

# Flocking Formation under Communication Failures for a Class of Cucker-Smale Systems

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**Seminar of the CAGE INRIA Team  
LJLL, Paris-Sorbonne University**

May 15, 2020

# Outline of the talk

Multi-agent systems and pattern formation

A quick overview of the Cucker-Smale flocking

Cucker-Smale flocking under communication failures

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A multi-agent system is a large ensemble of interacting things



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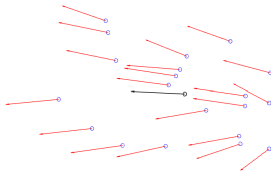
# Introduction – *Pattern formation*

## Central observation (pattern formation)

Interacting multi-agent systems may form **interesting global structures** starting from **elementary** interaction rules.

## Examples of classical patterns

- ◇ **Consensus** (everybody tends to agree on something) :  
↪ *aggregation models in biology, opinion models, etc...*
- ◇ **Flocking** (everybody goes in the same direction) :  
↪ *flocks of birds, herds analysis, opinion formation, etc...*



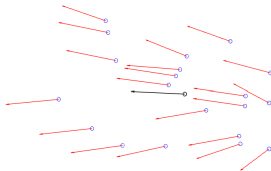
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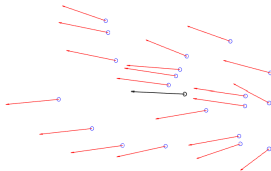
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# Multi-agent systems – ODE models

Multi-agents dynamics are described by **systems of ODEs**

$$\dot{\mathbf{x}}_i(t) = \mathbf{V}_N[\mathbf{x}(t)](t, \mathbf{x}_i(t)),$$

where

- ◇  $\mathbf{x}(\cdot) = (\mathbf{x}_1(\cdot), \dots, \mathbf{x}_N(\cdot)) \in (\mathbb{R}^d)^N$  is the state of the system,
- ◇  $\mathbf{V}_N : [0, T] \times (\mathbb{R}^d)^N \times \mathbb{R}^d \rightarrow \mathbb{R}^d$  is a **non-local** velocity field.

Example (Discrete convolution with a kernel)

$$\mathbf{V}_N[\mathbf{x}](t, \mathbf{x}_i) := \frac{1}{N} \sum_{j=1}^N K(t, \mathbf{x}_j - \mathbf{x}_i).$$

Question : What choice for  $K$  ?

↔ Depends on the **agent modelling** (pedestrians, animals, opinions...) and the **interactions** (physics-based, etc...).

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$$(CS') \quad \begin{cases} \dot{x}_i(t) = v_i(t), \\ \dot{v}_i(t) = \frac{1}{N} \sum_{j=1}^N \xi_{ij}(t) \phi(|x_i(t) - x_j(t)|) (v_j(t) - v_i(t)), \end{cases}$$

where

- ◇  $\phi(\cdot)$  is **radial**  $\rightsquigarrow$  interactions depend on **relative distance**,
- ◇  $\xi_{ij}(\cdot) \in L^\infty(\mathbb{R}_+, [0, 1])$  are **symmetric communication rates**  
 $\rightsquigarrow$  agents  $i$  and  $j$  fully communicate only when  $\xi_{ij}(t) = 1$ .

$\rightsquigarrow$  **Intuitive idea** : each agent tries to **align** its velocity with that of the other agents, with a **weight** depending on their relative distance.

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## Alignment models (Cucker & Smale '07)

Consider the **full-communication** case where  $\xi_{ij}(\cdot) \equiv 1$ , i.e.

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where  $\phi \in \text{Lip}(\mathbb{R}_+, \mathbb{R}_+)$  is a **positive** and **non-increasing** kernel.

## Definition (Asymptotic flocking for (CS))

A solution  $(x(\cdot), v(\cdot))$  of (CS) **converges to flocking** if

$$\sup_{t \geq 0} |x_i(t) - \bar{x}(t)| < +\infty \quad \text{and} \quad \lim_{t \rightarrow +\infty} |v_i(t) - \bar{v}| = 0.$$

where  $\bar{x}(\cdot)$  and  $\bar{v}$  are the position-velocity barycenters.

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# Cucker-Smale systems – Convergence analysis framework

## First question

How do we characterise flocking formation ?

↪ Good idea : find a suitable **dissipative Lyapunov** structure

Definition (Variance bilinear form and standard deviation)

Consider the variance bilinear form

$$B : (\mathbf{x}, \mathbf{y}) \in (\mathbb{R}^d)^N \times (\mathbb{R}^d)^N \mapsto \frac{1}{N} \sum_{i=1}^N \langle x_i, y_i \rangle - \langle \bar{\mathbf{x}}, \bar{\mathbf{y}} \rangle.$$

Characterisation of flocking

A solution  $(\mathbf{x}(\cdot), \mathbf{v}(\cdot))$  of (CS) converges to flocking **if and only if**

$$\sup_{t \geq 0} X(t) < +\infty \quad \text{and} \quad \lim_{t \rightarrow +\infty} V(t) = 0,$$

where  $X(t) := \sqrt{B(\mathbf{x}(t), \mathbf{x}(t))}$  and  $V(t) := \sqrt{B(\mathbf{v}(t), \mathbf{v}(t))}$ .

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# Generalised flocking – *Underlying dissipative structure*

## Definition (Graph Laplacians)

Consider the operator  $\mathbf{L} : (\mathbb{R}^d)^N \rightarrow \mathcal{L}((\mathbb{R}^d)^N)$  defined by

$$(\mathbf{L}(\mathbf{x})\mathbf{v})_i = \frac{1}{N} \sum_{j=1}^N \phi(|\mathbf{x}_i - \mathbf{x}_j|)(\mathbf{v}_i - \mathbf{v}_j),$$

for all  $i \in \{1, \dots, N\}$ .

## Proposition (Interesting things about graph Laplacians)

- ◇ Allows to rewrite (CS) as the **semilinear** system

$$\dot{\mathbf{x}}(t) = \mathbf{v}(t), \quad \dot{\mathbf{v}}(t) = -\mathbf{L}(\mathbf{x}(t))\mathbf{v}(t).$$

- ◇ It holds that  $B(\mathbf{L}(\mathbf{x})\mathbf{v}, \mathbf{v}) \geq 0$  for all  $\mathbf{x}, \mathbf{v} \in (\mathbb{R}^d)^N$ .
- ◇ The strength of the interactions in the system is quantified by the **eigenvalues** of  $\mathbf{L}(\mathbf{x}(t))$ .

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## Cucker-Smale systems – *Known convergence results*

**Observation :**  $\dot{X}(t) \leq V(t)$  and  $\dot{V}(t) \leq -\phi(2NX(t))V(t)$

Theorem (Flocking formation) [Cucker & Smale '07, Ha & Liu '09]

Suppose that  $\phi(\cdot) \in \text{Lip}(\mathbb{R}_+, \mathbb{R}_+)$  is **positive** and **non-increasing**.

- ◇ If  $\phi(\cdot)$  is **lower-bounded**, then flocking **always occurs**  
 $\rightsquigarrow V(\cdot)$  exponentially converges towards 0,
- ◇ If  $\phi(\cdot)$  **vanishes at infinity** but  $\phi \notin L^1(\mathbb{R}_+, \mathbb{R}_+)$ , then flocking **always occurs**  
 $\rightsquigarrow$  one has  $\phi \notin L^1 \implies X(t) \leq X_M$  for some  $X_M > 0$ ,
- ◇ If  $\phi(\cdot)$  **vanishes at infinity** and  $\phi \in L^1(\mathbb{R}_+, \mathbb{R}_+)$ , then flocking **may fail to occur...**  $\rightsquigarrow$  One needs small  $(X(0), V(0))$ .

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# Outline of the talk

Multi-agent systems and pattern formation

A quick overview of the Cucker-Smale flocking

Cucker-Smale flocking under communication failures



# Generalised flocking – *Modelling communication failures*

Back to the weighted model

Consider the Cucker-Smale system

$$\dot{\mathbf{x}}(t) = \mathbf{v}(t), \quad \dot{\mathbf{v}}(t) = -\mathbf{L}(t, \mathbf{x}(t))\mathbf{v}(t)$$

with the **time-dependent** graph Laplacian

$$(\mathbf{L}(t, \mathbf{x})\mathbf{v})_i = \frac{1}{N} \sum_{j=1}^N \xi_{ij}(t) \phi(|x_i - x_j|) (v_i - v_j)$$

Problem (communication weights)

↪ The  $\xi_{ij}(\cdot)$  may vanish or be small on possibly long time-intervals.

Main question

Under what kind of assumption on  $\xi_{ij}(\cdot)$  do we recover flocking ?

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**Second idea** : Agents  $i$  and  $j$  directly communicate if  $\xi_{ij}(t) > 0$ , but they can still **indirectly communicate** when  $\xi_{ij}(t) = 0$ .



**Figure:** In both situation  $\xi_{34}(t) = 0$  but agents 3 and 4 communicate

**First idea** : All the agents do not **need** to interact at all times, we only need a lower-bound on the **average interactions**.

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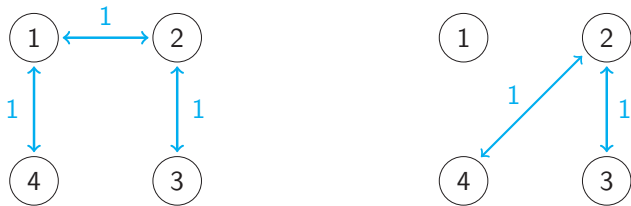
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# Generalised flocking – *Persistence and graph Laplacian*

## Definition (Graph Laplacian of the weights)

Consider the operator  $L_\xi : \mathbb{R}_+ \rightarrow \mathcal{L}((\mathbb{R}^d)^N)$  defined by

$$(L_\xi(t)\mathbf{v})_i = \frac{1}{N} \sum_{j=1}^N \xi_{ij}(t)(\mathbf{v}_i - \mathbf{v}_j).$$

## Definition (Persistence condition)

The weights  $\xi_{ij}(\cdot)$  satisfy the **persistence condition** (PE) if

$$B\left(\left(\frac{1}{\tau} \int_t^{t+\tau} L_\xi(s) ds\right) \mathbf{v}, \mathbf{v}\right) \geq \mu B(\mathbf{v}, \mathbf{v}), \quad (\text{PE}_{\tau, \mu})$$

for all  $(t, \mathbf{v}) \in \mathbb{R}_+ \times (\mathbb{R}^d)^N$ , where  $(\tau, \mu) \in \mathbb{R}_+ \times (0, 1]$ .

## Heuristic meaning

On every time window of length  $\tau$ , the average of interaction magnitudes (both **direct** and **indirect**) between agents is **at least**  $\mu$ .

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# Generalised flocking – *Main convergence result*

Theorem (Flocking formation) [B. & Flayac '20]

Let  $(\mathbf{x}^0, \mathbf{v}^0) \in (\mathbb{R}^d)^N \times (\mathbb{R}^d)^N$  and assume the following holds.

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$$\phi(r) \geq \frac{K}{(\sigma + r)^\beta}. \quad (\text{H})$$

Then, the solution  $(\mathbf{x}(\cdot), \mathbf{v}(\cdot))$  of (CS') **converges to flocking**.

Remarks (sharpness of the assumptions)

- ◊ Hypothesis (H) is probably not sharp... we expect  $\beta \in (0, 1)$
- ◊ The persistence assumption (PE) **seems sharp** !
  - Average connectivity is necessary even for consensus
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→ Flocking convergence is proved for  $\beta \in (0, 1)$  and for persistence assumption (PE) replaced by a weaker one (see [10])

→ Quantitative flocking estimates are obtained in [10]

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Then, the solution  $(\mathbf{x}(\cdot), \mathbf{v}(\cdot))$  of (CS') **converges to flocking**.

Remarks (sharpness of the assumptions)

- ◇ Hypothesis **(H)** is probably not sharp... we expect  $\beta \in (0, 1)$
- ◇ The persistence assumption (PE) **seems sharp** !
  - ↪ Average connectedness is **necessary** even for consensus,
  - ↪ **Quantitative** dissipation estimates are needed for flocking.

# Generalised flocking – *Main convergence result*

Theorem (Flocking formation) [B. & Flayac '20]

Let  $(\mathbf{x}^0, \mathbf{v}^0) \in (\mathbb{R}^d)^N \times (\mathbb{R}^d)^N$  and assume the following holds.

- (i) The weights  $\xi_{ij}(\cdot)$  satisfy (PE) for some  $(\tau, \mu) \in \mathbb{R}_+ \times (0, 1]$ .
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## Generalised flocking – *Elements of proof*

**Problem** : Lack of dissipation for  $V(\cdot)$   $\rightsquigarrow$  strict Lyapunov design !

- 1) Define the **time-varying** family of operators

$$\psi_\tau(t) = (1 + c^2)\tau \text{Id} - \frac{1}{\tau} \int_t^{t+\tau} \int_t^s \mathbf{L}(\sigma, \mathbf{x}(\sigma)) d\sigma ds$$

and consider the candidate Lyapunov functional

$$\mathcal{V}_\tau(t) = \lambda(t)V(t) + \sqrt{B(\psi_\tau(t)\mathbf{v}(t), \mathbf{v}(t))}$$

where  $\lambda(\cdot)$  is a tuning parameter (e.g. Mazenc & Malisoff '09).

- 2) After some (heavy) Lyapunov using (PE) and (**H**), we have

$$V(T) \leq V(0) \exp \left( - C_{\tau, \mu} T^{\frac{1-2\beta}{2(1-\beta)}} \right)$$

where  $T$  is the **maximal existence time** of  $\lambda(\cdot)$  !



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# Generalised flocking – *Conclusion and open perspective*

## Conclusive remarks

We have identified a synthetic and fairly minimalist persistence condition for multi-agent flocking via Lyapunov methods  $\rightsquigarrow$  **Nice !**

## Open questions and coming work

- 1) Recover the **sharp** exponent range  $\beta \in (0, 1)$   
 $\hookrightarrow$  Try a **better Lyapunov design** / perform better estimates ?
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All in all...

# Thank you for your attention !

