

# Nonlinear Cross Diffusion Models for Crowds

Bärbel Schlake

Westfälische Wilhelms-Universität Münster  
Institute für Computational und Applied Mathematics

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## Motivation

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One-Dimensional Model

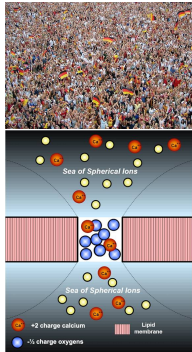
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Analysis

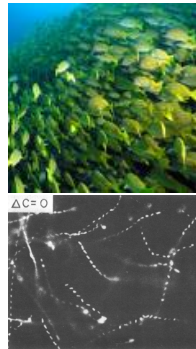
# Motivation

**aim:** modelling of diffusing particles with size exclusion



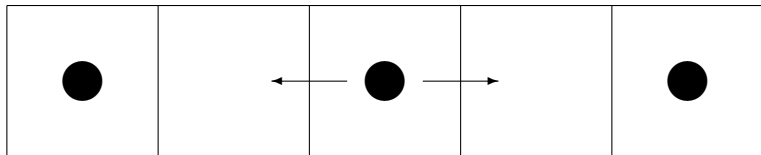
**application:**

- ▶ human crowds
- ▶ swarming
- ▶ ion channels
- ▶ chemotaxis



## Derivation of Model

**one-dimensional hopping model:**



Probabilities

$r(x, t) = P(\text{red particle at position } x \text{ at time } t)$

$b(x, t) = P(\text{blue particle at position } x \text{ at time } t)$

## Derivation of Model

- ▶ **transition rate:**

$$\Pi_+^{r/b}(x, t) =$$

$P(\text{jump of } r/b \text{ from position } x \text{ to } x + h \text{ in } (t, t + \Delta t)) \cdot$

$$\frac{1}{\Delta t} \cdot P(x + h \text{ is empty})$$

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- ▶ **probability** that a red particle is located at position  $x$  at time  $t + \Delta t$ :

$$r(x, t + \Delta t) = r(x, t)(1 - \Pi_+(x, t) - \Pi_-(x, t))$$

$$+ r(x + h, t)\Pi_-(x + h, t) + r(x - h, t)\Pi_+(x - h, t)$$

## Derivation of Model

### Resulting Model

$$\begin{aligned}\frac{\partial r}{\partial t} &= \frac{\partial}{\partial x} \left( (1-m) \frac{\partial r}{\partial x} + r \frac{\partial m}{\partial x} - \mu_r r (1-m) \frac{\partial V}{\partial x} \right) \\ \frac{\partial b}{\partial t} &= \frac{\partial}{\partial x} \left( D \left( (1-m) \frac{\partial b}{\partial x} + b \frac{\partial m}{\partial x} + \mu_b b (1-m) \frac{\partial V}{\partial x} \right) \right)\end{aligned}$$

**mass density**  $\mathbf{m(x,t)} = r(x, t) + b(x, t)$ ,

**diffusion** coefficient  $\mathbf{D}$ ,

**potential**  $\mathbf{V(x)}$  (e.g. preferred walking direction),

scaled **mobility** constants  $\mu_r, \mu_b$

## Multidimensional Model

$$\partial_t r = \nabla \cdot ((1 - m)\nabla r + r\nabla m - \mu_r r(1 - m)\nabla V)$$

$$\partial_t b = \nabla \cdot (D((1 - m)\nabla b + b\nabla m + \mu_b b(1 - m)\nabla V))$$

we apply **von-Neumann boundary conditions** on all boundaries:

$$((1 - m)\nabla r + r\nabla m - \mu_r r(1 - m)\nabla V) \cdot n = 0$$

$$((1 - m)\nabla b + b\nabla m + \mu_b b(1 - m)\nabla V) \cdot n = 0$$

## Problems in the Analysis

### System of equations

$$\partial_t r = \nabla \cdot ((1 - m)\nabla r + r\nabla m - \mu_r r(1 - m)\nabla V)$$

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**nonlinear cross diffusion**  $\Rightarrow$  few literature available

- ▶ **existence** and **uniqueness** of a solution?
- ▶ **no** a-priori estimates
- ▶ **no** maximum principle (only  $0 \leq r, b, m \leq 1$ )

# Entropy

## Entropy

$$E(r, b) = \int (r \log(r) + b \log(b) + (1 - m) \log(1 - m) - \mu_r r V + \mu_b b V) dx$$

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- ▶  $\frac{\partial E}{\partial t} = - \int r(1 - m) |\nabla \xi_1|^2 + Db(1 - m) |\nabla \xi_2|^2 dx$

$$\xi_1 = \xi_1(r, b, V) \quad \xi_2 = \xi_2(r, b, V)$$

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$$\xi_1 = \xi_1(r, b, V) \quad \xi_2 = \xi_2(r, b, V)$$

- ▶ E is **decreasing** during the process
- ▶ E is **minimal** in equilibrium state

## Minima of Entropy

$$E = \int (r \log(r) + b \log(b) + (1 - m) \log(1 - m) - \mu_r r V + \mu_b b V) dx$$

### Lagrange Functional

$$L(r, b, \lambda_r, \lambda_b) = E(r, b) + \lambda_r (\int r - m_r) + \lambda_b (\int b - m_b)$$

$m_r$ : mass of red particles       $m_b$ : mass of blue particles

$$\frac{\partial L}{\partial r} = \frac{\partial E}{\partial r} + \lambda_r = 0$$

$$\frac{\partial L}{\partial b} = \frac{\partial E}{\partial b} + \lambda_b = 0$$

$\Rightarrow$  **equilibrium solutions**

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►  $m \equiv 1 \Rightarrow r_{\text{eq}} = k_1 \exp(\mu_r V), \quad b_{\text{eq}} = k_2 \exp(-\mu_b V)$

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▶  $m \equiv 1 \Rightarrow r_{\text{eq}} = k_1 \exp(\mu_r V), \quad b_{\text{eq}} = k_2 \exp(-\mu_b V)$

▶  $b \equiv 0 \Rightarrow r_t = \nabla \cdot (\nabla r - r(1-r)\nabla V) \Rightarrow r_{\text{eq}} = \frac{k_1 \exp(\mu_r V)}{k_1 \exp(\mu_r V) + 1}$

## Solutions for Equilibrium

$$\begin{aligned}\partial_t r &= \nabla \cdot ((1 - m)\nabla r + r\nabla m - \mu_r r(1 - m)\nabla V) \\ \partial_t b &= \nabla \cdot (D((1 - m)\nabla b + b\nabla m + \mu_b b(1 - m)\nabla V))\end{aligned}$$

### Equilibrium Solutions

$$\begin{aligned}r_{\text{eq}}(x, t) &= \frac{k_1 \exp(\mu_r V(x))}{k_1 \exp(\mu_r V(x)) + k_2 \exp(-\mu_b V(x)) + 1} \\ b_{\text{eq}}(x, t) &= \frac{k_2 \exp(-\mu_b V(x))}{k_1 \exp(\mu_r V(x)) + k_2 \exp(-\mu_b V(x)) + 1}\end{aligned}$$

- ▶  $k_1$  and  $k_2$  are constants that can be determined from total mass,  $k_1 = \exp(-\lambda_r)$ ,  $k_2 = \exp(-\lambda_b)$

## Special Case $V(x) = 0$

system of equations with  $V(x) = 0$ :

$$\partial_t r = \nabla \cdot ((1 - m)\nabla r + r\nabla m)$$

$$\partial_t b = \nabla \cdot (D((1 - m)\nabla b + b\nabla m))$$

**equilibrium solutions:** constants  $\bar{n}, \bar{p}$

First Order Linearization

$$\partial u_t = (1 - \bar{p})\Delta u + \bar{n}\Delta v$$

$$\partial v_t = D((1 - \bar{n})\Delta v + \bar{p}\Delta u)$$

for  $w = u + \alpha v$ , we obtain the heat equation

$$\partial_t w = k\Delta w \quad k \geq 0$$

$\Rightarrow$  **stability** around equilibria

## Special Case $V(x) = 0$

$$\begin{aligned}\partial_t r &= \nabla \cdot ((1 - m)\nabla r + r\nabla m) \\ \partial_t b &= \nabla \cdot (D((1 - m)\nabla b + b\nabla m))\end{aligned}$$

### Transformation

$$u = F(r, b) = G\left(\frac{1-r-b}{(r-b-\alpha)^\alpha}\right) \quad \alpha = \frac{D-1}{D+1}$$

we can show that  $u$  satisfies a **maximum-principle**.

special cases:

$$D = 0: \quad u = G((1 - r - b)(r - b - 1))$$

$$D = 1: \quad u = G(1 - m)$$

## Transformation to Slotboom-Variables

$$\begin{aligned}\partial_t r &= \nabla \cdot ((1 - m)\nabla r + r\nabla m - \mu_r r(1 - m)\nabla V) \\ \partial_t b &= \nabla \cdot (D((1 - m)\nabla b + b\nabla m + \mu_b b(1 - m)\nabla V))\end{aligned}$$

The system is not easy to solve. Hence we try to **transform** the variables to obtain a **simplified system**. In classical semiconductor theory, the variables after the transformation are called 'Slotboom-Variables'.

- ▶ transformation function  $F_1(r, b) = \log r - \log(1 - m)$
- ▶ transformation 
$$\begin{aligned}u &= F_1^{-1}(F_1(r, b) - \mu_r V) \\ v &= F_2^{-1}(F_2(r, b) + \mu_b V)\end{aligned}$$

## Open Questions

- ▶ existence for the general case?
- ▶ uniqueness?
- ▶ longtime behaviour for the general case?

# Acknowledgements

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