

Anomalous dynamics of cell migration

P. Dieterich¹ R. Klages² R. Preuss³ A. Schwab⁴

¹Institute for Physiology, Dresden University of Technology

²School of Mathematical Sciences, Queen Mary University of London

³Center for Interdisciplinary Plasma Science, MPI for Plasma Physics, Garching

⁴Institute for Physiology II, University of Münster

University of Potsdam, 7 June 2010



Outline

- 1 **Cell migration:** motivation and some biological details
- 2 **Brownian motion:** theory in a nutshell
- 3 **Experimental results:** statistics of cell migration
- 4 **Theoretical modeling:** fractional stochastic equation
- 5 **Conclusions:** physical and biological interpretations?

Setting the scene

I. Cell migration

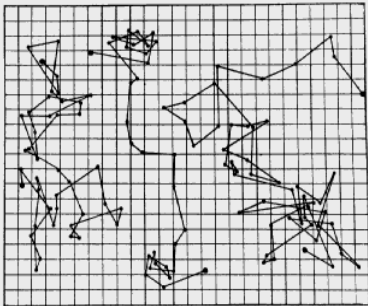
animation: **Brownian motion vs. cell migration**

J. Ingenhousz (1785)

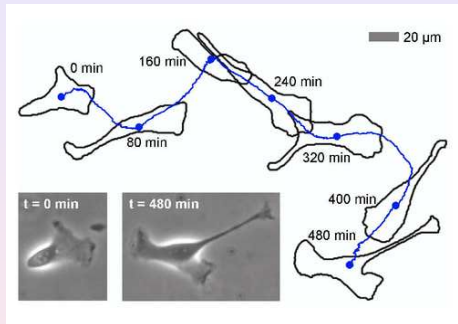
R. Brown (1827)

Brownian motion of migrating cells?

Brownian motion



3 colloidal particles of radius $0.53\mu\text{m}$; positions every 30 seconds, joined by straight lines (Perrin, 1913)



single biological cell crawling on a substrate (Dieterich, R.K. et al., PNAS, 2008)

Brownian motion?

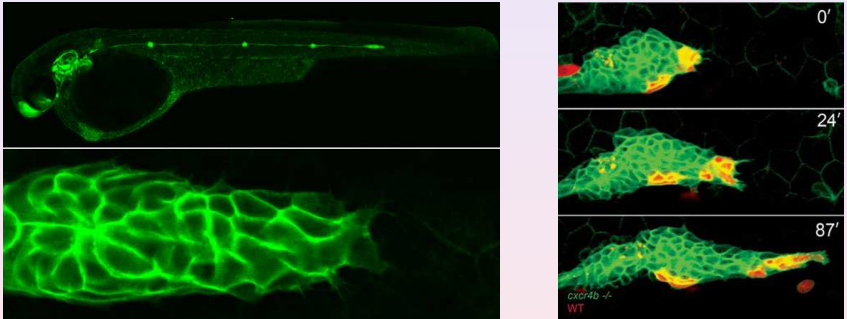
Brownian motion of migrating cells?

yes: Dunn, Brown (1987); Stokes et al. (1991)

not quite: Hartmann et al. (1994); Upadhyaya et al. (2001);
T.-Norrelykke, Jülicher (2007); H.Takagi et al. (2008)

Why cell migration?

motion of the *primordium* in developing zebrafish (Gilmour, 2008):



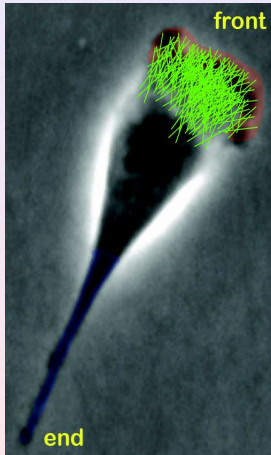
positive aspects:

- morphogenesis
- immune defense

negative aspects:

- tumor metastases
- inflammation reactions

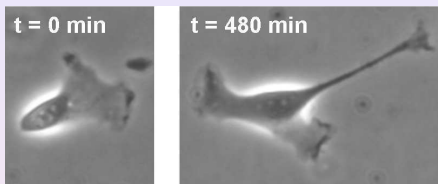
How do cells migrate?



- **membrane protrusions and retractions** ~ force generation:
 - lamellipodia (front)
 - uropod (end)
 - actin-myosin network
- formation of a **polarized state**
front/end
- cell-substrate **adhesion**

note: here we do not study the *microscopic origin* of cell migration, which is a *highly complex process* involving a huge number of proteins and signaling mechanisms

Our cell types and some typical scales



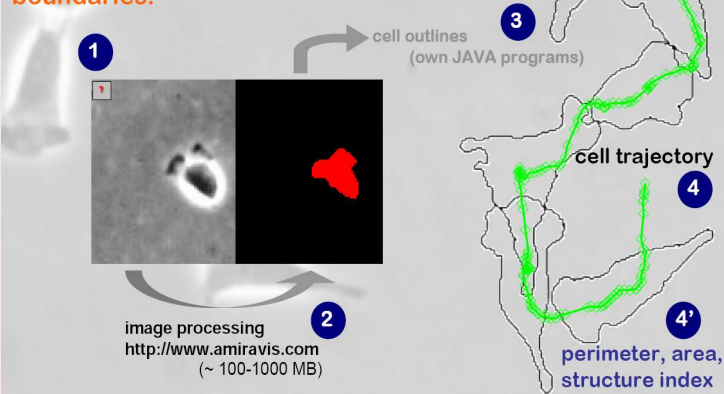
- **renal epithelial MDCK-F (Madin-Darby canine kidney) cells**; two types: wildtype (NHE^+) and NHE -deficient (NHE^-)
- observed up to **1000 minutes**: here *no* limit $t \rightarrow \infty$!
- cell diameter **$20-50\mu\text{m}$** ; mean velocity $\sim 1\mu\text{m}/\text{min}$; lamellipodial dynamics \sim **seconds**

movies: NHE+: t=210min, dt=3min

NHE-: t=171min, dt=1min

Measuring cell migration

Sequences of microscopic phase contrast images **are segmented** to obtain the **cell boundaries**.



II. Brownian motion

The Langevin equation

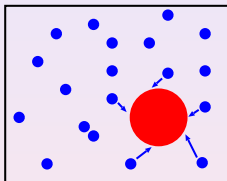
microscopic understanding of Brownian motion: **Einstein (1905)**

simple theory suggested by **Langevin (1908)**:

Newton's law for a particle of mass m and velocity \underline{v} immersed in a fluid

$$m\dot{\underline{v}} = \underline{F}_d(t) + \underline{F}_r(t)$$

with total force of surrounding particles decomposed into *viscous damping* $\underline{F}_d(t)$ and *random kicks* $\underline{F}_r(t)$



suppose $\underline{F}_d(t)/m = -\kappa\underline{v}$ and $\underline{F}_r(t)/m = \sqrt{\zeta} \underline{\xi}(t)$ as *Gaussian white noise* of strength $\sqrt{\zeta}$:

$$\dot{\underline{v}} + \kappa\underline{v} = \sqrt{\zeta} \underline{\xi}(t)$$

Langevin equation

‘Newton's law of stochastic physics’: apply to cell migration?

Solving the Langevin equation

calculate three important quantities (in d dimensions):

1. the **diffusion coefficient** $D := \lim_{t \rightarrow \infty} \text{msd}(t)/(2dt)$

with *mean square displacement* $\text{msd}(t) := \langle [\underline{x}(t) - \underline{x}(0)]^2 \rangle$
over ensemble average $\langle \dots \rangle$; for Langevin eq. one obtains

$$\text{msd}(t) = 2dv_{th}^2 (t - \kappa^{-1}(1 - \exp(-\kappa t))) / \kappa$$

with $v_{th}^2 = kT/m$; note that $\text{msd}(t) \sim t^2$ ($t \rightarrow 0$) and
 $\text{msd}(t) \sim t$ ($t \rightarrow \infty$) $\Rightarrow \exists D$

2. the **velocity autocorrelation function** $v_{ac}(t) := \langle \underline{v}(t) \cdot \underline{v}(0) \rangle$

for Langevin eq. one finds

$$v_{ac}(t) = v_{th}^2 \exp(-\kappa t)$$

Fokker-Planck equations and the like

3. the **probability distribution function** $P(x, v, t)$ (ff in one dimension):

- Langevin dynamics obeys (for $\kappa \gg 1$) the **diffusion equation**

$$\frac{\partial P}{\partial t} = D \frac{\partial^2 P}{\partial x^2}$$

solution for initial condition $P(x, 0) = \delta(x)$ yields *position distribution* $P(x, t) = \exp(-\frac{x^2}{4Dt}) / \sqrt{4\pi Dt}$

- for *velocity distribution* $P(v, t)$ of Langevin dynamics one can derive the **Fokker-Planck equation**

$$\frac{\partial P}{\partial t} = \kappa \left[\frac{\partial}{\partial v} v + v_{th}^2 \frac{\partial^2}{\partial v^2} \right] P$$

stationary solution is $P(v) = \exp(-\frac{v^2}{2v_{th}^2}) / \sqrt{2\pi} v_{th}$

- Fokker-Planck equation for position *and* velocity distribution $P(x, v, t)$ of Langevin dynamics is the **Klein-Kramers equation**

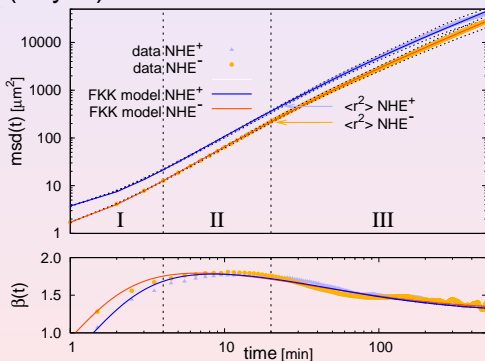
$$\frac{\partial P}{\partial t} = -\frac{\partial}{\partial x} [vP] + \kappa \left[\frac{\partial}{\partial v} v + v_{th}^2 \frac{\partial^2}{\partial v^2} \right] P$$

the above eqns. can be derived from it as special cases

III. Experimental results

Mean square displacement

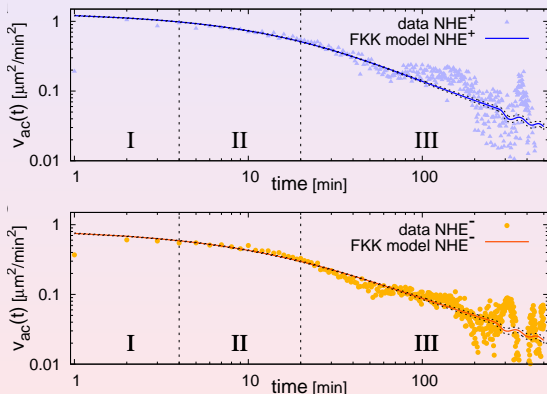
- $msd(t) := \langle [\underline{x}(t) - \underline{x}(0)]^2 \rangle \sim t^\beta$ with $\beta \rightarrow 2$ ($t \rightarrow 0$) and $\beta \rightarrow 1$ ($t \rightarrow \infty$) for Brownian motion; $\beta(t) = d \ln msd(t) / d \ln t$
- *solid lines*: (Bayes) fits from our model



anomalous diffusion if $\beta \neq 1$: here **superdiffusion** for $t \rightarrow \infty$

Velocity autocorrelation function

- $v_{ac}(t) := \langle \underline{v}(t) \cdot \underline{v}(0) \rangle \sim \exp(-\kappa t)$ for Brownian motion
- solid lines: fits from our model; same parameter values as $msd(t)$



⇒ crossover from **stretched exponential** to **power law behavior**

Position distribution function

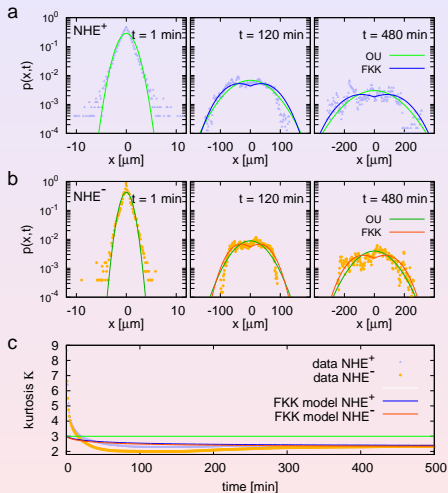
- $P(x, t) \rightarrow$ Gaussian ($t \rightarrow \infty$)
and kurtosis

$$\kappa(t) := \frac{\langle x^4(t) \rangle}{\langle x^2(t) \rangle^2} \rightarrow 3 \quad (t \rightarrow \infty)$$

for Brownian motion (green lines, in 1d)

- *other solid lines*: fits from our model; parameter values as before

remark: model does not yet explain short-time distributions



\Rightarrow crossover from peaked to broad **non-Gaussian distributions**

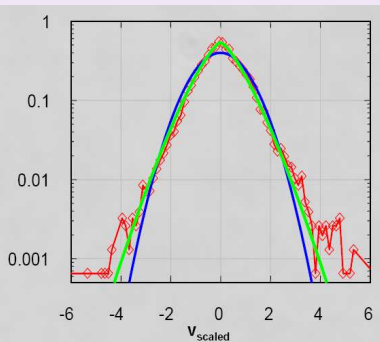
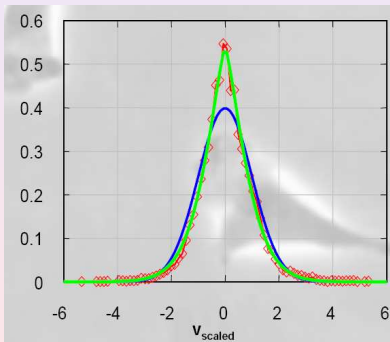
Velocity distribution functions

$P(v) = \frac{1}{\sqrt{2\pi}v_{th}} \exp\left(-\frac{v^2}{2v_{th}^2}\right)$ for Brownian motion;

fit by stretched exponential: $P(v) = c \exp\left(-\frac{b}{2}\left(\frac{v}{v_{th}}\right)^a\right)$

linear plot

semi-log plot



IV. Theoretical modeling

The model

Fractional Klein-Kramers equation (Barkai, Silbey, 2000):

$$\frac{\partial P}{\partial t} = -\frac{\partial}{\partial x} [vP] + \frac{\partial^{1-\alpha}}{\partial t^{1-\alpha}} \kappa \left[\frac{\partial}{\partial v} v + v_{th}^2 \frac{\partial^2}{\partial v^2} \right] P$$

with probability distribution $P = P(x, v, t)$, damping term κ , thermal velocity v_{th} and *Riemann-Liouville fractional derivative of order $1 - \alpha$* defined by

$$\frac{\partial^\gamma P}{\partial t^\gamma} := \begin{cases} \frac{\partial^m P}{\partial t^m} & , \quad \gamma = m \\ \frac{\partial^m}{\partial t^m} \left[\frac{1}{\Gamma(m-\gamma)} \int_0^t dt' \frac{P(t')}{(t-t')^{\gamma+1-m}} \right] & , \quad m-1 < \gamma < m \end{cases}$$

with $m \in \mathbb{N}$; for $\alpha = 1$ ordinary Klein-Kramers equation recovered

Fractional derivative

interlude – what is a fractional derivative?

letter from **Leibniz to L'Hôpital (1695)**: $\frac{d^{1/2}}{dx^{1/2}} = ?$

one way to proceed: we know that for integer m, n

$$\frac{d^m}{dx^m} x^n = \frac{n!}{(n-m)!} x^{n-m} = \frac{\Gamma(n+1)}{\Gamma(n-m+1)} x^{n-m};$$

assume that this also holds for $m = 1/2, n = 1$

$$\Rightarrow \frac{d^{1/2}}{dx^{1/2}} x = \frac{2}{\sqrt{\pi}} x^{1/2}$$

extension leads to the *Riemann-Liouville fractional derivative*, which yields power laws in Fourier (Laplace) space:

$$\frac{d^\gamma}{dx^\gamma} F(x) \leftrightarrow (ik)^\gamma \tilde{F}(k)$$

∃ well-developed mathematical theory of **fractional calculus**, see **Sokolov, Klafter, Blumen, Phys. Today 2002** for a short intro

Solutions for this model

analytical solutions (Barkai, Silbey, 2000):

- **mean square displacement:**

$$msd(t) = 2v_{th}^2 t^2 E_{\alpha,3}(-\kappa t^\alpha) \rightarrow 2 \frac{D_\alpha t^{2-\alpha}}{\Gamma(3-\alpha)} (t \rightarrow \infty)$$

with $D_\alpha = v_{th}^2/\kappa$ and *generalized Mittag-Leffler function*

$$E_{\alpha,\beta}(z) = \sum_{k=0}^{\infty} \frac{z^k}{\Gamma(\alpha k + \beta)}, \quad \alpha, \beta > 0, \quad z \in \mathbb{C};$$

note that $E_{1,1}(z) = \exp(z)$: $E_{\alpha,\beta}(z)$ is a generalized exponential function

- **velocity autocorrelation function:**

$$v_{ac}(t) = v_{th}^2 E_{\alpha,1}(-\kappa t^\alpha) \rightarrow \frac{1}{\kappa \Gamma(1-\alpha) t^\alpha} (t \rightarrow \infty)$$

- for $\kappa \rightarrow \infty$ fractional Klein-Kramers reduces to a *fractional diffusion equation* yielding $P(x, t)$ in terms of a Fox function (Schneider, Wyss, 1989)

note:

3 fit parameters $v_{th}, \alpha \simeq 0.7, \kappa$ plus another one by adding “biological noise” of variance η^2 to msd ,

$$msd_{noise}(t) := msd(t) + 2\eta^2;$$

mimicks measurement errors and cytoskeleton fluctuations

V. Conclusions

Possible physical interpretation

- **physical meaning of the fractional derivative?**

fractional Klein-Kramers equation is *approximately* related to the generalized Langevin equation

$$\dot{v} + \int_0^t dt' \kappa(t-t')v(t') = \sqrt{\zeta} \xi(t)$$

e.g., Mori, Kubo, 1965/66; Lutz, 2001

with **time-dependent friction coefficient** $\kappa(t) \sim t^{-\alpha}$

cell anomalies might originate from *soft glassy behavior* of the cytoskeleton gel, where power law exponents are conjectured to be universal (Fabry et al., 2003; Kroy et al., 2008)

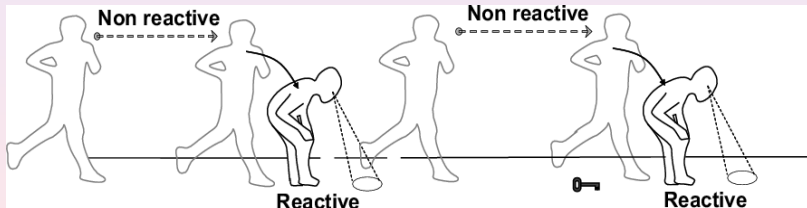
note: anomalous dynamics observed for *6 different cell types*

Possible biological interpretation

- **biological meaning of the anomalous cell migration?**

experimental data and theoretical modeling suggest *slower diffusion for small times* while *long-time motion is faster*

compare with **intermittent optimal search strategies** of foraging animals (Bénichou et al., 2006)



note: ∃ current controversy about *modeling the migration of foraging animals* (albatross, bumblebees, fruitflies,...)

Thanks and literature

- **Thanks** to A.V.Chechkin and E.Lutz for helpful discussions.
- **reference to this talk:**

P.Dieterich, R.K., R.Preuss, A.Schwab, *Anomalous Dynamics of Cell Migration*, PNAS **105**, 459 (2008)

- **as a general reference:**

R.K., G.Radons, I.M.Sokolov (Eds.),
Anomalous transport (Wiley-VCH,
July 2008)

see www.maths.qmul.ac.uk/~klages
for further information

