



Mathematical
Institute

Models for collective behavior: qualitative properties and model hierarchy

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Virtual Summer school on Kinetic and fluid equations for collective dynamics

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Oxford
Mathematics

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Outline

- 1 **Self-Organization - Swarming**
 - **Collective Behavior Models**
 - Variations
 - Fixed Speed models
 - 1st order Models

- 2 Macroscopic Models: Nonlinear Fokker-Planck Models
 - Nonlinear diffusions
 - Modelling Chemotaxis
 - First Properties
 - Pure Mathematics: Gradient Flows

- 3 Outline of the course

- 4 Transversal Tool: Wasserstein Distances
 - Definition
 - Properties

Swarming by Nature or by design?



physics today
October 2007



The physics of flocking



Fish schools and Birds flocks.

Individual Based Models (Particle models)

Swarming = Aggregation of agents of similar size and body type generally moving in a coordinated way.

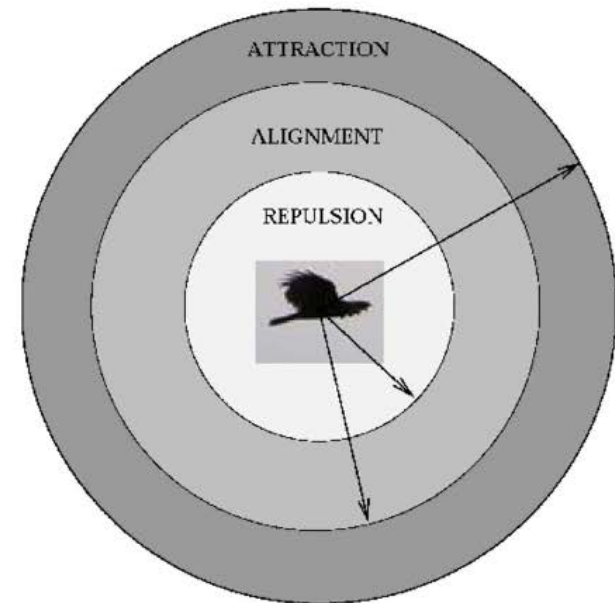
Highly developed social organization: insects (locusts, ants, bees ...), fishes, birds, micro-organisms (myxo-bacteria, ...) and artificial robots for unmanned vehicle operation.

Interaction regions between individuals^a

^a Aoki, Helmerijk et al., Barbaro, Birnir et al.

- **Repulsion** Region: R_k .
- **Attraction** Region: A_k .
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Metric versus Topological Interaction



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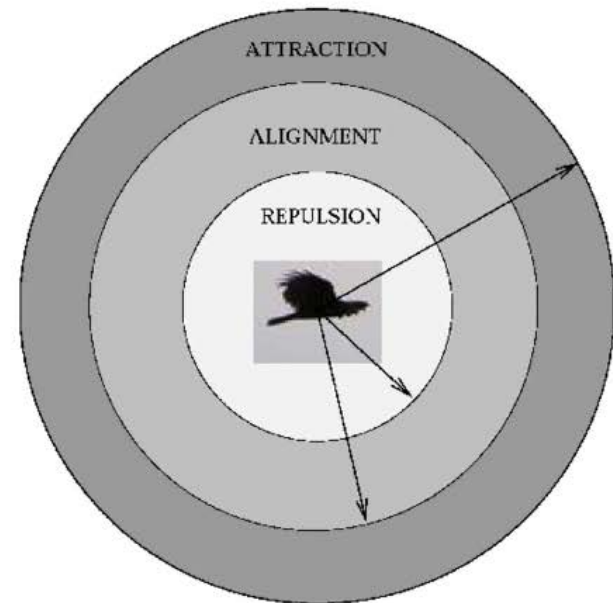
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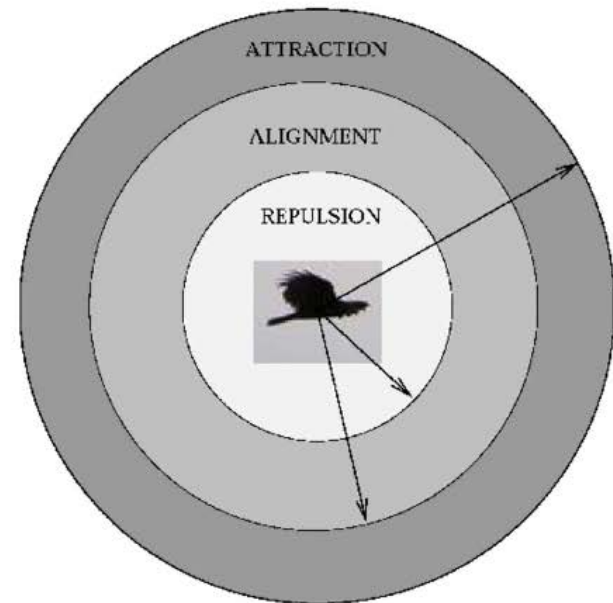
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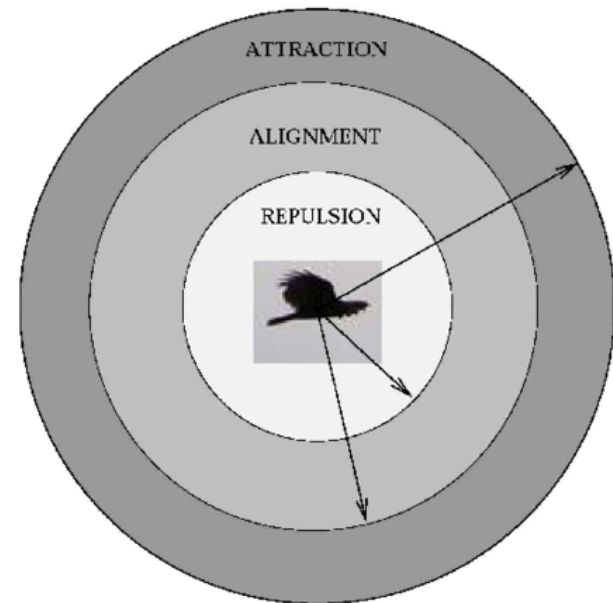
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2nd Order Model: Newton's like equations



D'Orsogna, Bertozzi et al. model (PRL 2006):

$$\begin{cases} \frac{dx_i}{dt} = v_i, \\ m \frac{dv_i}{dt} = (\alpha - \beta |v_i|^2) v_i - \sum_{j \neq i} \nabla U(|x_i - x_j|). \end{cases}$$

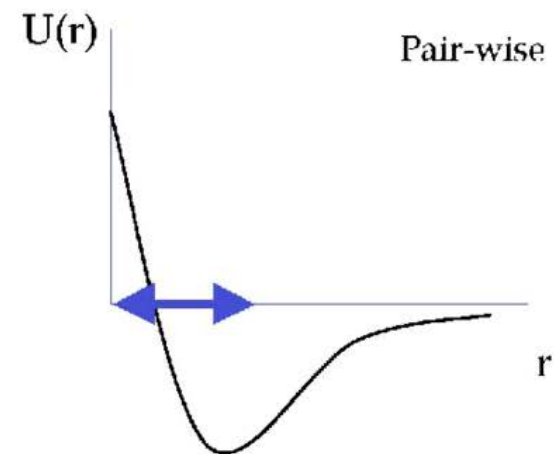
Model assumptions:

- Self-propulsion and friction terms determines an asymptotic speed of $\sqrt{\alpha/\beta}$.
- Attraction/Repulsion modeled by an effective pairwise potential $U(x)$.

$$U(r) = -C_A e^{-r/\ell_A} + C_R e^{-r/\ell_R}.$$

One can also use Bessel functions in 2D and 3D to produce such a potential.

$C = C_R/C_A > 1$, $\ell = \ell_R/\ell_A < 1$ and $C\ell^2 < 1$:



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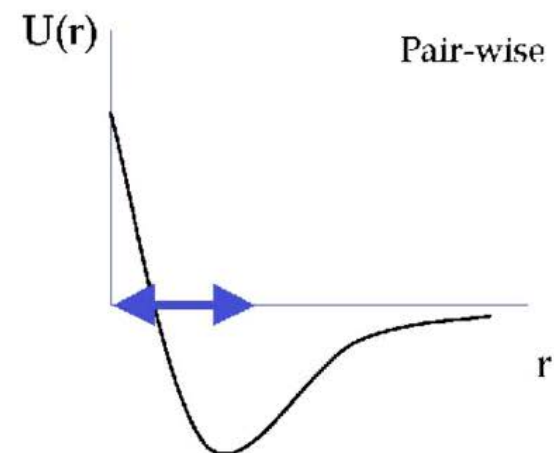
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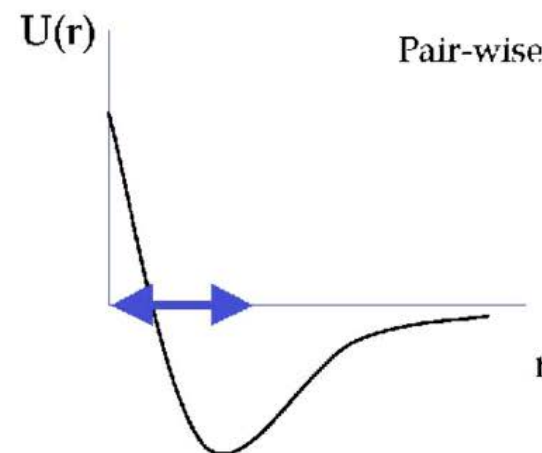
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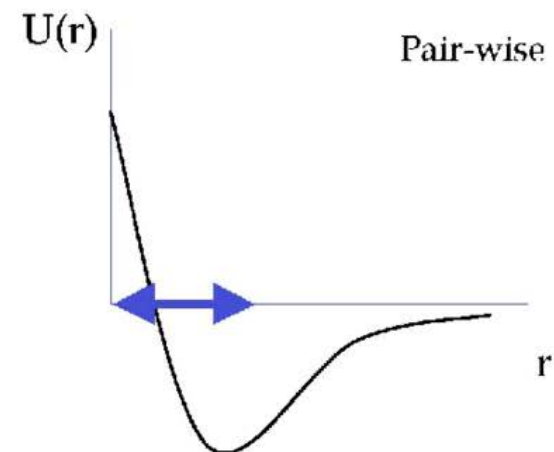
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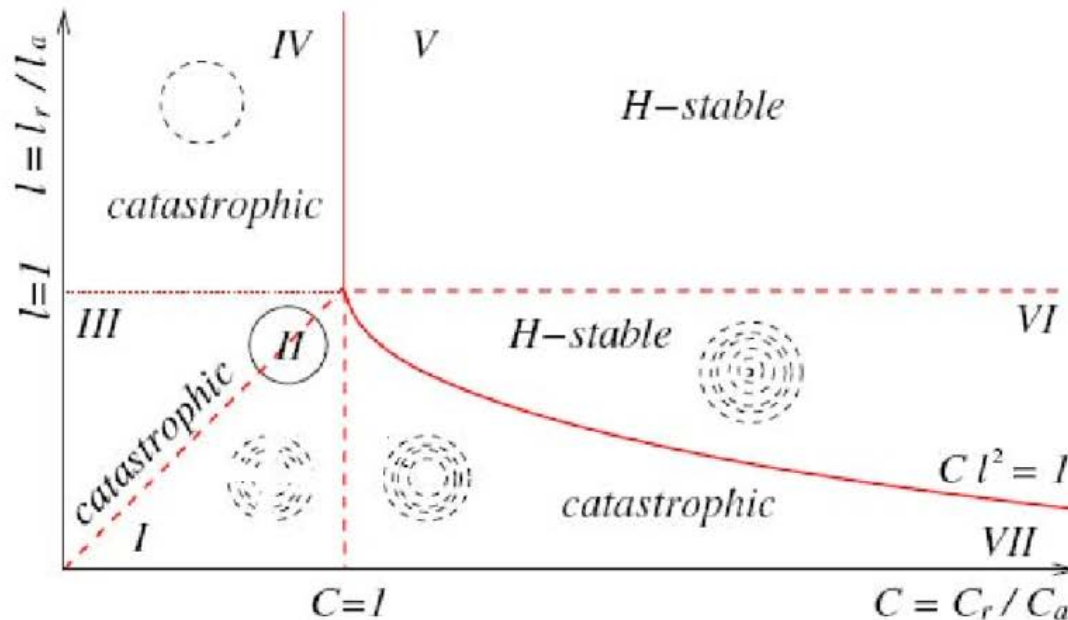
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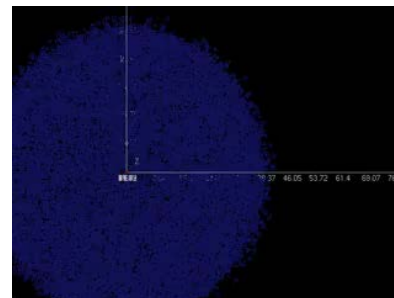
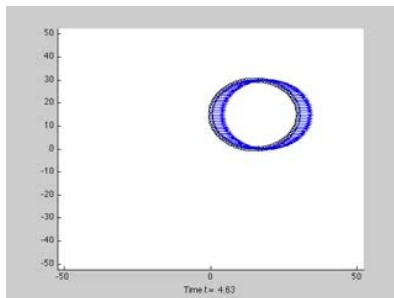
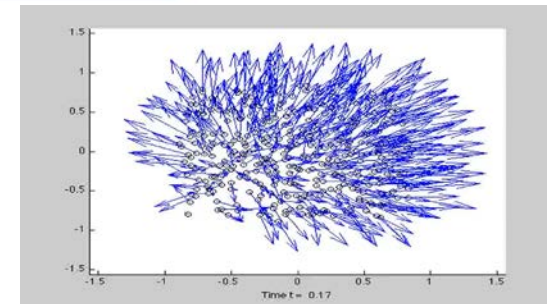
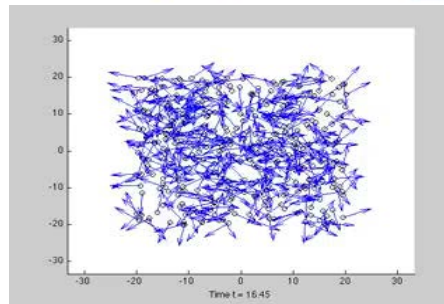
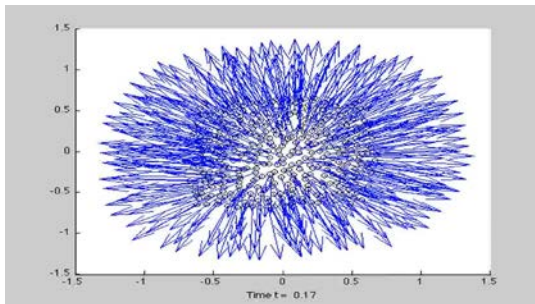
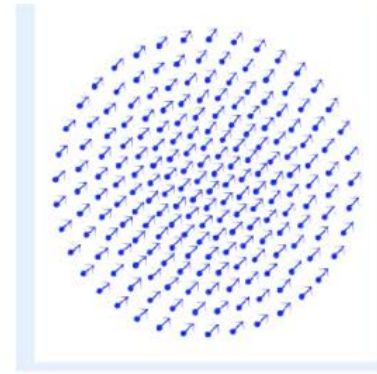
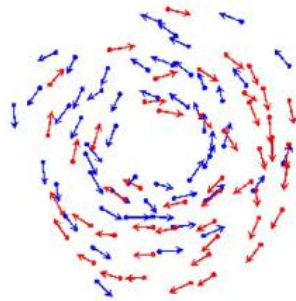
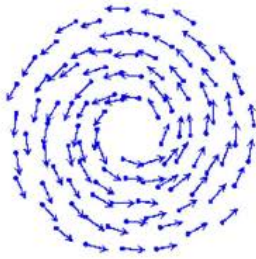
Model with an asymptotic velocity

Classification of possible patterns: Morse potential. D'Orsogna, Bertozzi et al. model (PRL 2006).



Model with an asymptotic speed

Typical patterns: milling, double milling or flocking:



Velocity consensus model

Cucker-Smale Model (IEEE Automatic Control 2007):

$$\begin{cases} \frac{dx_i}{dt} = v_i, \\ \frac{dv_i}{dt} = \sum_{j=1}^N a_{ij} (v_j - v_i), \end{cases}$$

with the communication rate, $\gamma \geq 0$:

$$a_{ij} = a(|x_i - x_j|) = \frac{1}{(1 + |x_i - x_j|^2)^\gamma}.$$

Asymptotic flocking: $\gamma < 1/2$; Cucker-Smale.

General Proof for $0 < \gamma \leq 1/2$; C.-Fornasier-Rosado-Toscani.

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Leadership, Geometrical Constraints, and Cone of Influence

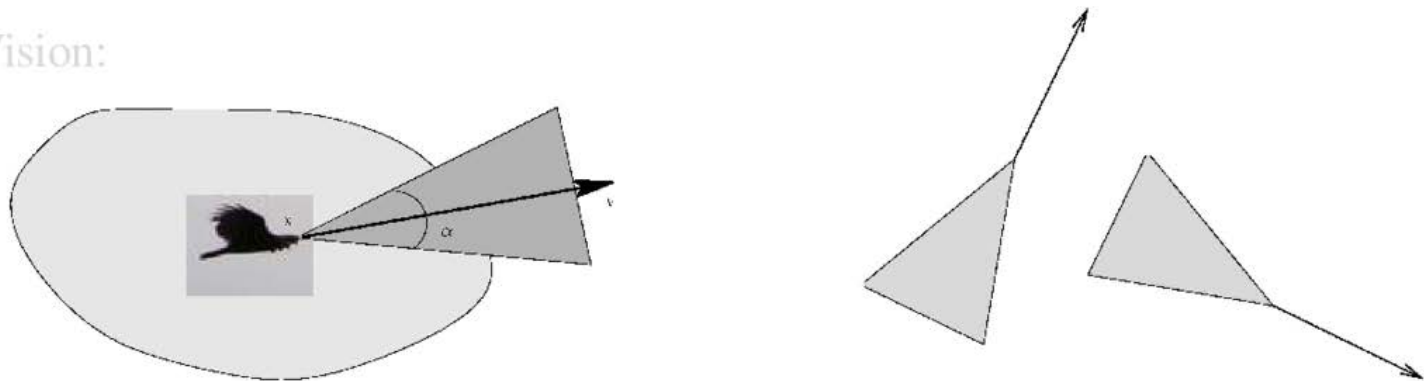
Cucker-Smale with local influence regions:

$$\begin{cases} \frac{dx_i}{dt} = v_i, \\ \frac{dv_i}{dt} = \sum_{j \in \Sigma_i(t)} a(|x_i - x_j|)(v_j - v_i), \end{cases}$$

where $\Sigma_i(t) \subset \{1, \dots, N\}$ is the set of dependence, given by

$$\Sigma_i(t) := \left\{ 1 \leq \ell \leq N : \frac{(x_\ell - x_i) \cdot v_i}{|x_\ell - x_i| |v_i|} \geq \alpha \right\}.$$

Cone of Vision:



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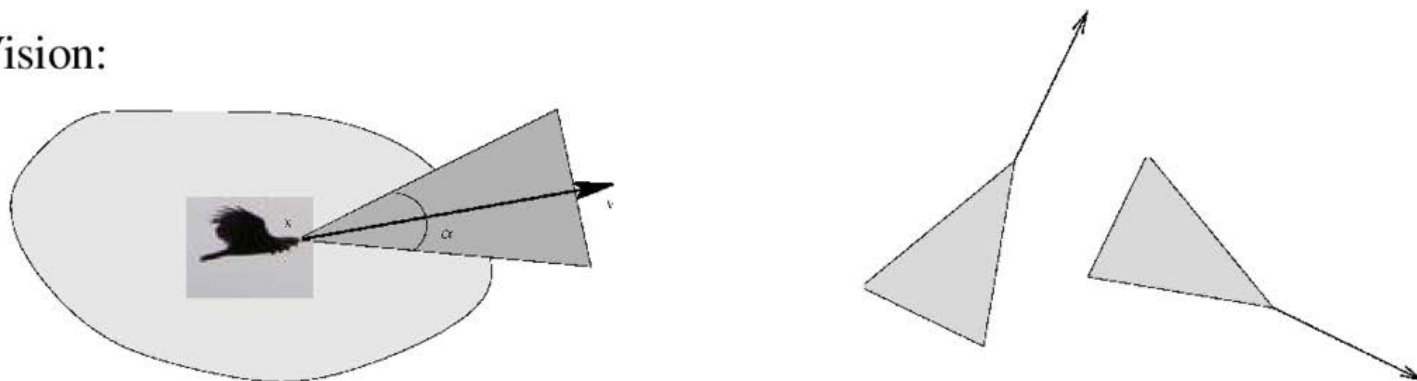
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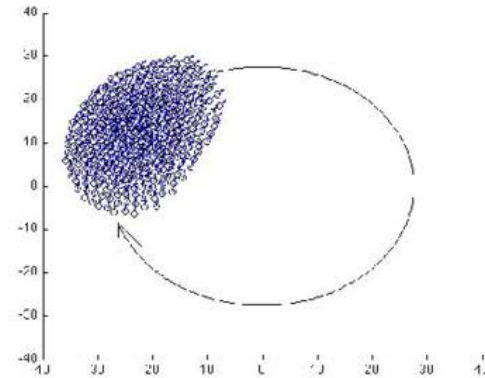
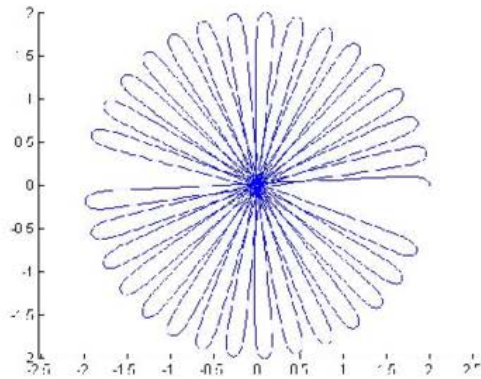
Roosting Forces

Adding a roosting area to the model:

$$\begin{cases} \frac{dx_i}{dt} = v_i, \\ \frac{dv_i}{dt} = (\alpha - \beta |v_i|^2)v_i - \sum_{j \neq i} \nabla U(|x_i - x_j|) - v_i^\perp \nabla_{x_i} [\phi(x_i) \cdot v_i^\perp]. \end{cases}$$

with the roosting potential ϕ given by $\phi(x) := \frac{b}{4} \left(\frac{|x|}{R_{\text{Roost}}} \right)^4$.

Roosting effect: milling flocks $N = 400$, $R_{\text{roost}} = 20$.



Adding Noise

Self-Propelling/Friction/Interaction with Noise Particle Model:

$$\begin{cases} \dot{x}_i = v_i, \\ dv_i = \left[(\alpha - \beta |v_i|^2) v_i - \nabla_{x_i} \sum_{j \neq i} U(|x_i - x_j|) \right] dt + \sqrt{2\sigma} d\Gamma_i(t), \end{cases}$$

where $\Gamma_i(t)$ are N independent copies of standard Wiener processes with values in \mathbb{R}^d and $\sigma > 0$ is the noise strength. The Cucker–Smale Particle Model with Noise:

$$\begin{cases} dx_i = v_i dt, \\ dv_i = \sum_{j=1}^N a(|x_j - x_i|) (v_j - v_i) dt + \sqrt{2\sigma \sum_{j=1}^N a(|x_j - x_i|)} d\Gamma_i(t). \end{cases}$$

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Vicsek's model

Assume N particles moving at **unit speed**: reorientation & diffusion:

$$\begin{cases} dX_t^i = V_t^i dt, \\ dV_t^i = \sqrt{2} P(V_t^i) \circ dB_t^i - P(V_t^i) \left(\frac{1}{N} \sum_{j=1}^N K(X_t^i - X_t^j) (V_t^i - V_t^j) \right) dt. \end{cases}$$

Here $P(v)$ is the projection operator on the tangent space at $v/|v|$ to the unit sphere in \mathbb{R}^d , i.e.,

$$P(v) = I - \frac{v \otimes v}{|v|^2}.$$

Noise in the **Stratonovich sense**: imposed by the rigorous construction of the Brownian motion on a manifold. Rigorous derivation: Bolley-Cañizo-C.

Main issue: **phase transition?** Degond-Liu-Frouvelle.

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1st Order Friction Model:

Edelshtein-Keshet, Mogilner (JMB 2000): Assume the variations of the velocity and speed are much smaller than spatial variations, then from Newton's equation:

$$m \frac{d^2 x_i}{dt^2} + \alpha \frac{dx_i}{dt} + \sum_{j \neq i} \nabla U(|x_i - x_j|) = 0$$

$$\frac{dx_i}{dt} = - \sum_{j \neq i} \nabla U(|x_i - x_j|) \quad \text{in the continuum setting} \Rightarrow \begin{cases} \frac{\partial \rho}{\partial t} + \operatorname{div}(\rho v) = 0 \\ v = -\nabla U * \rho \end{cases}$$

Flock Solutions: stationary states x_i^s of the 1st order model are connected to particular solutions of the Bertozzi et al 2nd order model of the form

$$x_i(t) = x_i^s + t v_0$$

with v_0 fixed with $|v_0|^2 = \frac{\alpha}{\beta}$.

For which potentials do we evolve towards some nontrivial steady states/patterns?

Is there any implication of the stability from first to 2nd order models?

If repulsion is very strong and localized while attraction has a larger length-scale, we assume $U = U_a + \delta_0$, and thus

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For which potentials do we evolve towards some nontrivial steady states/patterns?

Is there any implication of the stability from first to 2nd order models?

If repulsion is very strong and localized while attraction has a larger length-scale, we assume $U = U_a + \delta_0$, and thus

$$\frac{\partial \rho}{\partial t} = \operatorname{div}(\rho \nabla U_a * \rho) + \Delta \rho^2$$

1st Order Friction Model:

Edelshtein-Keshet, Mogilner (JMB 2000): Assume the variations of the velocity and speed are much smaller than spatial variations, then from Newton's equation:

$$m \frac{d^2 x_i}{dt^2} + \alpha \frac{dx_i}{dt} + \sum_{j \neq i} \nabla U(|x_i - x_j|) = 0$$

$$\frac{dx_i}{dt} = - \sum_{j \neq i} \nabla U(|x_i - x_j|) \quad \text{in the continuum setting} \Rightarrow \begin{cases} \frac{\partial \rho}{\partial t} + \operatorname{div}(\rho v) = 0 \\ v = -\nabla U * \rho \end{cases}$$

Flock Solutions: stationary states x_i^s of the 1st order model are connected to particular solutions of the Bertozzi et al 2nd order model of the form

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- 1 Kinetic Models and measure solutions
 - Vlasov-like Models
 - Proof
- 2 Mean-Field Limit for 1st Order Model
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- 3 Stochastic Mean-Field Limit
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Mesoscopic models

Model with asymptotic velocity + Attraction/Repulsion:

$$\frac{\partial f}{\partial t} + v \cdot \nabla_x f + \operatorname{div}_v [(\alpha - \beta|v|^2)v f] - \operatorname{div}_v [(\nabla_x U \star \rho) f] = 0.$$

Velocity consensus Model:

$$\frac{\partial f}{\partial t} + v \cdot \nabla_x f = \nabla_v \cdot \left[\underbrace{\left(\int_{\mathbb{R}^{2d}} \frac{v-w}{(1+|x-y|^2)^\gamma} f(y, w, t) dy dw \right)}_{:=\xi(f)(x, v, t)} f(x, v, t) \right]$$

Orientation, Attraction and Repulsion:

$$\frac{\partial f}{\partial t} + v \cdot \nabla_x f - \operatorname{div}_v [(\nabla_x U \star \rho) f] = \nabla_v \cdot [\xi(f)(x, v, t) f(x, v, t)].$$

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Definition of the distance

Transporting measures:

Given $T : \mathbb{R}^d \rightarrow \mathbb{R}^d$ measurable, we say that $\nu = T\#\mu$, if $\nu[K] := \mu[T^{-1}(K)]$ for all measurable sets $K \subset \mathbb{R}^d$, equivalently

$$\int_{\mathbb{R}^d} \varphi d\nu = \int_{\mathbb{R}^d} (\varphi \circ T) d\mu \quad \text{for all } \varphi \in C_o(\mathbb{R}^d).$$

Random variables:

Say that X is a random variable with law given by μ , is to say

$X : (\Omega, \mathcal{A}, P) \rightarrow (\mathbb{R}^d, \mathcal{B}_d)$ is a measurable map such that $X\#P = \mu$, i.e.,

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Kantorovich-Rubinstein-Wasserstein Distance $p = 1, 2$:

$$W_p^p(\mu, \nu) = \inf_{(X,Y)} \{\mathbb{E}[|X - Y|^p]\}$$

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Well-posedness in probability measures¹

Existence, uniqueness and stability

Take a potential $U \in \mathcal{C}_b^2(\mathbb{R}^d)$, and f_0 a measure on $\mathbb{R}^d \times \mathbb{R}^d$ with compact support. There exists a solution $f \in \mathcal{C}([0, +\infty); \mathcal{P}_1(\mathbb{R}^d))$ in the sense of solving the equation through the characteristics: $f_t := P^t \# f_0$ with P^t the flow map associated to the equation.

Moreover, the solutions remains compactly supported for all time with a possibly growing in time support.

Moreover, given any two solutions f and g with initial data f_0 and g_0 , there is an increasing function depending on the size of the support of the solutions and the parameters, such that

$$W_1(f_t, g_t) \leq \alpha(t) W_1(f_0, g_0)$$

¹Dobrushin-Hepp-Neunzert, 1977-79 for the Vlasov.

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Convergence of the particle method

- **Empirical measures:** if $x_i, v_i : [0, T) \rightarrow \mathbb{R}^d$, for $i = 1, \dots, N$, is a solution to the ODE system,

$$\begin{cases} \frac{dx_i}{dt} = v_i, \\ \frac{dv_i}{dt} = \underbrace{(\alpha - \beta |v_i|^2)v_i}_{\text{propulsion-friction}} - \underbrace{\sum_{j \neq i} m_j \nabla U(|x_i - x_j|)}_{\text{attraction-repulsion}} + \underbrace{\sum_{j=1}^N m_j a_{ij} (v_j - v_i)}_{\text{orientation}}. \end{cases}$$

then the $f : [0, T) \rightarrow \mathcal{P}_1(\mathbb{R}^d)$ given by

$$f_N(t) := \sum_{i=1}^N m_i \delta_{(x_i(t), v_i(t))}$$

is the solution corresponding to initial atomic measures.

- Convergence of approximations of measures by particles due to the stability at any given time T as an alternative derivation of the kinetic models.

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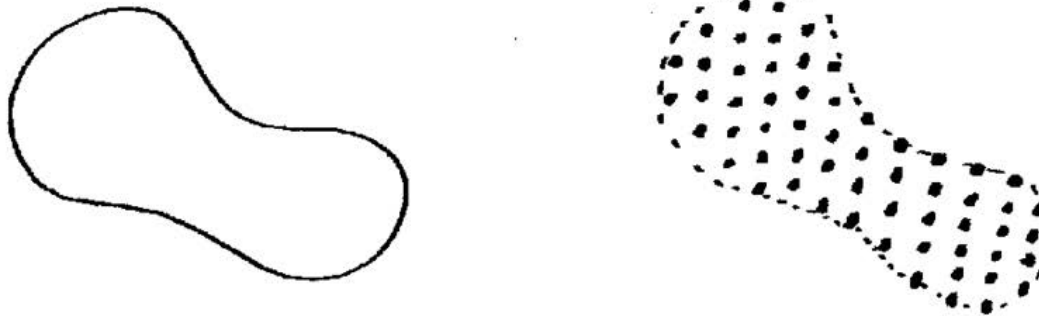
Mean-Field Limit

Just take as many particles as needed in order to have

$$W_1(f_t, f_t^N) \leq \alpha(t) W_1(f_0, f_0^N) \rightarrow 0 \quad \text{as } N \rightarrow \infty$$

by sampling the initial data in a suitable way.

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Hauray-Jabin 2011: mean field limit for Vlasov with potentials such that $|\nabla U| \leq r^{-\alpha}$, with $\alpha < 1$ with initial data for Vlasov in $L^1 \cap L^\infty$.

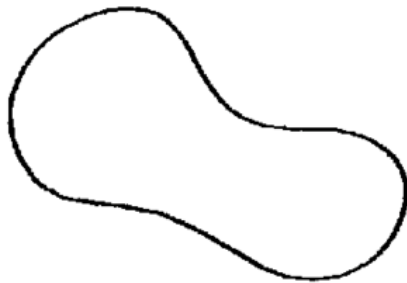
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Proof of the Theorem

Conditions on E :

① E is continuous on $[0, T] \times \mathbb{R}^d$,

② For some $C > 0$,

$$|E(t, x)| \leq C_E(1 + |x|), \quad \text{for all } t, x \in [0, T] \times \mathbb{R}^d, \text{ and}$$

③ E is **locally Lipschitz with respect to x** , i.e., for any compact set $K \subseteq \mathbb{R}^d$ there is some $L_K > 0$ such that

$$|E(t, x) - E(t, y)| \leq L_K |x - y|, \quad t \in [0, T], \quad x, y \in K.$$

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$$\partial_t f + v \cdot \nabla_x f + E \cdot \nabla_v f + \operatorname{div}_v((\alpha - \beta |v|^2)vf) = 0,$$

which is a linear first-order equation. The associated characteristic system of ODE's is

$$\begin{aligned} \frac{d}{dt} X &= V, \\ \frac{d}{dt} V &= E(t, X) + V(\alpha - \beta |V|^2). \end{aligned}$$

Flow Map:

Given $(X_0, V_0) \in \mathbb{R}^d \times \mathbb{R}^d$ there exists a unique solution (X, V) to the ODE system in $C^1([0, T]; \mathbb{R}^d \times \mathbb{R}^d)$ satisfying $X(0) = X_0$ and $V(0) = V_0$. In addition, there exists a constant C which depends only on $T, |X_0|, |V_0|, \alpha, \beta$ and the constant C_E , such that

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$$\mathcal{T}_E^t : \mathbb{R}^d \times \mathbb{R}^d \rightarrow \mathbb{R}^d \times \mathbb{R}^d.$$

Again by basic results in ode's, the map $(t, x, v) \mapsto \mathcal{T}_E^t(x, v) = (X, V)$ with (X, V) the solution at time t to the ODE system with initial data (x, v) , is jointly continuous in (t, x, v) .

For a measure $f_0 \in \mathcal{P}_1(\mathbb{R}^d \times \mathbb{R}^d)$, the function

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Estimates on characteristics:

- Taking characteristics with initial data inside a fixed ball then there exists $R > 0$ depending on T , in which the whole trajectories are inside a possibly larger ball of radius R for all times $t \in [0, T]$.
- For some constant C which depends only on α, β, R and $\text{Lip}_R(E^i)$, for all P^0 in B_R

$$\left| \mathcal{T}_{E^1}^t(P^0) - \mathcal{T}_{E^2}^t(P^0) \right| \leq \frac{e^{Ct} - 1}{C} \sup_{s \in [0, T]} \left\| E_s^1 - E_s^2 \right\|_{L^\infty(B_R)},$$

- For some constant C as before

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Error on transported measures through different flows:

Let $\mathcal{T}_1, \mathcal{T}_2 : \mathbb{R}^d \rightarrow \mathbb{R}^d$ be two Borel measurable functions. Also, take $f \in \mathcal{P}_1(\mathbb{R}^d)$. Then,

$$W_1(\mathcal{T}_1 \# f, \mathcal{T}_2 \# f) \leq \|\mathcal{T}_1 - \mathcal{T}_2\|_{L^\infty(\text{supp} f)}.$$

Continuity in time for solutions of the linear transport:

$$W_1(\mathcal{T}_E^s \# f, \mathcal{T}_E^t \# f) \leq C |t - s|, \quad \text{for any } t, s \in [0, T].$$

Error on transported measures through different initial data:

Take a locally Lipschitz map $\mathcal{T} : \mathbb{R}^d \rightarrow \mathbb{R}^d$ and $f, g \in \mathcal{P}_1(\mathbb{R}^d)$, both with compact support contained in the ball B_R . Then,

$$W_1(\mathcal{T} \# f, \mathcal{T} \# g) \leq L W_1(f, g),$$

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 &\leq \|\mathcal{T}_f^t - \mathcal{T}_g^t\|_{L^\infty(\text{supp}f_0)} + L_t W_1(f_0, g_0) \\
 &\leq C_2 \int_0^t e^{C_2(t-s)} \|E[f_s] - E[g_s]\|_{L^\infty(B_R)} ds + L_t W_1(f_0, g_0) \\
 &\leq C_3 \text{Lip}_{2R}(\nabla U) \int_0^t e^{C_4(t-s)} W_1(f_s, g_s) ds + e^{C_1 t} W_1(f_0, g_0).
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2nd order models

The Bertozzi-D'Orsogna model:

$$\begin{cases} \dot{x}_j = v_j \\ \dot{v}_j = (\alpha - \beta|v_j|^2)v_j + \frac{1}{N} \sum_{\substack{l=1 \\ l \neq j}}^N \nabla U(x_l - x_j) \end{cases}, \quad j = 1, \dots, N,$$

with $\alpha, \beta > 0$. Particular case $U(x) = k(|x|)$ with

$$k(r) = \frac{r^a}{a} - \frac{r^b}{b}, \quad a > b > 0.$$

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Asymptotic solutions

Definition

- We call a *flock ring*, the solution such that $\{x_j\}_{j=1}^N$ are equally distributed on a circle with a certain radius, R and $\{v_j\}_{j=1}^N = u_0$, with $|u_0| = \sqrt{\alpha/\beta}$.
- We call a *mill ring*, the solution such that $\{x_j\}_{j=1}^N$ are equally distributed on a circle with a certain radius, R and $\{v_j\}_{j=1}^N = \sqrt{\alpha/\beta} x_j^\perp / |x_j|$ with x_j^\perp the orthogonal vector.

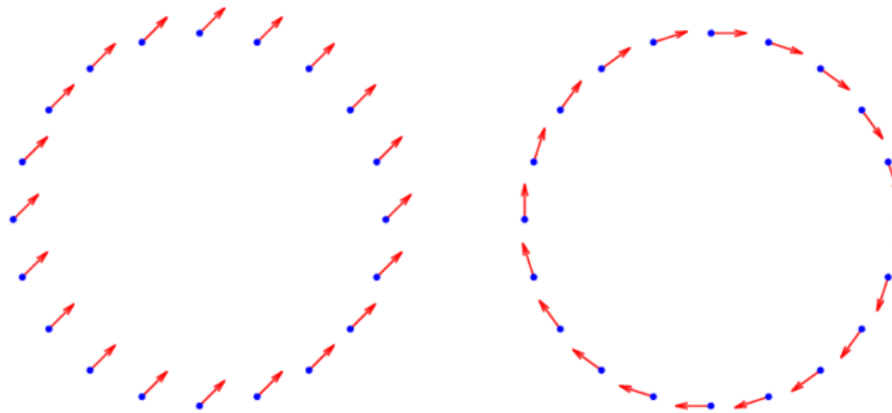


Figure : Flock and mill ring solutions.

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Change of Variables

- Change of variables to the comoving frame:

$$\begin{cases} y_j = x_j(t) - u_0 t \\ z_j = v_j(t) - u_0 \end{cases}, j = 1, \dots, N,$$

Then the system reads

$$\begin{cases} \dot{y}_j = z_j \\ \dot{z}_j = (\alpha - \beta |z_j|^2)(z_j + u_0) + \frac{1}{N} \sum_{\substack{l=1 \\ l \neq j}}^N \nabla U(y_l - y_j) \end{cases}, j = 1, \dots, N.$$

Write the stationary ring $(y_j^0, z_j^0) = (Re^{i\theta_j}, 0)$ where $\theta_j = \frac{2\pi j}{N}$, for $j = 1, \dots, N$.
A general flock spatial profile will be denoted by $(\hat{x}_j, 0)$.

- Consider the following type of perturbations:

$$\tilde{y}_j(t) = \hat{x}_j + h_j(t), \quad \text{with} \quad |h_j| \ll 1.$$

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Analysis of the stability of flocks (I)

- Write the matrix of the linearized system for these perturbations

$$L = \begin{pmatrix} 0_{2N} & \text{Id}_{2N} \\ \mathbf{M} & -2\beta\mathcal{U}_0 \end{pmatrix},$$

where \mathbf{M} is symmetric and represents the $2N \times 2N$ Jacobian that results from linearizing the first order model, $M = (G_{ij})$ with G_{ij} being the 2×2 -blocks defined as

$$G_{ij} = \begin{cases} -\sum_{j \neq i} \text{Hess } U(\hat{x}_i - \hat{x}_j) & \text{for } i = j \\ \text{Hess } U(\hat{x}_i - \hat{x}_j) & \text{for } i \neq j \end{cases},$$

with $\text{Hess } U$ denoting the Hessian matrix of the interaction potential U .

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Analysis of the stability of flocks (II)

Symmetries & Linear Instability

Due to translational invariance and rotational invariance of the velocity configuration, zero is always an eigenvalue of the linearized matrix L .

Moreover, there is always a generalized eigenvector associated to the zero eigenvalue generated from the eigenvector due to rotational invariance of the velocity configuration.

Therefore, a flock solution is always linearly unstable.

Instability Result - Spectral Equivalence

The linearized second order system around the flock solution has an eigenvalue with positive real part **if and only if** the linearized first order system around the flock solution has a positive eigenvalue.

(Albi, Balagué, C., von Brecht; submitted)

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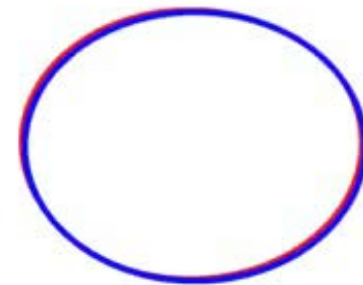
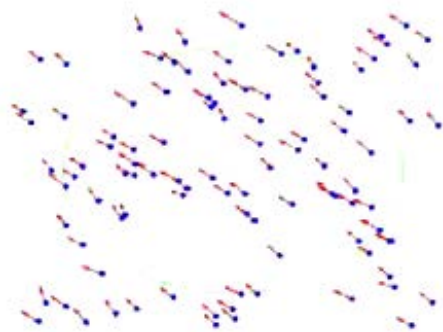
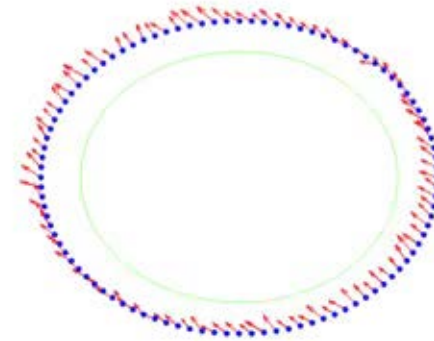
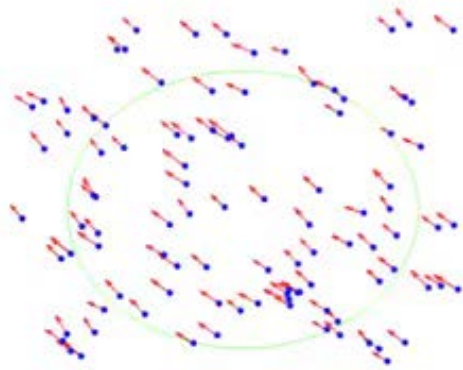
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Particle Simulations: Perturbation of flocks



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Stability: New change of variables

- Original coordinates: flock transversal profile
 - New coordinates: relative to $m(t) = \frac{1}{N} \sum_i v_i(t)$.
- all flocks are stationary, $4N + 2$ -dimensional dynamics $z \mapsto \mathcal{F}(z)$
- Reduce dynamics to mean-velocity consistent states, by choosing an invariant base B :
 $\mathcal{F}_B^B := \mathcal{F}|_{\text{span } B} \rightarrow \text{span } B$.

→ Study the linearisation $z \approx z_F + F_B^B(z - z_f)$

$$\begin{pmatrix} 0_{2N \times 2N} & I_{2N-2} & 0_{2N \times 2} \\ & -1_{N-1}^T \otimes I_2 & \\ [G(\hat{x})] & -I_{N-1} \otimes 2\beta(m \otimes m^T) & 0_{2N-2 \times 2} \\ 0_{2 \times 2N} & 0_{2 \times 2N-2} & -2\beta(m \otimes m^T) \end{pmatrix}.$$

$$\dot{x}_1 = \dots$$

$$\vdots$$

$$\dot{x}_N = \dots$$

$$\dot{v}_1 = \dots$$

$$\vdots$$

$$\dot{v}_N = \dots$$

flock solution:

$$z_F = (\hat{x} + v_0 t, v_0)^T, \quad |v_0| = \sqrt{\alpha/\beta}.$$

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flock solution:

$$z_F = (\hat{x}, 0, m), \quad |m| = \sqrt{\alpha/\beta}.$$

Stability: New change of variables

- Original coordinates: flock transversal profile
 - New coordinates: relative to mean velocity
 $m(t) = \frac{1}{N} \sum_i v_i(t)$.
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Result

Suppose the first-order aggregation system

$$\frac{dx_i}{dt} = - \sum_{i \neq j} \nabla U(x_i - x_j),$$

is **linearly stable** except for translational and rotational invariance at a stationary profile \hat{x} .

Then the transformed second-order system behaves well:

- F_B^B has no generalised eigenvector for eigenvalue zero.
- $\dim(\text{eig}(F_B^B, 0)) = 4$ with 4 eigenvectors that all represent linearised flow within the set of stationary flock solutions.
2 \rightsquigarrow translation in space, 1 \rightsquigarrow rotation in space, 1 \rightsquigarrow rotation in mean velocity
- All non-zero eigenvalues of F_B^B have negative real-part.

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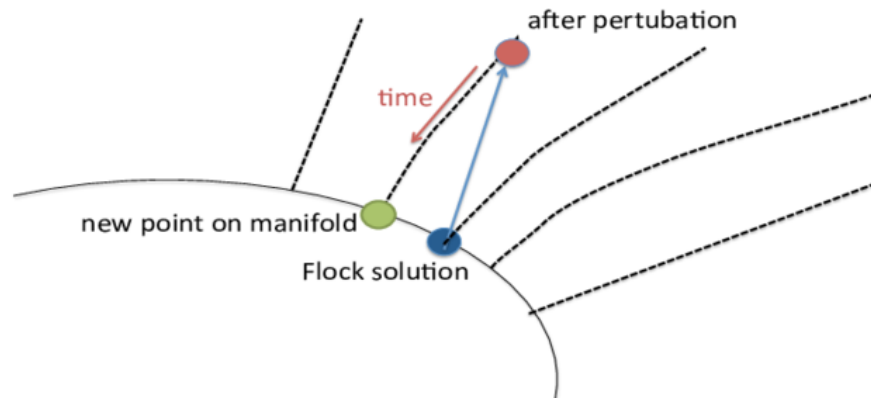
Stability Theorem

This is sufficient to establish that the family of flock solutions

$$Z_F = \left\{ (x^*, 0, m), x^* = T_x R[\phi] \hat{x}, |m| = \sqrt{\alpha/\beta} \right\}$$

is a **normally hyperbolic invariant manifold** with a purely stable tangent-bundle splitting and exponentially decaying local stability (T_x translation, $R[\phi]$ rotation).

(C., Huang, Martin; Nonlinear Analysis: Real World Applications 2014)



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Convergence of the particle method

Empirical measures: if $x_i, v_i : [0, T) \rightarrow \mathbb{R}^d$, for $i = 1, \dots, N$, is a solution to the ODE system,

$$\left\{ \begin{array}{l} \frac{dx_i}{dt} = v_i, \\ \frac{dv_i}{dt} = \underbrace{(\alpha - \beta |v_i|^2) v_i}_{\text{propulsion-friction}} - \underbrace{\sum_{j \neq i} m_j \nabla U(|x_i - x_j|)}_{\text{attraction-repulsion}} + \underbrace{\sum_{j=1}^N m_j a_{ij} (v_j - v_i)}_{\text{orientation}}. \end{array} \right.$$

then the $f_N : [0, T) \rightarrow \mathcal{P}_1(\mathbb{R}^d)$ given by

$$f_N(t) := \sum_{i=1}^N m_i \delta_{(x_i(t), v_i(t))} \quad \text{with} \quad \sum_{i=1}^N m_i = 1,$$

is expected to be the solution corresponding to initial atomic measures.

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Mesoscopic models

Model with asymptotic velocity + Attraction/Repulsion:

$$\frac{\partial f}{\partial t} + v \cdot \nabla_x f + \operatorname{div}_v [(\alpha - \beta|v|^2)v f] - \operatorname{div}_v [(\nabla_x U \star \rho) f] = 0.$$

Velocity consensus Model:

$$\frac{\partial f}{\partial t} + v \cdot \nabla_x f = \nabla_v \cdot \left[\underbrace{\left(\int_{\mathbb{R}^{2d}} \frac{v-w}{(1+|x-y|^2)^\gamma} f(y, w, t) dy dw \right)}_{:=\xi(f)(x, v, t)} f(x, v, t) \right]$$

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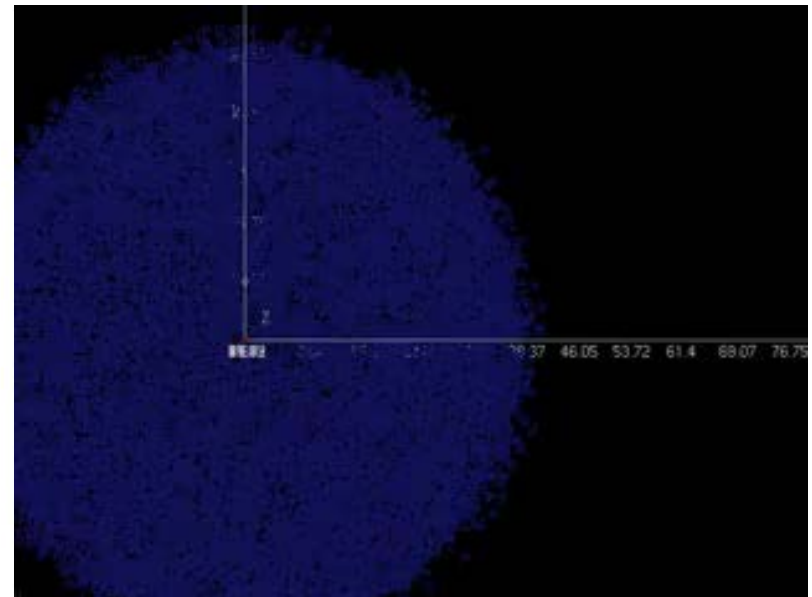
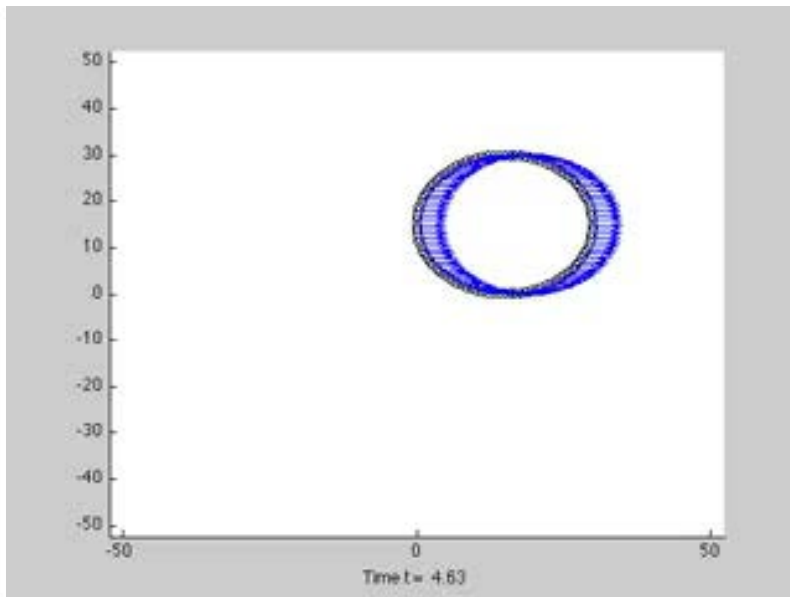
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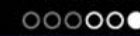
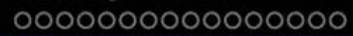
Macroscopic equations

Monokinetic Solutions

Assuming that there is a deterministic velocity for each position and time, $f(x, v, t) = \rho(x, t) \delta(v - u(x, t))$ is a distributional solution if and only if,

$$\begin{cases} \frac{\partial \rho}{\partial t} + \operatorname{div}_x(\rho u) = 0, \\ \rho \frac{\partial u}{\partial t} + \rho (u \cdot \nabla_x) u = \rho (\alpha - \beta |u|^2) u - \rho (\nabla_x U \star \rho). \end{cases}$$





What about mills?



Conclusions & Open Problems

- **Simple modelling of the three main mechanisms leads to complicated patterns.**
More information from particular species should be included to make more realistic models (Helmelrijk & collaborators, ...)
- Stability of flocks is understood. However, mill's stability remains unknown.
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