P06009]
- Here we consider only the free flow phase.

Updates

Cellular automaton = geometry + rules + update

- Frozen shuffle update

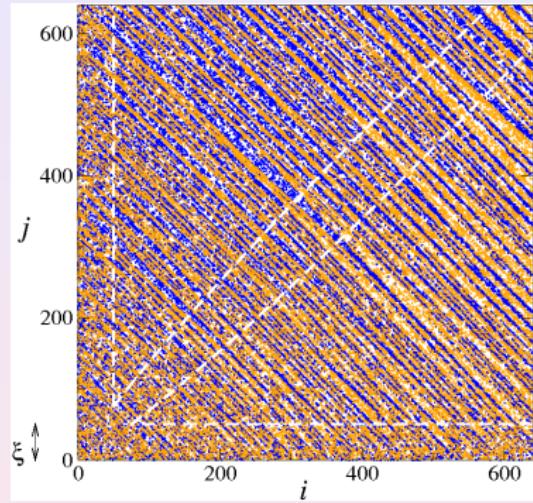
- Each particle has a phase $\tau_i \in [0, 1[$
- At each time step, update in the order of increasing phase.



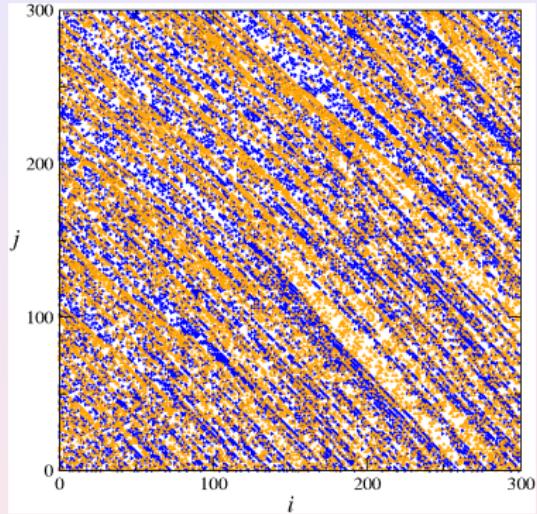
- Alternating parallel update

- \mathcal{E} particles are updated in parallel at integer times t
- \mathcal{N} particles are updated in parallel between integer times, at $t + \frac{1}{2}$

Observations



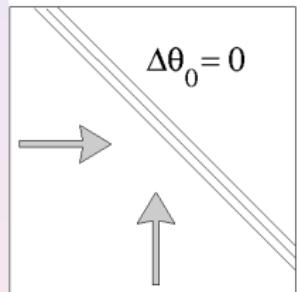
- frozen shuffle update
- $M = 640$



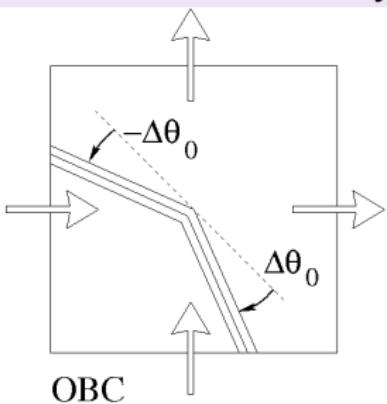
- alternating parallel update
- $M = 300$

Observations

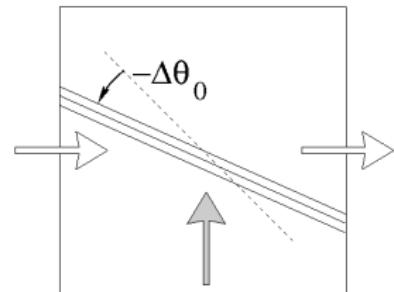
Summary: pattern depends on the boundary conditions



PBC



OBC



CBC

Mean field equations

We postulate some mean-field equations:

$$\begin{aligned}\rho_{t+1}^{\mathcal{E}}(\mathbf{r}) &= [1 - \rho_t^{\mathcal{N}}(\mathbf{r})]\rho_t^{\mathcal{E}}(\mathbf{r} - \mathbf{e}_x) + \rho_t^{\mathcal{N}}(\mathbf{r} + \mathbf{e}_x)\rho_t^{\mathcal{E}}(\mathbf{r}) \\ \rho_{t+1}^{\mathcal{N}}(\mathbf{r}) &= [1 - \rho_t^{\mathcal{E}}(\mathbf{r})]\rho_t^{\mathcal{N}}(\mathbf{r} - \mathbf{e}_y) + \rho_t^{\mathcal{E}}(\mathbf{r} + \mathbf{e}_y)\rho_t^{\mathcal{N}}(\mathbf{r})\end{aligned}$$

- pair correlations $\langle n^{\mathcal{E}} n^{\mathcal{N}} \rangle$ have been factorized
- interaction terms $\langle n^X n^X \rangle$ between same-type particles have been neglected (low density)

Simulations: same patterns as for the particle model

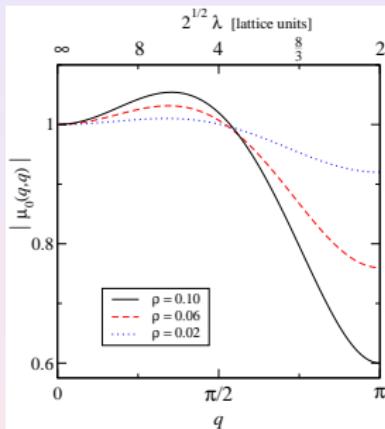
Mean field equations

◆ PBC

- Linear stability analysis

$$\rho_t^{\mathcal{E}, \mathcal{N}}(\mathbf{r}) = \bar{\rho} + \delta \rho_t^{\mathcal{E}, \mathcal{N}}(\mathbf{r})$$

- Most unstable mode traveling in the $(1, 1)$ direction with wavelength



$$\lambda_{\max} = 2\pi/|\mathbf{q}|_{\max} = 3\sqrt{2}[1 - (\sqrt{3}/\pi)\bar{\rho}] + \mathcal{O}(\bar{\rho}^2),$$

Mean field equations

◆ OBC

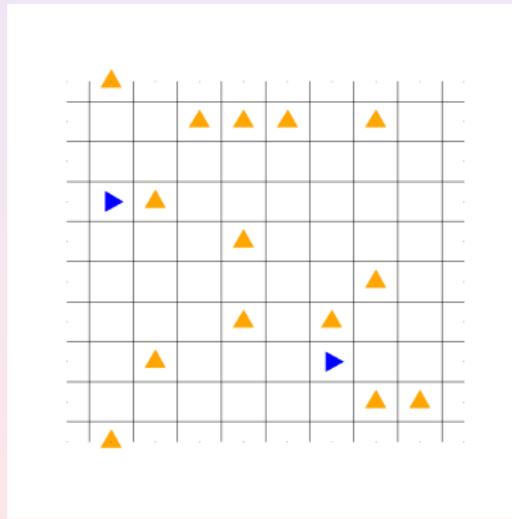
- Linear stability analysis:
 - ➡ Calculation of Green function
[Cividini & Hilhorst (2014) arXiv:1406.5394]
 - ➡ diagonals, but no sign of the chevron effect

Chevron effect = non linear effect

Effective interactions

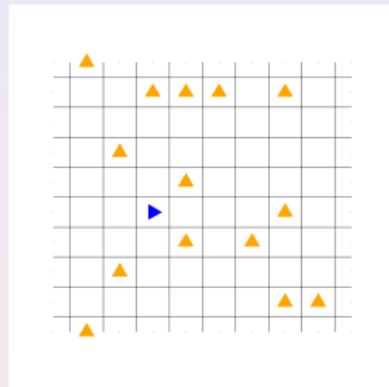
From which microscopic mechanism does the (tilted) diagonal pattern emerge?

→ effective interaction between two \mathcal{E} particles crossing a flow of \mathcal{N} particles

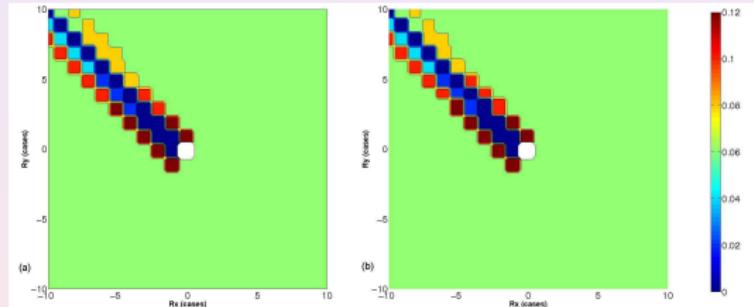


Wake of a single \mathcal{E} particle

Ensemble averaged wake



Frozen shuffle update

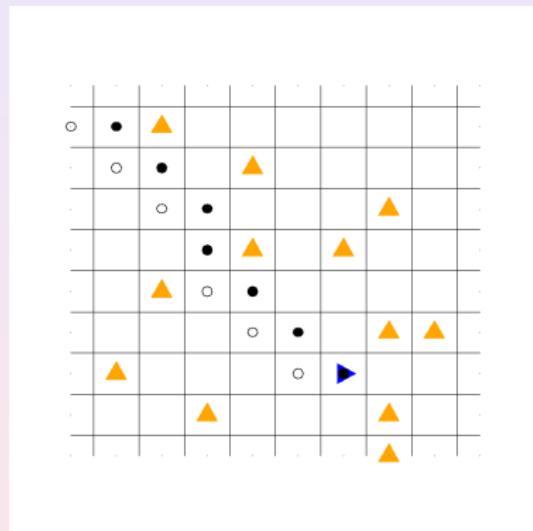


Theory

Simulation

Wake of a single \mathcal{E} particle

Microscopic structure of the wake:



Central part of the wake : the shadow

Construction:

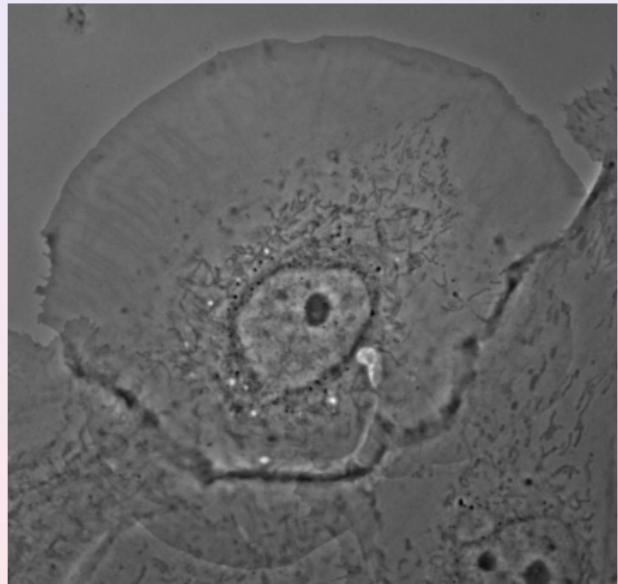
- Before move: white dot
- After move: black dot

At low density, $\tan\theta \simeq 1 - \rho^N$

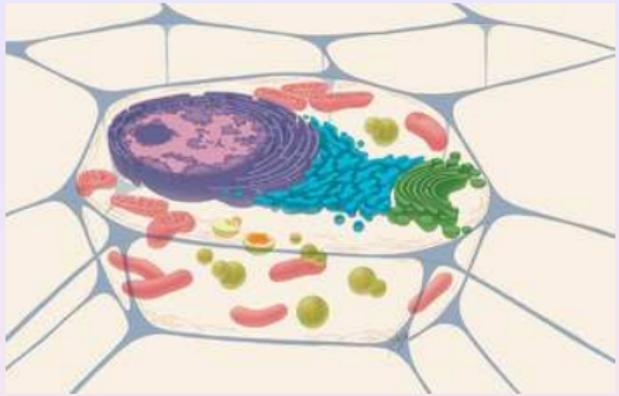
INTRACELLULAR TRANSPORT

Intra-cellular transport

- Need for transport



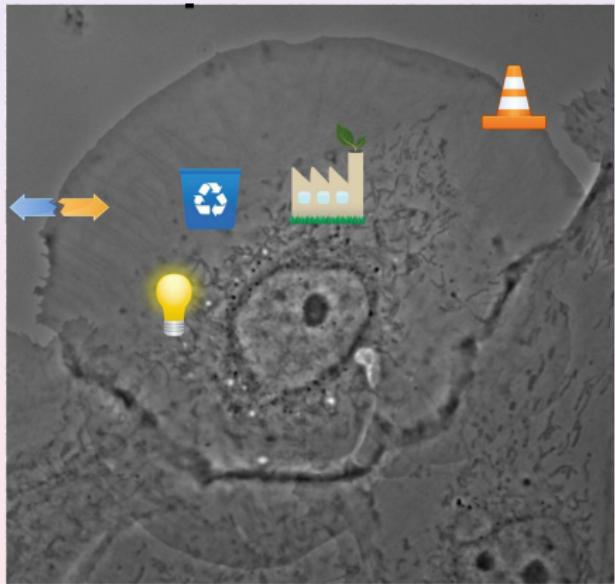
From [Wittmann et al, J. Cell Biol. 161:845 (2003)])



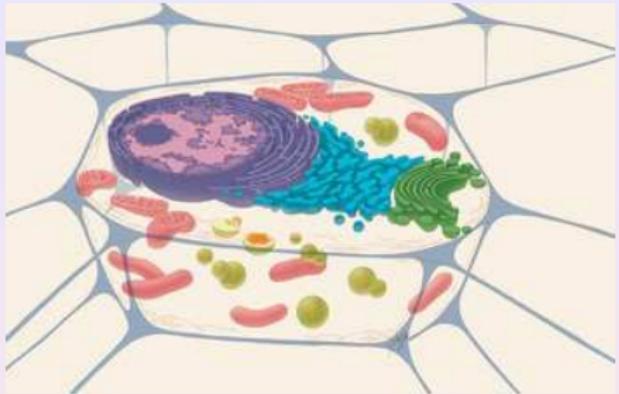
From [Judith Stoffer, NIGMS]

Intra-cellular transport

- Need for transport

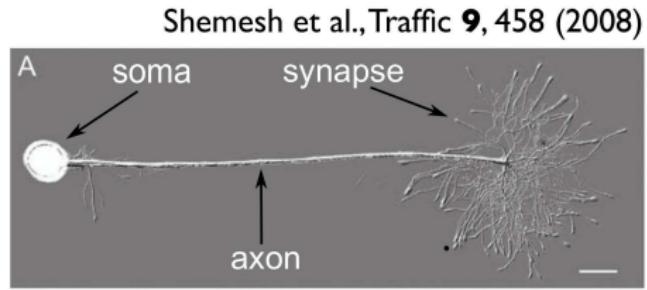


From [Wittmann et al, J. Cell Biol. 161:845 (2003)])

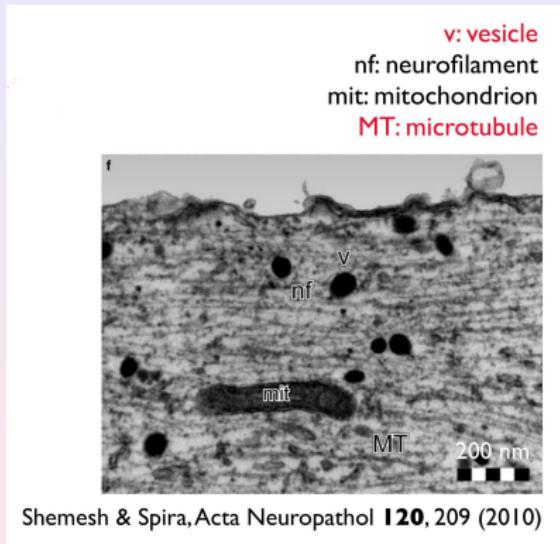


From [Judith Stoffer, NIGMS]

Intra-cellular transport



- Particular case: the axon
 - up to 1 m in human beings, a few microns for the diameter
 - crowded environment



Cytoskeleton

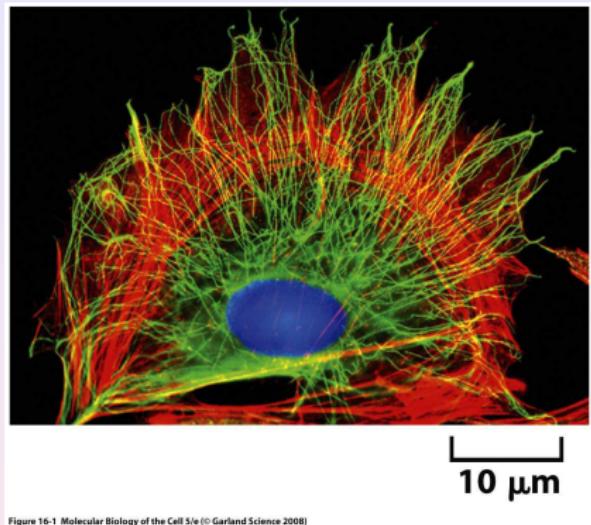
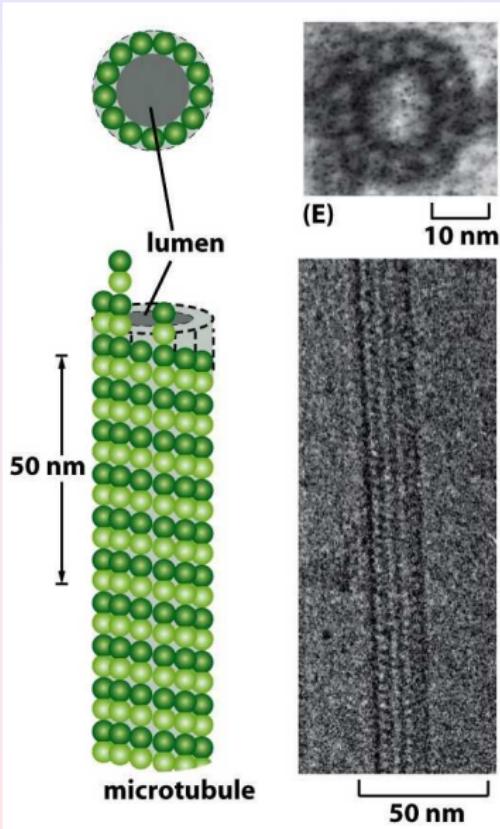


Figure 16-1 Molecular Biology of the Cell 5/e (© Garland Science 2008)

From [Alberts et al, *Molecular Biology of the Cell*, 5th ed. (2008)]

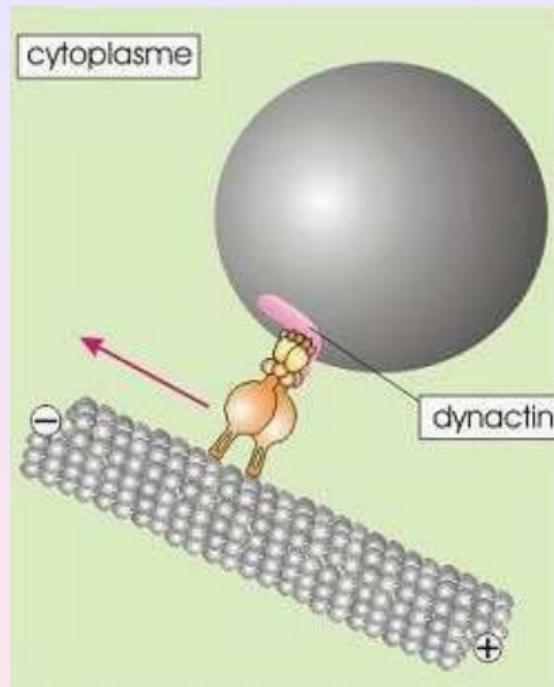
- Green = Microtubule
- Red = Actin
- Blue = DNA



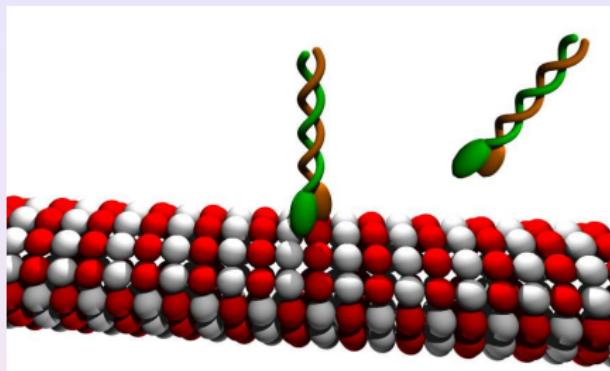
Molecular Motors

[National Institute on Aging - NIH]

Molecular Motors



[From www.ulysse.u-bordeaux.fr/atelier/ikramer/biocell_diffusion]

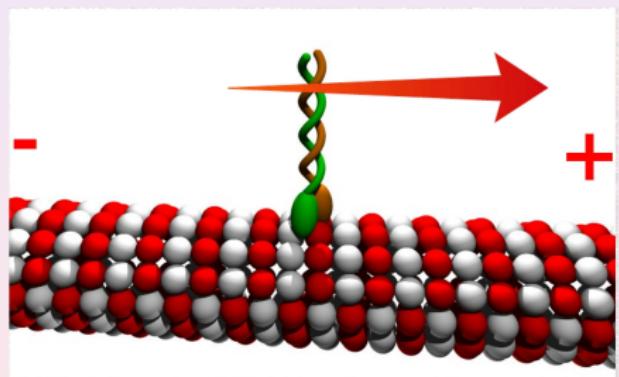


[Image crée à partir d'une image de wikipedia de Kebes]

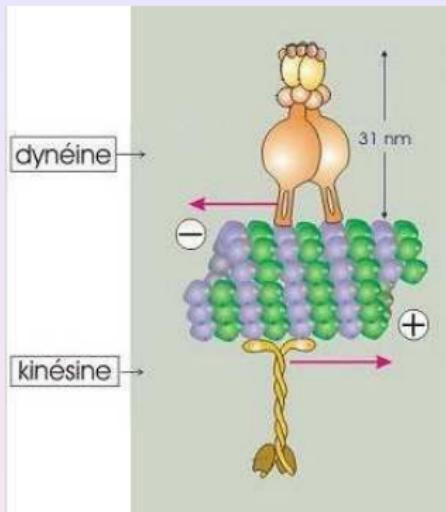
Molecular motors can attach and detach from the MT
→ Processive and diffusive phases

Molecular Motors

Microtubules are polarized

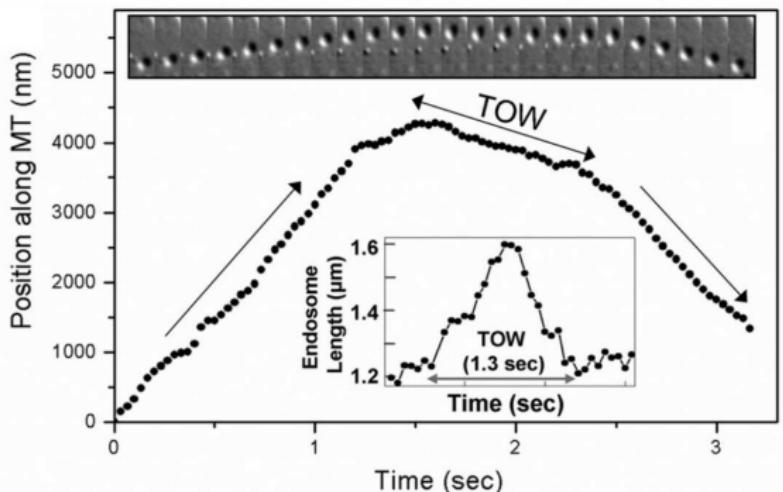


[Image créée à partir d'une image de wikipedia de Kebes]



[Modified from www.ulysse.u-bordeaux.fr/atelier/ikramer/biocell_diffusion]

Tug-of-war



Endosome inside
Dictyostelium cells.

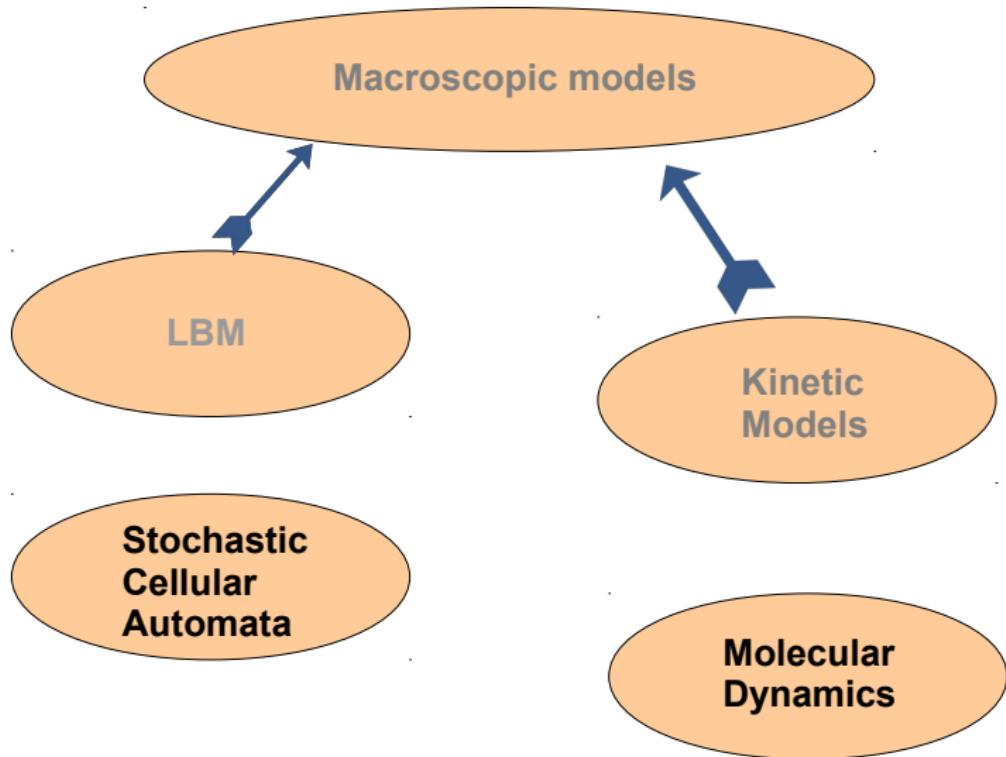
[Soppina et al (2009)
PNAS]



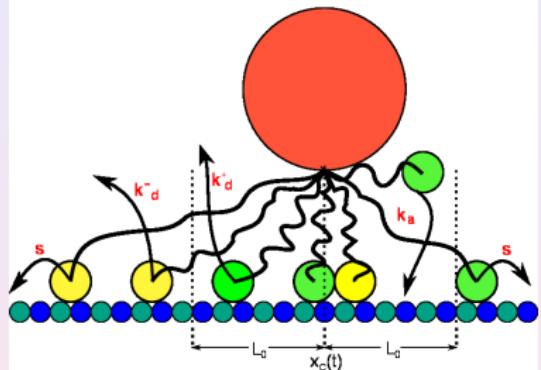
Tug-of-war

[LEX Commons]

Modèles pour le transport intracellulaire



Explicit Position Based Model



Stochastic Motor Dynamics:

- attachment rate $\tilde{\omega}$
- stepping rate $p = p(F_i)$
- detachment rate $\omega = \omega(F_i)$

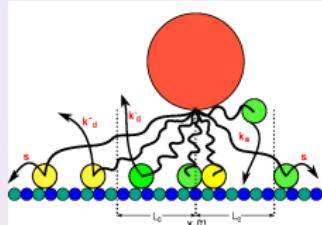
Cargo dynamics

$$m \frac{\partial^2 x_C(t)}{\partial t^2} = -\beta \frac{\partial x_C(t)}{\partial t} + F(x_C, \{x_i\}) \quad \text{where } F = \sum_i F_i$$

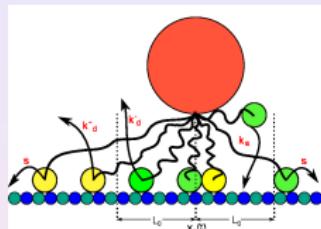
Tug-of-war, asymmetric motors

Asymmetric teams

Kinesins and dyneins behave differently

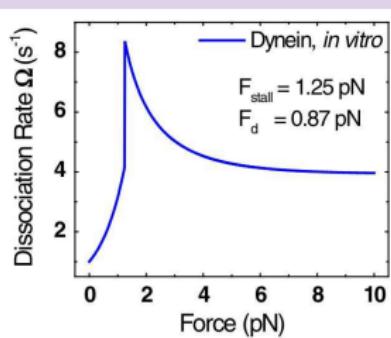
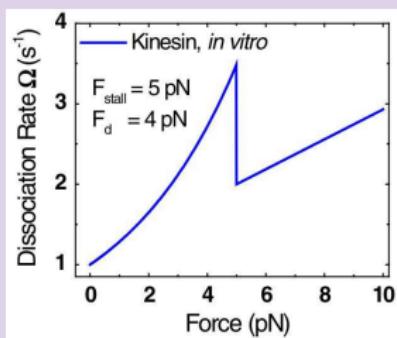


Tug-of-war, asymmetric motors



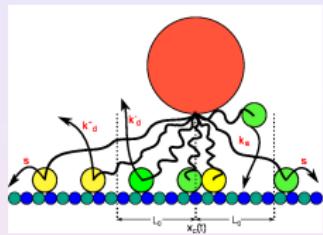
Stochastic motor dynamics

Detachment rate



From [Kunwar et al (2011) PNAS]

Tug-of-war, asymmetric motors



Stochastic motor dynamics

- Stepping rate (for F_i below stall force) :

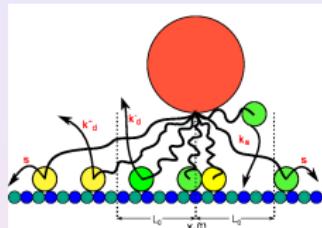
$$s(|F_i|, [ATP]) = \frac{k_{\text{cat}}(|F_i|)[ATP]}{[ATP] + k_{\text{cat}}(|F_i|)k_b(|F_i|)^{-1}},$$

Michaelis-Menten kinetics

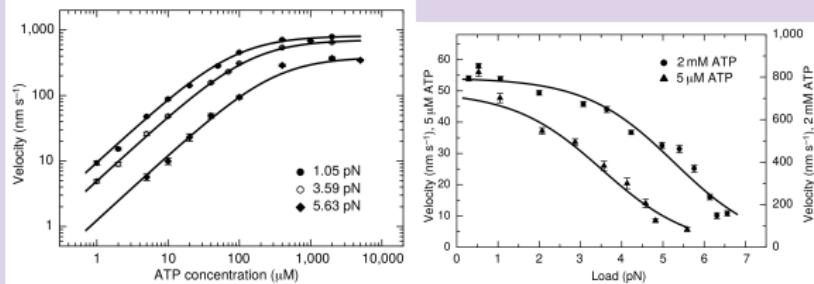
From [Schnitzer et al (2000) Nat. Cell Biol.]

- Stepping rate (for F_i above stall force) :
backward stepping $s_b = v_b/d$

Tug-of-war, asymmetric motors



Stochastic motor dynamics [ATP] and force dependence



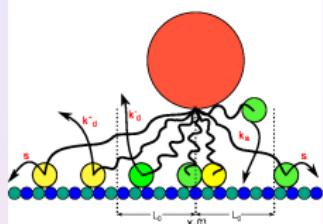
Comparison for kinesin

From [Schnitzer et al (2000) Nat. Cell Biol.]

From [Visscher et al (1999) Nature]

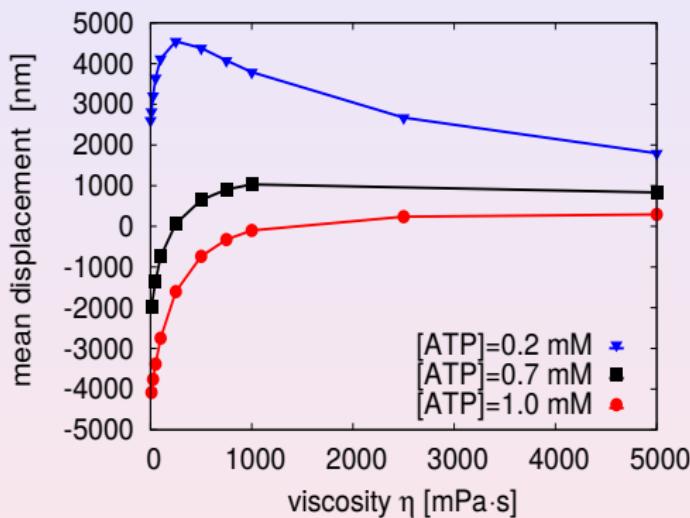
Tug-of-war, asymmetric motors

How does this cargo-motors complex behave?



Control by external force

Effective viscosity dependence



Advantage

Easy control of the cargo-motors complex by a single external parameter

➡ Change of behavior in crowded areas?

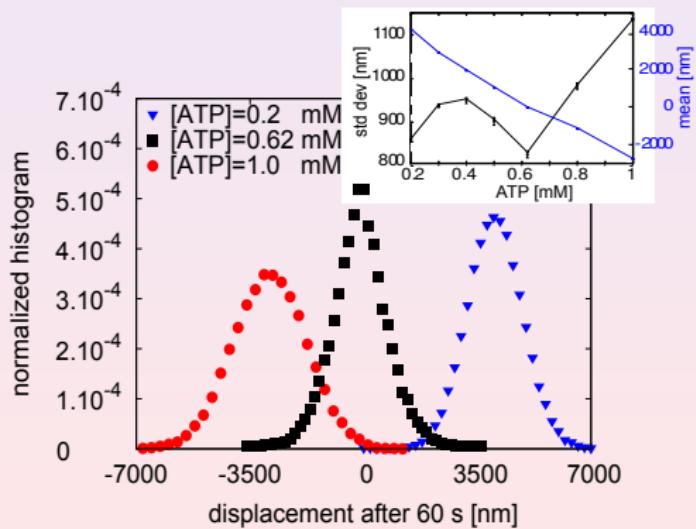
$$N_+ = N_- = 5$$

From [Klein et al (2014) EPL]

Control by energy supply

Stall force ATP dependance

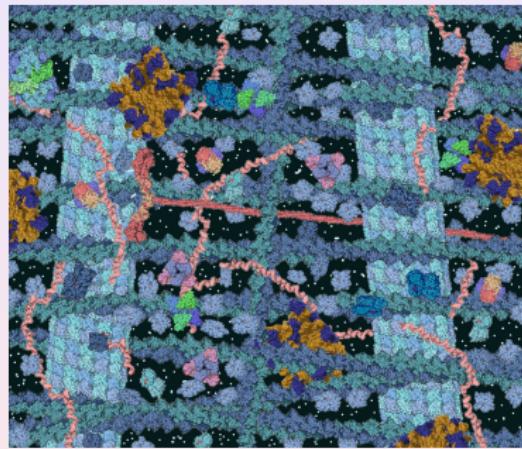
- Dynein: F_s varies linearly from 0.3 pN at vanishing [ATP] to 1.2 pN for saturating [ATP]
- Kinesin: constant $F_s = 2.6$ pN



$$N_+ = N_- = 5$$

From [Klein et al (2014) EPL]

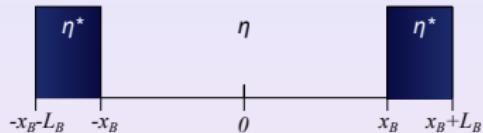
Microtubule based transport



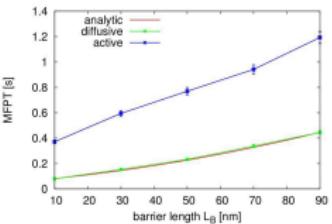
Why pulling by two opposite teams?

- Easy control
- More efficient in a crowded environment

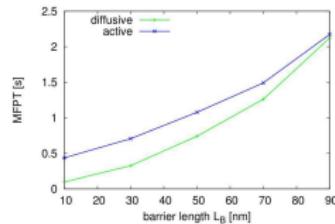
Active transport versus diffusion



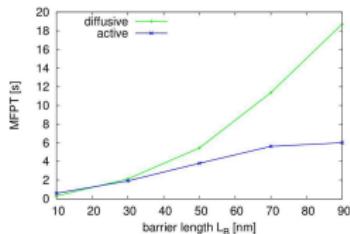
- (a) $\eta^* = \eta$,
- (b) $\eta^* = 10\eta$,
- (c) $\eta^* = 100\eta$



(a)



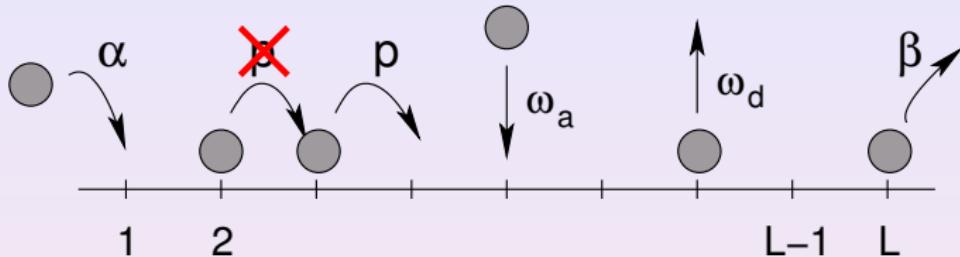
(b)



(c)

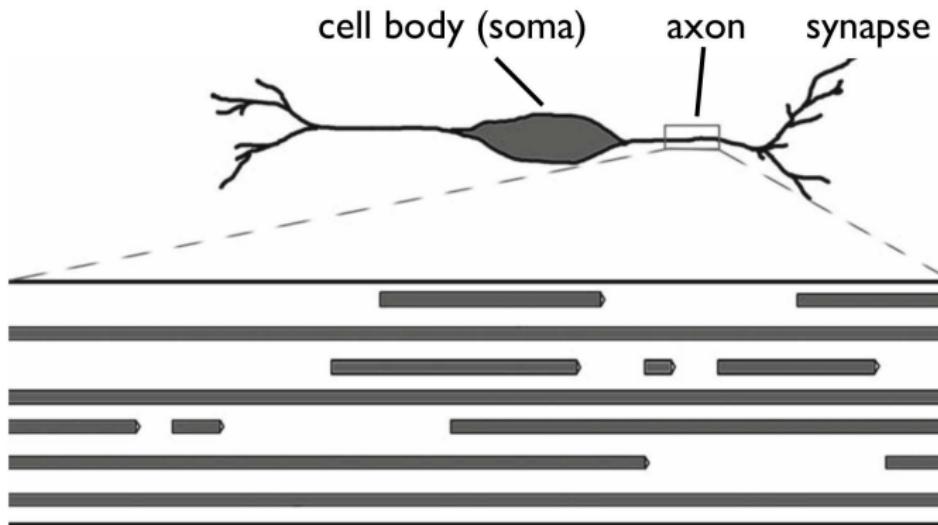
[Klein et al, EPJST (2014)]

Collective effects



- Cellular automata models with one type of motors
 - [Lipowsky, Klumpp, & Nieuwenhuizen, P.R.L. (2001)]
 - [Parmeggiani, Franosch, & Frey, P.R.L. (2003)]
 - [J. Tailleur, M. Evans, & Y. Kafri, P.R.L. (2009)]
- well suited for motility assays (in vitro), predicts the experimentally observed bulk localization of high and low density domains [Nishinari, Okada, Schadschneider, & Chowdhury, P.R.L. (2005)].

Axonal transport



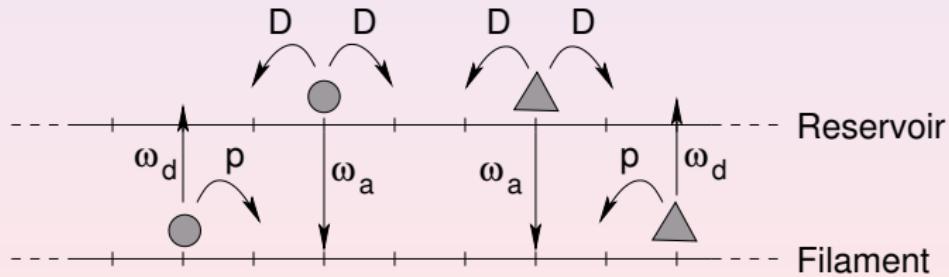
Falnikar & Baas, Res. Prob. Cell. Diff. **48**, 47 (2009)

Bidirectional intracellular traffic

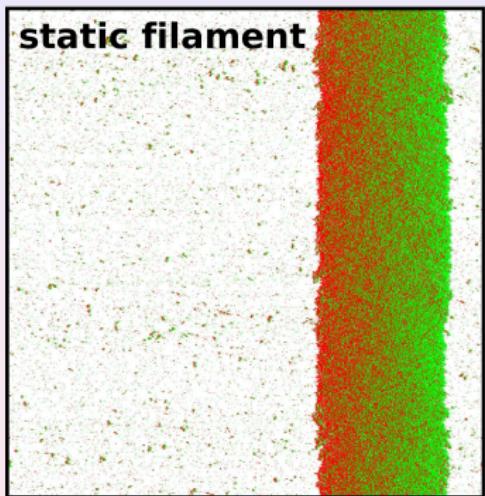
[M. Ebbinghaus and L. Santen, J. Stat. Mech. (2009)]

Ingredients

- Two types of motors going in opposite directions
- Confined diffusion in the surrounding cytoplasm

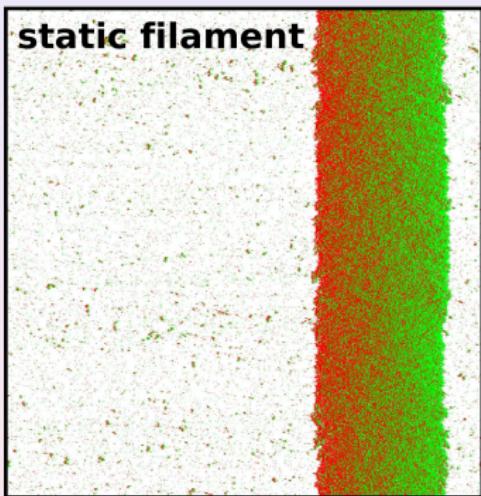


Bidirectional intracellular traffic



- Particles accumulate in a large cluster
 - Clustering increases with system size
- ➡ No transport in thermodynamic limit

Bidirectional intracellular traffic



- Particles accumulate in a large cluster
- Clustering increases with system size

Offering multiple filaments enhances cluster formation.

Intra-cellular traffic

MTs exhibit stochastic switching between a shrinking and a growing state, termed dynamic instability.

[A. Viel, R. A. Lue and J. Liebler, BioVisions project, <http://multi media.mcb.harvard.edu>]

Microtubules seen by fluorescence in *S. pombe* (yeast)

[M. Erent, D.R. Drummond, R.A. Cross (2012) PLoS ONE 7(2): e30738]

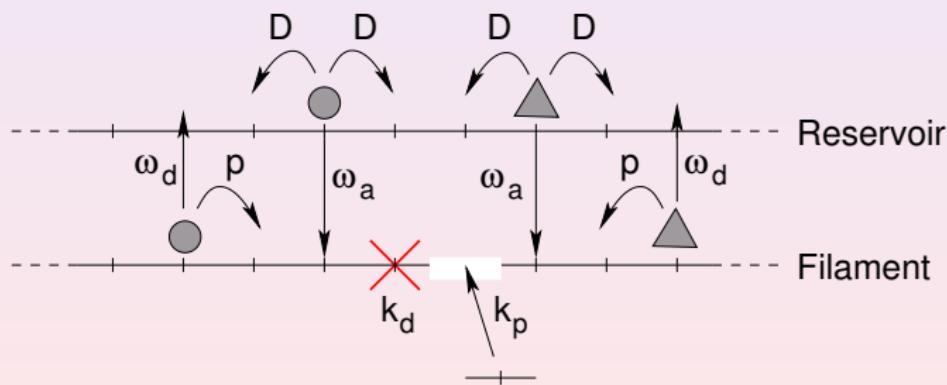
Intra-cellular traffic

Experiment by
[Shemesh and Spira, *Traffic* (2008)]

1s (video) = 120s (real time)
Scale bar = 10 μm

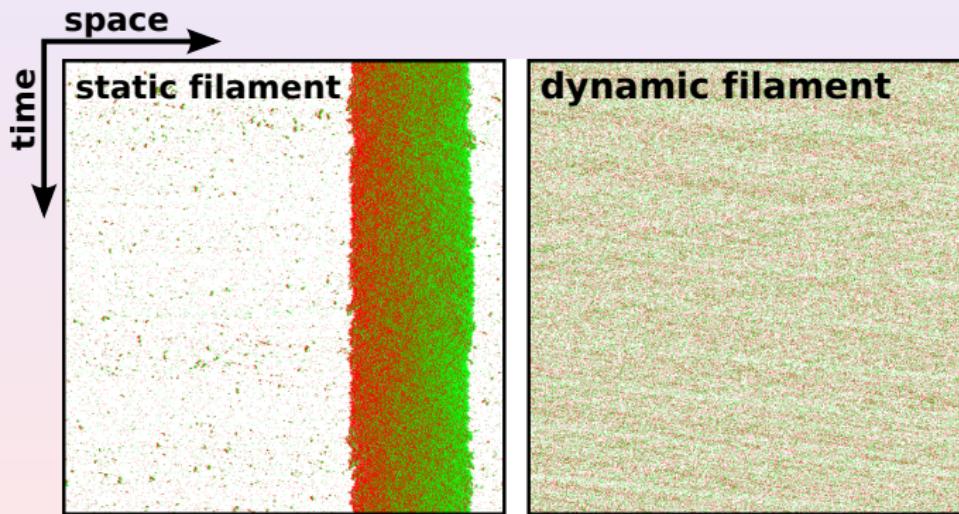
Dynamics of the lattice

- Dynamics of the lattice
 - Some sites of the microtubule are eliminated with rate k_d and recreated with rate k_p .



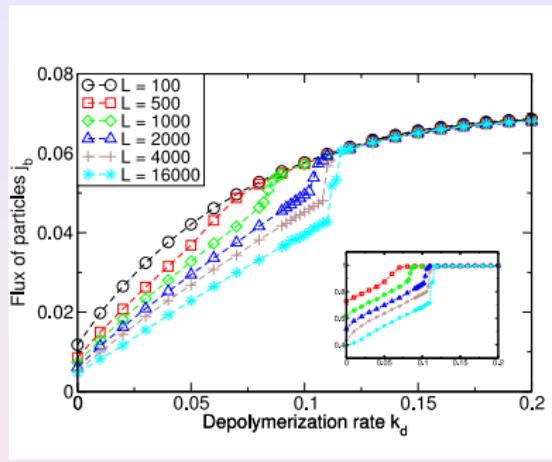
Dynamics of the lattice

- Dynamics of the lattice
 - Some sites of the microtubule are eliminated with rate k_d and recreated with rate k_p .



Bidirectional intracellular traffic

- Recovery of efficient transport through rapid dissolution of emerging clusters (optimal value of k_d).
- Transition to a density-dependent current.



[Ebbinghaus, Appert, Santen, PRE 82 (2010) 040901]

Robust for several types of lattice dynamics

Bidirectional intracellular traffic

- ☞ Drugs modifying the dynamics of the microtubules induce jams!
 - video 1: microtubule dynamics with and without drugs (Paclitaxel)

[*Shemesh and Spira, Acta Neuropathol (2009)*]

Bidirectional intracellular traffic

- ☞ Drugs modifying the dynamics of the microtubules induce jams!
 - video 2: microtubule dynamics and pinocytotic vesicles transport without drugs
[Shemesh and Spira, *Acta Neuropathol* (2009)]

Bidirectional intracellular traffic

- ☞ Drugs modifying the dynamics of the microtubules induce jams!
 - video 3: microtubule dynamics and pinocytotic vesicles transport with drugs
- [Shemesh and Spira, *Acta Neuropathol* (2009)]

THE END

THANK-YOU !!!

For more details:

http://www.th.u-psud.fr/page_perso/Appert/

Thank-you