

How to steer high-dimensional Cucker-Smale systems to consensus using low-dimensional information only

Benjamin Scharf

Technische Universität München - Chair for Applied Numerical Analysis

benjamin.scharf@ma.tum.de

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The Cucker-Smale model - Introduction

... a dynamical system used to describe the nature of a group of moving agents, i. e. birds, but also the formation/evolution of languages etc.

$$\begin{cases} \dot{x}_i(t) = v_i(t) \\ \dot{v}_i(t) = \frac{1}{N} \sum_{j=1}^N a(\|x_j(t) - x_i(t)\|) \cdot (v_j(t) - v_i(t)), \end{cases}$$

where $x_1, \dots, x_N, v_1, \dots, v_N \in \mathbb{R}^d$ with given initial values at 0 and a is a *non-increasing positive Lipschitz function*. Example of Cucker and Smale:

$$a(x) = \frac{K}{(\sigma^2 + x^2)^\beta}, \quad K, \sigma > 0, \beta \geq 0$$

References:

F. Cucker and S. Smale. Emergent behavior in flocks. IEEE Trans. Automat. Control, 52(5):852–862, 2007.

F. Cucker and S. Smale. On the mathematics of emergence. Jpn. J. Math., 2(1):197–227, 2007.

The Cucker-Smale model - First observations

First observations:

- 1 Bigger difference between velocities \Rightarrow bigger change of velocity
- 2 Bigger distance of particles \Rightarrow smaller influence on the change of velocity
- 3 Mean velocity $\bar{v}(t) = \frac{1}{N} \sum_{j=1}^N v_j(t)$ is a constant of the system
- 4 Rotation of the start parameters $x_1(0), \dots, x_N(0), v_1(0), \dots, v_N(0)$ results in rotation of the system

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- ④ Rotation of the start parameters $x_1(0), \dots, x_N(0), v_1(0), \dots, v_N(0)$ results in rotation of the system
- ⑤ We can rewrite the system as

$$\begin{cases} \dot{x} = v \\ \dot{v} = -L_x v, \end{cases} \quad \text{with } L_x = (a_{ij})_{i,j=1}^N \text{ and } a_{ii} = \sum_{j \neq i} -a_{ij},$$

symmetric L_x , $a_{ii} \geq 0$, $a_{ij} \leq 0$ and hence L_x positive semi-definite.

The Cucker-Smale model - Main parameters

To measure the distances of the particles as well as their velocities we introduce:

$$X(t) := \frac{1}{2N^2} \sum_{i,j=1}^N \|x_i(t) - x_j(t)\|^2 = \frac{1}{N} \sum_{i=1}^N \|x_i(t) - \bar{x}(t)\|^2 = \overline{x^2} - \bar{x}^2,$$

$$V(t) := \frac{1}{2N^2} \sum_{i,j=1}^N \|v_i(t) - v_j(t)\|^2 = \frac{1}{N} \sum_{i=1}^N \|v_i(t) - \bar{v}(t)\|^2 = \overline{v^2} - \bar{v}^2$$

$$v_i^\perp(t) := v_i(t) - \bar{v}(t).$$

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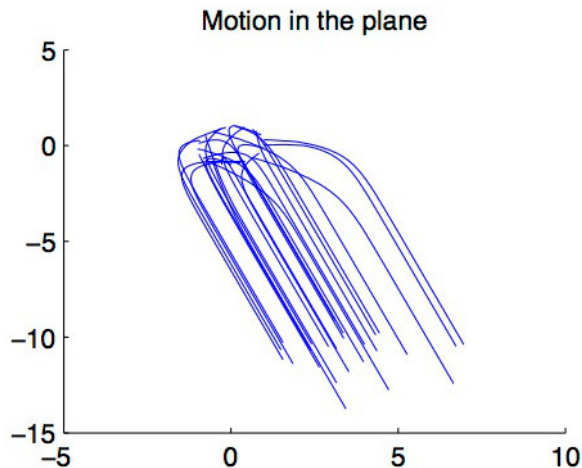
The main question is: Does the systems tend to consensus?

$$? \lim_{t \rightarrow \infty} v_i(t) = \bar{v} \text{ or equivalently } \lim_{t \rightarrow \infty} v_i^\perp(t) = 0 \text{ resp. } \lim_{t \rightarrow \infty} V(t) = 0?$$

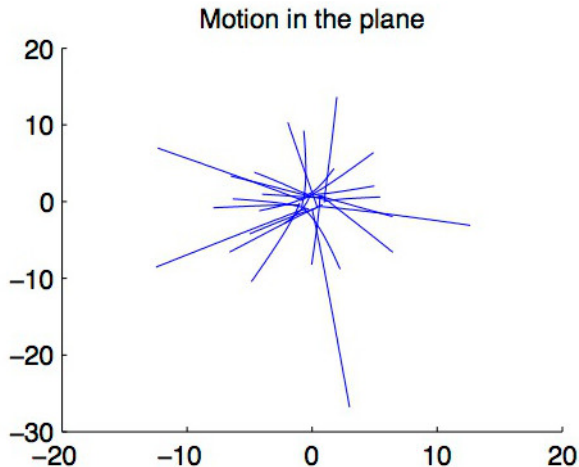
This would imply: The system moves as a swarm, i. e.

$$x(t) \approx x(t_0) + (t - t_0)\bar{v}$$

The Cucker-Smale model - Consensus



The Cucker-Smale model - Explosion



The Cucker-Smale model - Consensus

First observe

$$\begin{aligned} \frac{d}{dt} V(t) &= \frac{1}{N} \sum_{i=1}^N \frac{d}{dt} \|v_i(t)\|^2 = \frac{2}{N} \sum_{i=1}^N \langle v_i(t), \dot{v}_i(t) \rangle = - \langle v, L_x v \rangle_{\mathbb{R}^{d \times n}} \\ &= - \frac{1}{N^2} \sum_{i,j=1}^N a(\|x_j(t) - x_i(t)\|) \cdot \|v_j(t) - v_i(t)\|^2. \end{aligned}$$

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Lemma (Lyapunov functional behaviour)

$$\frac{d}{dt} V(t) \leq a \left(\sqrt{2NX(t)} \right) \sqrt{V(t)} \text{ as long as } V(t) > 0$$

Hence: If $X(t)$ is bounded, the system tends to consensus.

The Cucker-Smale model - Consensus (ii)

Theorem (Ha, Ha, Kim 2010)

$$\text{If } \int_{\sqrt{X(0)}}^{\infty} a(\sqrt{2Nr}) \, dr \geq \sqrt{V(0)}, \text{ then } \lim_{t \rightarrow \infty} V(t) = 0.$$

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Remarks:

- ① a not integrable \Rightarrow the system tends to consensus independent of the start parameters
- ② Otherwise: If the distance of the actors is not too large resp. the starting velocities are not too different, the system tends to consensus

Example

Classical C.-S. distance $a(x) = \frac{1}{(1+x^2)^\beta}$

- $\beta \leq 1/2$: always consensus (strong enough forces)
- $\beta > 1/2$: depends on the initial values

The Cucker-Smale model - Consensus (iii)

Example

Two agents, $\beta = 1$, consider their distance $x = x_1 - x_2$ and difference of velocity $v = v_1 - v_2$:

$$\dot{x} = v, \quad \dot{v} = -\frac{v}{1+x^2}$$

with initial distance $x(0) = x_0$ and diff. of velocities $v(0) = v_0 > 0$. Hence $0 < v(t) \leq v_0$ since $|v(t)|$ is decreasing and $v(t') = 0 \Rightarrow v(t) = 0, t \geq t'$.

This yields $v(t) - v_0 = -\arctan x(t) + \arctan x_0$.

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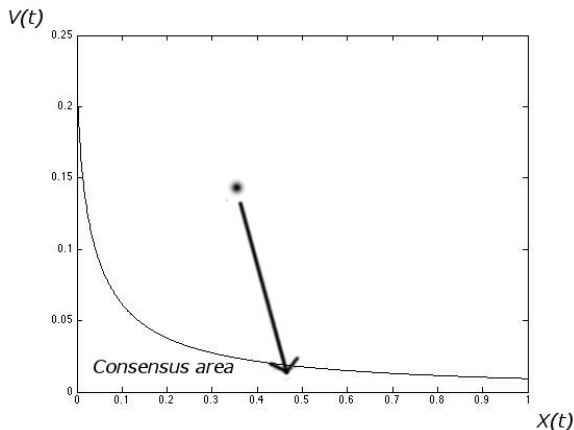
- $\arctan x_0 + v_0 < \pi/2 \Rightarrow x(t)$ bounded:
 - a) $\arctan x(t) \leq \arctan x(t) + v(t) < \pi/2$
 - b) $\arctan x(t) \geq (v_0 - v(t)) + \arctan x_0 \geq \arctan x_0$
- $\arctan x_0 + v_0 = \pi/2 \Rightarrow v(t) + \arctan x(t) = \pi/2 \Rightarrow v(t) \downarrow 0$ or $x(t)$ bound.
- $\arctan x_0 + v_0 = \pi/2 + \varepsilon \Rightarrow v(t) + \arctan x(t) = \pi/2 + \varepsilon \Rightarrow v(t) \geq \varepsilon$

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The consensus manifold

Idea: If we are not in the consensus manifold, infer (sparse) control



Ref.: *M. Caponigro, M. Fornasier, B. Piccoli and E. Trelat. Sparse stabilization and control of the Cucker-Smale model. submitted, 2012.*

Sparsely Controlled Cucker-Smale system

Goal: Steer the system to the consensus area using control and then stop the control. Minimize the necessary "control steps" - minimize the time to consensus and the number of agents to act on:

$$\begin{cases} \dot{x}_i(t) = v_i(t) \\ \dot{v}_i(t) = \frac{1}{N} \sum_{j=1}^N a(\|x_j(t) - x_i(t)\|) \cdot (v_j(t) - v_i(t)) + u_i(t). \end{cases}$$

with $\ell_1^N - \ell_2^d$ -norm constraint (compare to compressed sensing)

$$\sum_{i=1}^N \|u_i(t)\|_2 \leq \Theta.$$

Observe: \bar{v} is not constant anymore.

Maximizing the decay of $V(t)$

Maximizing the decay of $V(t)$ with respect to the $\ell_1^N - \ell_2^d$ -norm constraint leads to the so-called shepherd dog (Schäferhund) strategy:

$$\begin{aligned} \frac{d}{dt} V(t) &= \frac{d}{dt} \langle v - \bar{v}, v - \bar{v} \rangle = 2 \langle \frac{d}{dt} v^\perp, v^\perp \rangle \\ &= 2 \langle \dot{v}, v^\perp \rangle = - \langle L_x v, v \rangle + \langle u, v^\perp \rangle \\ \Rightarrow u_i &= \begin{cases} -M \frac{v_i^\perp}{\|v_i^\perp\|} & \text{if } i \text{ is first } i : \|v_i^\perp\| = \max_{j=1, \dots, N} \|v_j^\perp\| \\ 0 & \text{otherwise} \end{cases} \end{aligned}$$

is (one/the) maximizer under $\sum_{i=1}^N \|u_i(t)\|_2 \leq \Theta$.

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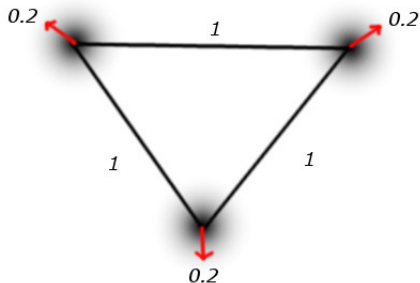
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is (one/the) maximizer under $\sum_{i=1}^N \|u_i(t)\|_2 \leq \Theta$.

The control only acts on the most stubborn guy!

How to construct controls - Paradox of switching controls

The controls are defined pointwisely and influence the future. The following example shows the problem:



Assume u_1 is active for $[0, t] \Rightarrow v_1$ is nearer to \bar{v} at $t/2$ than v_2 ✘

How to construct controls - Sample and Hold

Sample and Hold idea: First construct solutions with controls constant on intervals $[k\tau, (k+1)\tau]$ - time-sparse controls.

Recursive construction of the sampling solution:

As long as we are not in the consensus manifold at $t = k\tau$ solve

$$\dot{z}(t) = f(z(t), u(z(k\tau))), \quad t \in [k\tau, (k+1)\tau]$$

with initial value $z(k\tau)$ and $u(k\tau)$ chosen as before.

Observe: The optimality criterion (decay of $V(t)$) doesn't hold anymore.

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Observe: The optimality criterion (decay of $V(t)$) doesn't hold anymore.

Theorem (Caponigro, Fornasier, Piccoli, Trelat)

For every Θ (constraint size) there exists $\tau_0 > 0$ such that for all sampling times $\tau \in [0, \tau_0]$ the sampling solution of the controlled Cucker-Smale system reaches the consensus region in finite time.

How to construct controls - Filippov solution

Convergence: Take the solutions x_τ with respect to the sampling time τ and let $\tau \rightarrow 0$. Prove that z_τ converges to a z in a suitable way.

$$z_\tau = z_0 + \int_0^t f(z_\tau(s)) + u_\tau(z_\tau(s)) ds.$$

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- ① z_τ are bounded on finite intervals (Gronwall estimate)
- ② z_τ are equicontinuous (equi-Lipschitz)
- ③ z_τ converges by Arzela-Ascoli in \mathcal{C} to $z \in Lip$.

④

$$\int_0^t u_\tau(z_\tau(s)) ds \rightarrow y(t)$$

- ⑤ Since u_τ are bounded, y is absolutely continuous, can be written as

$$y(t) = \int_0^t u(s) ds.$$

- ⑥ Density argument: $u_\tau(z(\tau)) \rightarrow u$ weakly in L_1

How to construct controls - Filippov solution

A deeper argument shows: The limit control u is of the form

$$u_i = \begin{cases} -\alpha_i \frac{v_i^\perp}{\|v_i^\perp\|} & , \text{ if } \|v_i^\perp\| = \max_{j=1,\dots,N} \|v_j^\perp\| \\ 0 & , \text{ otherwise} \end{cases}$$

until reaching consensus region and minimizes the decay of $V(t)$: It is possibly not sparse (Example!).

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Remarks and open problems:

- The time to consensus can be estimated from above depending on $X(0), V(0)$ and the constraint Θ
- Greedy minimization may not be optimal
- What is the minimal time to consensus?
- How much control interactions are necessary?

How to construct controls - picture

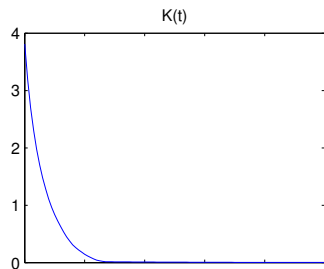
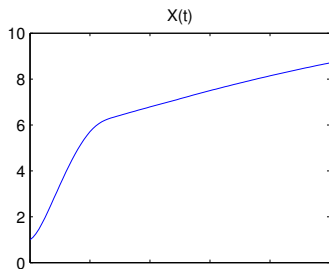
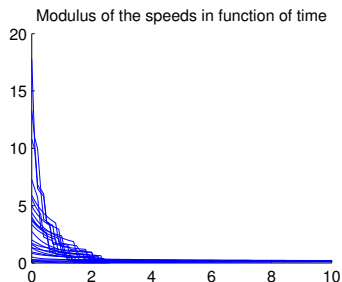
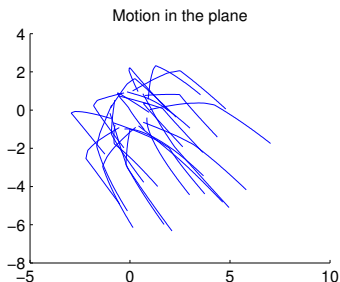


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Introduction

The case $N \rightarrow \infty$ (large number of agents) is widely considered in the literature:

- locations, velocities \Rightarrow density distributions
- dynamical system, ODE \Rightarrow PDE

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The case $d \rightarrow \infty$ (high dimension/many coordinates/variables) is of our interest.

Example: Social movement (panic), Financial movement

x not locations, more variables/state of the system

(Health, pulse, strength; situation on the market, IFO-Index etc.)

v describes the movement towards consensus

\Rightarrow Goal: Panic prevention, Black Swan prevention

Johnson-Lindenstrauss matrices

The main tool is the dimension reduction by Johnson-Lindenstrauss:

Lemma (Johnson-Lindenstrauss matrices (JLM))

Let x_1, \dots, x_N be points in \mathbb{R}^d . Given $\varepsilon > 0$, there exists a constant

$$k_0 = \mathcal{O}(\varepsilon^{-2} \log N),$$

such that for all integers $k \geq k_0$ there exists a $k \times d$ matrix M for which

$$(1 - \varepsilon)\|x_i\|^2 \leq \|Mx_i\|^2 \leq (1 + \varepsilon)\|x_i\|^2, \text{ for all } i = 1, \dots, N.$$

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Remarks:

- M can be understood as a low-dimensional replacement for a projection onto $\text{span}\{x_1, \dots, x_N\}$
- k_0 does not depend on the dimension, only logarithmically on the number of points N , usely $N \sim d^\alpha \Rightarrow$ logarithmically on d
- the construction of JLM uses random matrices, no deterministic construction known

How to reduce the dimension of the Cucker-Smale model

M. Fornasier, J. Haskovec and J. Vybiral. Particle systems and kinetic equations modeling interacting agents in high dimension, 2011.

⇒ Reduction of the Cucker-Smale-like models without control.

$$\begin{aligned} \dot{M}v_i(t) &= \frac{1}{N} \sum_{j=1}^N a(\|x_j(t) - x_i(t)\|) \cdot (Mv_j(t) - Mv_i(t)) \\ &\sim \frac{1}{N} \sum_{j=1}^N a(\|Mx_j(t) - Mx_i(t)\|) \cdot (Mv_j(t) - Mv_i(t)). \end{aligned}$$

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Idea: Consider a low-dimensional Cucker-Smale system in \mathbb{R}^k (low dimension JLM) with $(y_0, w_0) = (Mx_0, Mv_0)$ as initial values. They show:

JLM-projection of the high-dimensional system stays close to the low-dimensional system

or: first project, then dynamics \sim first dynamics, then project

First tool: A continuous Johnson-Lindenstrauss lemma

Lemma (Bongini, Fornasier, Scharf (BFS))

Let $\varphi : [0, 1] \rightarrow \mathbb{R}^d$ be a Lipschitz function (bound L_φ), $0 < \varepsilon < \varepsilon' < 1$, $\delta > 0$ and M be a Johnson-Lindenstrauss matrix in $\mathbb{R}^{k \times d}$ for

$$N \geq L_\varphi \frac{6d/k}{\delta(\varepsilon' - \varepsilon)}$$

points with high probability. Then for every $t \in [0, 1]$ one of the following holds (with the same high probability):

$$(1 - \varepsilon') \|\varphi(t)\| \leq \|M\varphi(t)\| \leq (1 + \varepsilon') \|\varphi(t)\|$$

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$$\|\varphi(t)\| \leq \delta \text{ and } \|M\varphi(t)\| \leq \delta.$$

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or

$$\|\varphi(t)\| \leq \delta \text{ and } \|M\varphi(t)\| \leq \delta.$$

Remarks: The original lemma of Fornasier, Haskovec, Vybiral assumed that φ has bounded curvature which is not given in the Cucker-Smale case.

What is the plan?

$$\begin{cases} \dot{x}_i(t) = v_i(t) \\ \dot{v}_i(t) = \frac{1}{N} \sum_{j=1}^N a(\|x_j(t) - x_i(t)\|) \cdot (v_j(t) - v_i(t)) + u_i(t). \end{cases}$$

- ① Project the high-dimensional initial values with JLM M to low-dimension
- ② Choose the index of sparse control ($u_i \neq 0$) from the low-dimensional system and apply it to the high-dimensional system
- ③ Show: If the systems stay close to each other, then
 - ▶ either both systems are in consensus or
 - ▶ the control is reasonable for both systems (decay of $V(t)$ is fast enough)

Norm estimates for high-dimensional control

Lemma (High-dimensional control is legit, BFS)

Let M be a Johnson-Lindenstrauss matrix with $\varepsilon = 1/2$ and δ for the points a_i . Assume $\|Ma_i - b_i\| \leq \delta$. Let i be the smallest index such that $\|b_i\| \geq \|b_j\|$ and

$$A := \frac{1}{N} \sum_{j=1}^N \|a_j\|^2 \text{ and } B := \frac{1}{N} \sum_{j=1}^N \|b_j\|^2.$$

If $\sqrt{B} \geq 2\delta$, then (c indep. of d, N)

$$\|a_i\| \geq \frac{\|b_i\|}{4}, \quad \|a_i\| \geq c \cdot \sqrt{A} \text{ and } B \leq 4NA.$$

If $\sqrt{B} \leq 2\delta$, then (C indep. of d, N)

$$\sqrt{A} \leq C\delta.$$

The main result

Theorem (BFS)

Let $M \in \mathbb{R}^{k \times d}$ be a continuous Johnson-Lindenstrauss matrix for the distances of $x(t), v(t)$ with ε and δ sufficiently (very, very) small. Choose the sparse control index according to the low k -dimensional Cucker-Smale system with initial values $(Mx(0), Mv(0))$.

Then for every Θ (constraint) and $\tau < \tau_0$ the sampling solution of the so controlled high-dimensional Cucker-Smale system reaches the consensus region in finite time.

Remarks:

- ε and δ (and everything else) do not depend on d , but heavily on N
- If $\Theta \gg 0$ and is constant with N , then ε can be chosen such that:

$$\varepsilon \sim c \frac{1}{Ne^{N/c}}$$

There is another problem...

In the theorem we suppose M is a JLM for the distances of $x(t)$, $v(t)$, but: The initial values of the low-dimensional system and hence the controls depend on M

⇒ the high-dimensional system depends on M : **Vicious circle**

Solutions so far:

- take M as JLM for all possible trajectories, in principal $N^{T/\tau}$ possibilities where T is the time until consensus ⇒ we have to estimate the exponent T/τ , problematic
- use different matrices of the same dimension for every choice of the control (at $k\tau$) ⇒ a lot of matrix-vector multiplications in dimension d , since T/τ depends on N at least linearly right now

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Thank you for your attention!