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Some kinetic models of swarming

J. A. Carrillo,

in collaboration with J. A. Cañizo and J. Rosado (UAB), to appear in M3AS.

ICREA - Universitat Autònoma de Barcelona

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Outline

Some Swarming Models

- Particle models.
- Kinetic Models and measure solutions.

Qualitative Properties

- Model with asymptotic velocity
- Cucker-Smale Kinetic model
- Variations

3 Conclusions

Swarming

Qualitative Properties

ysics odav The physics of flocking

Fish schools and Birds flocks.

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Swarming = Aggregation of agents of similar size and body

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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

^aBarbaro, Birnir et al. (2008).

Types of interaction

- **Repulsion** Region: R_k .
- Attraction Region: A_k.
- Orientation Region: O_k .



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Model with an asymptotic velocity

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

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

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*).

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



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Particle models.

Model with an asymptotic velocity

Typical patterns: milling, double milling or flocking.



Double milling patterns: Carrillo, D'Orsogna, Panferov (2009).

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Particle models.

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, $\gamma \ge 0$:

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

Unconditional flocking: $\gamma \leq 1/2$; Ha-Tadmor, Ha-Liu, Carrillo-Fornasier-Toscani-Rosado. Conditional flocking: $\gamma > 1/2$.

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Mesoscopic models

Kinetic Models and measure solutions.

Model with asymptotic velocity + Attraction/Repulsion:

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

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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Definition of the distance¹

Transporting measures:

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

$$\int_{\mathbb{R}^d} arphi \, d
u = \int_{\mathbb{R}^d} (arphi \circ T) \, d\mu$$

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

$$\int_{\mathbb{R}^d} \varphi(x) \, d\mu = \int_{\Omega} (\varphi \circ X) \, dP = \mathbb{E} \left[\varphi(X) \right].$$

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¹C. Villani, AMS Graduate Texts (2003).

Kinetic Models and measure solutions.

Definition of the distance

Kantorovich-Rubinstein-Wasserstein Distance:

$$W_1(\mu,\nu) = \inf_{\pi} \left\{ \iint_{\mathbb{R}^d \times \mathbb{R}^d} |x-y| \, d\pi(x,y) \right\} = \inf_{(X,Y)} \left\{ \mathbb{E} \left[|X-Y| \right] \right\}$$

where the transference plan π runs over the set of joint probability measures on $\mathbb{R}^d \times \mathbb{R}^d$ with marginals f and $g \in \mathcal{P}_1(\mathbb{R}^d)$ and (X, Y) are all possible couples of random variables with μ and ν as respective laws.

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Definition of the distance

Monge's optimal mass transport problem:

Find

$$I:=\inf_T\left\{\int_{\mathbb{R}^d}|x-T(x)|\,d\mu(x);\,\nu=T\#\mu\right\}.$$

Take $\gamma_T = (1_{\mathbb{R}^d} \times T) \# \mu$ as transference plan π .



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1-Wasserstein Distance

Basic Properties

Kinetic Models and measure solutions.

() Distance to a Dirac: $f \in \mathcal{P}_1(\mathbb{R}^d)$ and $a \in \mathbb{R}^d$, then

$$W_1(f,\delta_a) = \int_{\mathbb{R}^d} |x-a| df(x).$$

Translation: $f \in \mathcal{P}_1(\mathbb{R}^d)$ and $a \in \mathbb{R}^d$, let f_a denotes the translated f with vector a, then

- So **Convergence of measures:** $W_1(f_n, f) \to 0$ is equivalent to $f_n \rightharpoonup f$ weakly-* as measures and convergence of first moments.
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Well-posedness in probability measures²

Existence, uniqueness and stability

Take a potential $U \in C_b^2(\mathbb{R}^d)$, and f_0 a measure on $\mathbb{R}^d \times \mathbb{R}^d$ with compact support. There exists a solution $f \in C([0, +\infty); \mathcal{P}_1(\mathbb{R}^d))$ 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

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

²Dobrushin-Hepp-Neunzert, 1977-79 for the Vlasov.

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Well-posedness in probability measures²

Existence, uniqueness and stability

Take a potential $U \in C_b^2(\mathbb{R}^d)$, and f_0 a measure on $\mathbb{R}^d \times \mathbb{R}^d$ with compact support. There exists a solution $f \in C([0, +\infty); \mathcal{P}_1(\mathbb{R}^d))$ 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

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

²Dobrushin-Hepp-Neunzert, 1977-79 for the Vlasov.
Convergence of the particle method

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

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

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

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Model with asymptotic velocity

Outline

Some Swarming Models

- Particle models.
- Kinetic Models and measure solutions.

Qualitative Properties

- Model with asymptotic velocity
- Cucker-Smale Kinetic model
- Variations

3 Conclusions



Model with asymptotic velocity

Macroscopic equations

Monokinetic Solutions

Assuming that there is a deterministic velocity for each position and time, $f(x, v, t) = \rho(x, t) \,\delta(v - u(x, t)) \text{ is a distributional solution if and only if,} \\ \begin{cases} \frac{\partial \rho}{\partial t} + \operatorname{div}_x(\rho u) = 0, \\ \rho \frac{\partial u}{\partial t} + \rho (u \cdot \nabla_x)u = \rho (\alpha - \beta |u|^2)u - \rho (\nabla_x U \star \rho). \end{cases}$

Superposition of Monokinetic Solutions

 $f(x, v, t) = \rho_1(x, t) \,\delta(v - u_1(x, t)) + \rho_2(x, t) \,\delta(v - u_2(x, t))$ is a distributional solution if and only if

$$\left(\begin{array}{c} \frac{\partial(\rho_1+\rho_2)}{\partial t} + \operatorname{div}_x(\rho_1 u_1+\rho_2 u_2) = 0,\\ \sum_{i=1}^2 \rho_i \left[\frac{\partial u_i}{\partial t} + (u_i \cdot \nabla_x)u_i - (\alpha - \beta |u_i|^2)u_i\right] = -(\nabla_x U \star \rho) \rho.\end{array}\right)$$

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Model with asymptotic velocity

Particular solutions

Let us look for stationary solutions with an asymptotic speed value $\beta |u(x,t)|^2 = \alpha$.

Flocking

Traveling wave case, u = const such that $\beta |\mathbf{u}(\mathbf{x}, t)|^2 = \alpha$, then $\rho(x, t) = \tilde{\rho}(x - ut)$, and the density is determined by

 $\tilde{\rho}\left(\nabla_{\mathbf{x}}U\star\tilde{\rho}\right)=0,$

from which

$$U\star\tilde{\rho}=C,\quad\tilde{\rho}\neq0,$$

in the support of $\tilde{\rho}$ if the support has not empty interior.

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we set **u** in a rotatory state,

$$u = \pm \sqrt{\frac{\alpha}{\beta}} \, \frac{x^{\perp}}{|x|}$$

where $x = (x_1, x_2), x^{\perp} = (-x_2, x_1)$, and look for $\rho = \rho(|x|)$ radial, then

$$U \star \rho = D + \frac{\alpha}{\beta} \ln |x|, \text{ whenever } \rho \neq 0.$$

A special family of singular solutions are given by $\rho(r) = c \, \delta(r - r_0)$.

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Cucker-Smale Kinetic model

Asymptotic Flocking

Let us consider the N_p -particle system:

$$\begin{cases} \frac{dx_i}{dt} = v_i &, x_i(0) = x_i^0 \\ \frac{dv_i}{dt} = \sum_{j=1}^{N_p} m_j a(|x_i - x_j|) (v_j - v_i) &, v_i(0) = v_i^0, \end{cases}$$

Due to translation invariancy, w.l.o.g. the mean velocity is zero and thus the center of mass is preserved along the evolution, i.e.,

$$\sum_{i=1}^{N_p} m_i v_i(t) = 0$$
 and $\sum_{i=1}^{N_p} m_i x_i(t) = x_0$

for all $t \ge 0$ and $x_c \in \mathbb{R}^d$.

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Asymptotic Flocking

Let us fix any $R_0^x > 0$ and $R_0^v > 0$, such that all the initial velocities lie inside the ball $B(0, R_0^v)$ and all positions inside $B(x_c, R_0^x)$.

Let us define the function $R^{\nu}(t)$ to be

 $R^{\nu}(t) := \max\left\{\left|v_{i}(t)\right|, i = 1, \ldots, N_{p}\right\}.$

Choosing the label *i* to be the one achieving the maximum, we get

$$\frac{d}{dt}R^{\nu}(t)^{2} = \frac{d}{dt}|v_{i}|^{2} = -2\sum_{j\neq i}m_{j}\left[(v_{i}-v_{j})\cdot v_{i}\right]a(|x_{i}-x_{j}|).$$

Because of the choice of the label *i*, we have that $(v_i - v_j) \cdot v_i \ge 0$ for all $j \ne i$ that together with $a \ge 0$ imply $\mathbb{R}^{\nu}(t) \le \mathbb{R}^{\nu}_0$ for all $t \ge 0$.

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Asymptotic Flocking

Coming back to the equation for the positions,

$$|x_i(t) - x_i^0| \le R_0^{\nu} t$$
 for all $t \ge 0$ and all $i = 1, \dots, N_p$.

$$a(|x_i - x_j|) \ge \frac{1}{[1 + 4R_0^2(1+t)^2]^{\gamma}}$$
 for all $t \ge 0$ and all $i, j = 1, \dots, N_p$,

with $R_0 = \min(R_0^x, R_0^y)$. Coming back to the equation for the maximal velocity

$$\begin{aligned} \frac{d}{dt}R^{\nu}(t)^2 &= -2\sum_{j\neq i}m_j\left[(\nu_i - \nu_j) \cdot \nu_i\right] a(|x_i - x_j|) \\ &\leq -\frac{2}{\left[1 + 4R_0^2(1+t)^2\right]^{\gamma}}\sum_{j\neq i}m_j\left[(\nu_i - \nu_j) \cdot \nu_i\right] \\ &= -\frac{2}{\left[1 + 4R_0^2(1+t)^2\right]^{\gamma}}R^{\nu}(t)^2 := -f(t)R^{\nu}(t)^2, \end{aligned}$$

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Asymptotic Flocking

Gronwall's lemma:

$$R^{\nu}(t) \leq R_0^{\nu} \exp\left\{-\frac{1}{2}\int_0^t f(s)\,ds\right\}.$$

For $\gamma \leq 1/2$, the function f(t) is not integrable at ∞ and therefore

$$\lim_{t\to\infty}\int_0^t f(s)\,ds = +\infty$$

and $R^{\nu}(t) \to 0$ as $t \to \infty$ giving the convergence to a single point, its mean velocity, of the support for the velocity. Again for the position variables, we get

$$\begin{cases} \int_{0}^{t} |v_{i}(s)| \, ds \leq C_{1} \int_{0}^{t} (1+s)^{-1-\epsilon} \, ds \qquad \gamma < 1/2 \\ \int_{0}^{t} |v_{i}(s)| \, ds \leq C \int_{0}^{t} \frac{1}{1+s} \, ds = C \ln(1+t) \quad \gamma = 1/2, \end{cases}$$

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Cucker-Smale Kinetic model

Asymptotic Flocking

There exists $R_1^x > 0$ such that

 $|x_i(t) - x_i^0| \le R_1^x$

Now, $a(|x_i(t) - x_j(t)|) \ge a(2\overline{R}^x)$,

$$\frac{d}{dt}R^{\nu}(t)^{2} = -2\sum_{j\neq i}m_{j}\left[(v_{i}-v_{j})\cdot v_{i}\right]a(|x_{i}-x_{j}|)$$

$$\leq -2a(2\bar{R}^{x})\sum_{j\neq i}m_{j}\left[(v_{i}-v_{j})\cdot v_{i}\right] = -2a(2\bar{R}^{x})R^{\nu}(t)^{2}$$

from which we finally deduce the exponential decay to zero of $R^{\nu}(t)$.

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Asymptotic Flocking

Unconditional Non-universal Flocking Result for Particles

The unique measure-valued solution for the CS kinetic model with $\gamma \leq 1/2$, with a finite number of particles given by

$$\tilde{\mu}(t) = \sum_{i=1}^{N_p} m_i \,\delta(x - x_i(t)) \,\delta(v - v_i(t)),$$

satisfies that

 $\lim_{t\to\infty} W_1\left(\tilde{\mu}(t),\tilde{\mu}^\infty\right)=0$

with

$$\tilde{\mu}^{\infty} = \sum_{i=1}^{N_p} m_i \,\delta(x - x_i^{\infty} - mt) \,\delta(v - m)$$

with m the initial mean velocity of the particles.

Asymptotic Flocking

Unconditional Non-universal Flocking Result for general measures

Given $\mu_0 \in \mathcal{M}(\mathbb{R}^{2d})$ compactly supported, then the unique measure-valued solution to the CS kinetic model with $\gamma \leq 1/2$, satisfies the following bounds on their supports:

 $\operatorname{supp} \mu(t) \subset B(x_c(0) + mt, R^x(t)) \times B(m, R^v(t))$

for all $t \ge 0$, with $\mathbb{R}^{x}(t) \le \overline{\mathbb{R}}$ and $\mathbb{R}^{v}(t) \le \mathbb{R}_{0} e^{-\lambda t}$ with $\overline{\mathbb{R}}^{x}$ depending only on the initial support radius.

Moreover,

 $\lim_{t\to\infty} W_1(\mu_x^{mt}(t),L_\infty(\mu_0))=0,$

where the measure $L_{\infty}(\mu_0)$ is defined as

$$\int_{\mathbb{R}^d} \zeta(x) \, dL_{\infty}(\mu_0)(x) = \int_{\mathbb{R}^{2d}} \zeta\left(x + \int_0^{\infty} [V(s;x,v) - m] \, ds\right) \, d\mu_0(x,v),$$

for all $\zeta \in \mathcal{C}^0_b(\mathbb{R}^d)$.

Asymptotic Flocking

Unconditional Non-universal Flocking Result for general measures

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Outline

Some Swarming Models

- Particle models.
- Kinetic Models and measure solutions.

Qualitative Properties

- Model with asymptotic velocity
- Cucker-Smale Kinetic model
- Variations

3 Conclusions



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

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

Cone of Vision:





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Roosting Forces

Adding a roosting area to the model:

$$\begin{cases} \frac{dx_i}{dt} = v_i, \\ \frac{dv_i}{dt} = (\alpha - \beta |v_i|^2)v_i - \sum_{j \neq i} \nabla U(|x_i - x_j|) - v_i^{\perp} \nabla_{x_i} \left[\phi(x_i) \cdot v_i^{\perp}\right], \\ \text{with the roosting potential } \phi \text{ given by } \phi(x) := \frac{b}{4} \left(\frac{|x|}{R_{\text{Roost}}}\right)^4. \\ \text{Roosting effect: milling flocks } N = 400, R_{\text{roost}} = 20. \end{cases}$$



to appear in M3AS, in collaboration with A. Klar, S. Martin, S. Tiwari, and S. Sakara and S
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Variations

Adding Noise

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

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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.

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- Simple modelling of the three main phenomena: attraction, repulsion, and orientation; lead to complicated patterns which are observed in nature and not completely understood.
- Stability of these patterns will certainly be quite useful to understand more complicated situations.
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- Simple modelling of the three main phenomena: attraction, repulsion, and orientation; lead to complicated patterns which are observed in nature and not completely understood.
- Stability of these patterns will certainly be quite useful to understand more complicated situations.
- The results are also interested from the point of view of the control of electronic robots.
- More information from particular species should be included to make more realistic models: visual sectors for birds, more adapted interactions, pheromone trails for ants, ...