Experimental Studies of Social Collective Behaviors with feedback-controlled microswimmers

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submitted by Chun-Jen Chen

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First reviewer: Prof. Dr. Clemens Bechinger
Second reviewer: Prof. Dr. Stefan Karpitschka

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Examination Committee: Prof. Dr. Clemens Bechinger, Prof. Dr. Johannes Boneberg, Prof. Dr. Ulrich Nowak

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To all the wonderful encounters
in life, and at Bodensee
which brought me here
He had in his hands a circular device, and was looking at the sky between the two houses where a group of birds was flying in formation, and I quickly realized these were machine birds. He kept his gaze on them and when he touched his control, the birds responded by changing their pattern.

"Wow, they’re beautiful," Josie said, though still short of breath. "Are they new?"

Rick kept his gaze fixed on the birds, but said:

"Those two on the end are new. You can tell they don’t really match."

The birds swooped till they were hovering directly above us.

"Yeah, but real birds don’t all look the same either," Josie said.


Even at the time when an AI can accompany us and our children, bird flocks are still fascinating as well as puzzling to humans.
Acknowledgments

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Thank you, everyone!
Abstract

Social collective behaviors are recurring phenomena in the wild and in our daily life. Most gregarious animals, including human, develop into functional collective patterns. Such collective group motions exhibit fascinating physical properties regarding time and length scales, high responsiveness to environments, dynamical structures, etc. Studies of these collective behaviors in animals continue for more than half a century, from empirical group-level observations to modeling of individual social responses, then even detailed neurobiology in sensory and decision-making. Physics engage in these highly complex many-body systems in multiple stages. First, interactions between group members affecting the motion of individuals are modeled as “social forces”. Mechanics developed in active matter systems are particularly useful in this regard. Then, the statistical physics of complex and non-linear system apply to the emergent behaviors e.g. collective benefits. Such additional advantageous group properties or functions are the major reasoning for gregarious behaviors whose underlying mechanisms are not yet clear. Knowledge regarding symmetry, phase behavior and criticality also play roles in dynamics of transitions between collective patterns e.g. due to external stimuli. Last, network and information science focus on the sensing and consensus from individual to the whole group, effectively synchronizing all group members into one cooperative entity.

While studies regarding animal collective behaviors with social interactions often apply computer simulations, here in this thesis, we introduce experimental works with micron-sized robotic colloids as our social agents. These active colloids under a feedback loop controlling their forward motion and steering of orientation perform social interactions in a real world environment. We hence study the emergent collective behaviors in patterns, functioning and dynamics, as well as the robustness against environmental noise and additional physical interactions e.g. hydrodynamic effects. In the first study, we demonstrate the possibility to encode additional collective patterns in the interaction model of another pattern by simple induce symmetry breaking. We alter the model of rotational formation with replacement of local alignment for clockwise or counterclockwise rotation by a response to an external threat. This modification preserves the rotational nature of individual motion, however, the group perform flocking escaping motion upon the presence of the
Abstract

threat. Such a flocking formation emerge from a structure induced collective decision-making process and, hence, obtain tolerances to individual misinformation regarding the threat. The second work investigates effects of realistic 2-dimensional visual perception and finite attention capacity to a Vicsek-like flocking group. As social collective behaviors rely on each group member observing and responding to its neighboring peers, constraints related to these two abilities are supposedly crucial to the overall intra-group interactions. We examine visual constrains, i.e. range and obstructions between peers, as well as the individual capability to process information from multiple peers, i.e. attention limits, to the flocking stabilities. In experiments, a minimal attention corresponds to the stable flocking formation, which reflects the spatial geometry of the interaction network. Such a relation between real-space distribution and network-space connections is a profound characteristic in animal collective behaviors.

In general, our results with active matter experiments demonstrate the value of studying collective behaviors in model systems. The complexity in such realizations of social interaction models highlight the collective properties of both responsiveness and robustness to stimuli or noise. Nevertheless, our findings also have relevance to other many-body systems, e.g. robotic swarms where collective functioning reduces individual workloads.
Zusammenfassung


zusammenfassung
der Robustheit gegenüber Rauschen und weiteren physikalischen Einflüssen, wie zum Beispiel Hydrodynamik.


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Introduction

Collective groups of animals forming patterns in large scale and/or performing motion in cooperative manners frequently occur in our daily life. From displays of bird flocks consisting of hundreds of individuals or fish schools extending in a length of kilometers to a dozen of ants lifting an unlikely cargo or some tens of sparrows fleeing together, such collective behaviors are recurring across a wide range of spatial and temporal scales and various species. Undeniably, this also includes social behaviors of human crowds. Studies of animal collective behaviors shed light on these remarkable natural phenomena regarding the reason of occurrence, i.e. why, and the underlying mechanism, i.e. how. The answer to “why” extends our understanding regarding the biological meaning of gregarious behaviors: what are their interactions with the environments, and how they help individuals or certain species prevailing in the, so called, natural selection. This knowledge is useful for predicting the evolution of a biological system and, hence, the sustainable human activities regarding ecological environment. The answer to “how” inspires the developments in multibody systems and network science. Such knowledge enables not only the enhanced human-animal crowd interactions, e.g. fishery activities, beekeeping or locust plague prevention, but also robotic swarm designs. In the case of human society, crowd and traffic control are the relevant examples.

Biologists have first approached the mysteries of collective behaviors with general assumptions regarding group functions and individual abilities. As one of the most famous example, the many-eyes hypothesis suggests an increased vigilance to e.g. a predator as the reason for prey-grouping. Such an increased vigilance of the group arises from the more “eyes” scanning the surrounding, and the corresponding collective response to the predator is explained by the ability of group members to monitor and follow their peers. The focus on group-level behaviors directs these early studies to target mainly the “why” question. Later, agent-based models, where each agent represents a living animal and behaves, e.g. moves, according to the available information to this agent alone, provides opportunities to reveal the individual-collective relationship. By reproducing collective group patterns with only mutual interactions between group members, the answer to “how” can eventually be discussed. Meanwhile, the emergent properties in such self-organizing models suggest possible “why”, answered with the collective benefits. A collective benefit is an
Introduction

extra advantage obtained by each member by joining the group. Despite the fact that an agent-based model itself is an independent collective system in simulations apart from the real living systems, recently, data-driven modeling and model predictions of individual animal motions in collective groups attempt to fill the gap.

Physics of statistical mechanics, complex systems, nonlinear dynamics, etc. often play important roles in modern studies of collective behaviors. In general, a group of animals are considered as a system of active matters. As each biological entity consumes resources from its habitat, transforming its energy intake into kinetic energy, a system which only considers such biological entities, e.g. a group of birds, is out of thermal equilibrium and does not comply with energy conservation. (It’s an open system) These properties set clear differentiation between an active matter system and a typical thermodynamic system, and raise attention due to their biological relevance. For example, agent-based models often connect to self-propelled, i.e. active, particle systems, where the interaction between agents are modeled as social “forces” which act directly on the “particle” in action. In order to understand the cooperative movements in animal groups, nonlinear dynamics and network science are applied to unravel the information propagation and selection, which are crucial to collective decision-making. Concept of phase transitions and criticality is proposed to explain the responsiveness and plasticity of some collective groups that is especially sensitive to external stimuli.

In this thesis, we present an experimental approach to study collective behaviors with robotic active Brownian colloids. These micron-sized self-propelled particles, i.e. microswimmers, are powered and, hence, manipulated by light. With a feedback control for individual motion, these microswimmers become robotic agents with off-board power, sensor and computation units. We then demonstrate studies with agent-based social interaction models performed by such microswimmers. Our experimental studies exploit the conditions in real world, rather than the much simplified simulations, and inspire the field and experimental works with real animals.

Outline. Following the above flow of context, this thesis is structured in the total of 5 chapters: Chapter 1 introduces the open questions in biology. From observations in field studies to the current progress in ecology and behavioral science, this chapter ensures sufficient prior knowledge for further discussions. Chapter 2, then, provide the aspect from the physical society. For physicists, the details regarding specific animals are often negligible; however, the structures and interactions preserve, or even dominate. The topics in this chapter highly correspond to Chapter 1, and focus on the relevant concepts to Chapters 4 and 5.
Chapter 3 begins the major works with the experimental systems with microswimmers and the corresponding control mechanism.

Chapter 4 demonstrates one study with the collective response of a group of socially interacting microswimmers to the presence of a threat. In this work, we address the connection between vital group-level functions to individual social behaviors, with which the collective benefits can emerge.

Chapter 5 focus on the social behavioral modeling with the interaction network generated by individual perception and, at the same time, limited by the attention capacity. In this work, we probe the minimum attention sustainable for stable collective motion and the corresponding criterion in the structure of interaction network.

For Chapters 4 and 5, a short significance is provided before the section of introduction for the background knowledge of relevance.

**Overlapping publications.** Parts of this thesis cover contents of research articles:

“Collective response of microrobotic swarms to external threats”.

Chen, C.-J. and C. Bechinger (2024).
“Minimal attention for a stable flock”.
Manuscript in preparation.
Collective animal behavior describes the social behavior of an animal group which often exhibits characteristics of an unified entity and synergistic properties. As the term “collective behavior” was first introduced in human sociology (Smelser 1962), it refers to emergent social events which do not reflect the pre-existing social structures. When adopted to a group of animals, such a concept extends to all kinds of social behavior which exhibit certain degrees of coordination, e.g. spontaneous gatherings of pelagic fish (Blaxter and Hunter 1982), highly aligned relocations of migratory bird (Heppner 1974) and functional formations of ants (Feinerman et al. 2018). These collective animal behaviors occur across a wide range of scales, from the length of centimeters, e.g. in a mill of mint-sauce worms (Franks et al. 2016), to hundreds of kilometers, e.g. in pelagic fish (Pavlov, Kasumyan, et al. 2000); from the duration of a few hours, e.g. in the dusk for swarms of midges, to generations, e.g. for a lion pride; from the number of less than 10, e.g. in a school of cuttlefish (Yasumuro et al. 2015), to thousands, e.g. in a flock of bird (Ballerini et al. 2008); from rapid responses to ontogeny and evolution (Ioannou and Laskowski 2023). Despite the huge variety in animal collective behaviors, groups of collective animals are bound by the intra-group social interactions and manifest group-level activities similar to single entities.

Indeed, coordinated group motions can either result from social structures, e.g. in a hunting wolf pack, or emerge from the spontaneous social interactions between group members, e.g. in a mill of mint-sauce worms. In this thesis, we focus on the emerging collective behaviors. The lack of ruling hierarchical structure in such collective groups indicates a missing link between individual behaviors and group-level functioning. At the same time, any group member has essential contribution to the collective state of the group. For example, the action of one bird in a flock consisting of a thousand individuals is influential to any other bird in the same flock (Cavagna et al. 2010). Such group-individual relationship allow much complex and responsive collective patterns. Nevertheless, the high complexity and variety makes studies on these emergent collective behaviors equally complex and non-trivial.
1 Collective Behavior in Animals

**Collective States**

- **Swarm (unordered)**
- **Flock (polarized)**
- **Vortex (Mill; locally ordered)**

![Swarm](image1)  ![Flock](image2)  ![Vortex](image3)

**Figure 1.1:** Collective states sorted by alignment: a the swarm of unordered individuals, b the flock with global alignment, i.e. polarized, and the rotating vortex, e.g. the mill in c, by local alignment. Adapted from an experimental study with 150 fish by Tunstrøm et al. (2013, CC BY 4.0)

The early studies from ecologists regarding collective behaviors were mostly phenomenological and focusing on group-level behaviors. Due to the complex nature in both inter- and intra-group dynamics, field and experimental studies only resolved factors e.g. shapes of groups, general activities of group members and environmental conditions. From these results, biologists tried to connect group functions to different patterns of collective groups.

The breakthroughs occurred as agent-based modeling along with accessible computer simulation tools were introduced. In an agent-based model, each agent represents an animal and behaves, e.g. moves, according to the available information for this agent alone. Such models can directly prove (or disprove) the causal relation between social interactions and collective behaviors. The current progresses split into two major directions: neuroscience approaches which aim for realistic individual social behaviors (Harpaz et al. 2021) and model fitting where agent-based models are applied to experimental results for direct comparisons (Strandburg-Peshkin et al. 2013).

In this chapter, we list up current knowledge, as well as difficulties, from the biological aspect. We start with the group patterns defining “collective states” in Section 1.1. Then, Section 1.2 introduces hypothetical “purposes” or reasons of collective groups occurring in nature. Further, Section 1.3 discusses individual social behavioral processes which are the “mechanisms” of emergent collective behaviors. Last, Section 1.4 focuses on the “dynamics” in both group and individual levels.

### 1.1 Collective States

Collective states or collective patterns, to strictly differentiate from thermodynamic states, are certain configurations of the collective groups. These configurations are non-equilibrium steady
1.2 Purposes

states which corresponds to the individual behaviors and the environments. Figure 1.1 demonstrates one of the most general classification considering the alignment between group members which categorizes groups into three states: swarms, vortices and flocks. The “swarm” is a term for general assembly of individuals. When the intra-group order or structure is not obvious, literature often refers such groups as swarms. Here we describe collective states with only cohesion, i.e. unordered, as swarms. In contrast, if a group exhibits global alignment order, the corresponding collective state is a “flock”. These polarized groups obtain high mobility as the forward motion of individuals is not obstructed by group cohesion. Another stationary collective state arises when the group members only perform local alignment. This results in rotational pattern which can be generally described as a vortex. Names of such collective vortex behaviors (Delcourt et al. 2016) varies in literature, e.g. mills, swirls, tori, doughnuts, wheels. In this thesis, I apply two major kinds of vortex patterns which differ in the density distributions: the “swirls” are vortices with a dense central region which originates from the individual motion partially toward the group center; the “mills” are vortices without such dense core. On the contrary, a mill usually obtains a central void, e.g. in a ring or torus shape, as individuals circulate the geometrical center of the group steadily.

In empirical studies, slow vortices might be describes as non-polarized stationary group, e.g. Carvalho et al. (2007, see Figure 1.2). Such ambiguity emphasizes the needs for clear quantifiers to distinguish between collective states. In Chapter 4, we also discuss order parameters and hybrid collective patterns.

1.2 Purposes

The recurrence of collective patterns indicates that these cooperative behaviors are beneficial to the whole species and/or to the individual group members from the evolutionary aspect. Such benefits are hence considered as the purposes or functioning of gregarious or temporary gathering behaviors of animal groups. Especially, when considering the cost of group forming, e.g. less stealth and intra-group compositions, the collective benefits should compensate such disadvantages. In
this section, we put these contexts into three categories: collective benefits of group functioning, selfish individual purposes and meta-stable environmental-collective interactions.

1.2.1 Collective benefits of group functioning

In the case of reciprocity, the emergent collective benefits are either synergistic group functions or enhanced abilities exceeding the sum of individual capabilities. Many of such collective benefits are vital functioning, e.g. self-assembly of fire ants into waterproof rafts (Mlot et al. 2011), predator confusion (Bertram 1978) and collective vigilance (Lima 1995) in prey groups. Other collective benefits provide animal groups with advantages in thriving, e.g. collective foraging of fish generating vortex flow for food collection (Kitagawa et al. 2011), energy saving in bird flocks (Badgerow and Hainsworth 1981) or fish schools (L. Li et al. 2020), cooperative weight-lifting of ants (Feinerman et al. 2018). Such group functions correspond to certain collective patterns or configurations.

Most of these collective behaviors exhibit strong dependence to group size. The many-eyes hypotheses, a famous example of collective vigilance, describe that the more group members, i.e. eyes, contribute to vigilance, the higher sensitivity is the group to the predators (Lima 1995). While in the case of predator confusion, the effect increases monotonically and saturates, indicating a threshold in group size which ensures minimal predation rate (Cresswell and Quinn 2011).

In Chapter 4, we present one example of collective benefits regarding enhanced vigilance with a group of socially interacting microswimmers. Our results confirm the connection between individual behaviors and the group-level functioning where collective benefits emerge.

1.2.2 Selfish individual purposes

Apart from the collective benefits, selfishness can also promote individual tendency of group cohesion. Such selfish motivation mostly corresponds to predation. As an intuitive explanation, the dilution of risk describes the chance of individual under predation reduced to $1/n$ in a group consisting of $n$ members (Lehtonen and Jaatinen 2016), so individual animal prefer staying in a larger group. Another famous example is the “selfish herd” theory where individuals estimate the domain of danger, and attempt to minimize it (Hamilton 1971). In the case of random location of a predator attack, the domain of danger encloses area (volume) closest to certain prey. As a result, selfish herd generally promote aggregation of individuals (Monter et al. 2023).
1.3 Mechanisms

1.2.3 Environmental-collective interactions

Evolutionary advantages can emerge from collective behaviors not only through their positive effects on the group of animals, but also through the group’s interaction with the environment. While animals modify their surrounding through vital activities, and the conditions of the habitats feed back to the fitness of such animals, the species preserve only when the ecosystem reaches its steady state. Dalziel et al. (2021) demonstrates that collective animals stabilize ecosystems by restricting simultaneous resource exhaustion. Such restriction is seemingly detrimental for group population in the shorter time scale, but it is crucial for survival in a longer term as it prevents collapse of the whole e.g. producer-consumer ecosystem.

1.3 Mechanisms

The underlying mechanisms of emergent collective behaviors are the social interactions between group members, which do not exhibit obvious connections to group-level patterns or functioning. The interplay between different reactions or behavioral tendencies are also essential in such mechanisms. To unravel these nontrivial connections, agent-based simulations with social behavioral “rules” determining each suspected interactions and behaviors, as well as the interplay between them provide direct proof regarding emergence of certain collective behaviors (DeAngelis and Diaz 2019). From the aspect of biologists, such models must base on real properties of the target animals. In this section, we focus on three important biological factors in individual-level, from the perceptual inputs, the nature of behaviors responding to such inputs to how these behaviors achieve cooperative movements through interactions.

1.3.1 perceptual inputs for behaviors

In order for an individual to perform collective social interactions, this individual must acquire information about other group members through its perceptual inputs. This acquisition process consists of two steps: first, sensory inputs provide raw data of the surroundings; second, such data are then processed into perceptions. Obviously, the nature of such perceptions highly depends on the corresponding sensory sources. For example, position and orientation of a conspecific neighbor can be obtained rapidly with vision, however, it can be easily obstructed e.g. compared with the slower olfactory sensing. Agent-based modeling usually applies perceptual information without considering its sensory basis, which can result in non-realistic over-simplification.
1 Collective Behavior in Animals

1.3.2 Individual behaviors

In collective behaviors, complex environments induce hybrid responses. The behavior corresponding to all perceptual inputs reflects the nature of each response, decision-making processes and reaction capacities. For example, behavioral rules exploiting various sensory cues obtain different priorities (Zheng et al. 2001). In a flock of birds, Ballerini et al. (2008) report limited number of neighbors which a flock member can react to; such limit corresponds to the attention capacity. In contrast, optomotor responses (Bahl and Engert 2020) consider all moving objects as whole-field visual motion, and hence do not exceed such capacity.

1.3.3 Achieving cooperative movement

Cooperative movements require group consensus emerging from social interactions. Empirical studies provide some basic assumptions: e.g. a cohesive group suggests attractive social interactions. Vortex collective states show no long-range alignment between individuals across the two sides of the group’s geometric center. This evidence is crucial for constructing agent-based models which helps to reveal more details of emergent collective behaviors.

1.4 Dynamics

Collective states are non-equilibrium steady states corresponding to their environments; in other words, transitions between states according to external stimuli are possible. In fact, collective responses often involve transitions between different functional patterns: e.g. fish and birds change formation due to predatory risk (Sosna et al. 2019; Storms et al. 2019). During transitions, hybrid collective states, e.g. small vortices inside a flock (Brattstrom 1998), can occur. Most of the collective groups exhibit higher sensitivity in responsiveness (Rieucau et al. 2014; Gómez-Nava et al. 2023). Such phenomena connect to phase transition behavior and criticality (see Section 2.4).

The intra-group dynamics between group members are equally puzzling in collective motions. For example, propagation of information induces waving patterns in fish (Pitcher and Wyche 1983) and bird (Hemelrijk et al. 2019). Changes of formation can also arise spontaneously: e.g. a flock of pigeons changes relative positions during collective turnings (Yomosa et al. 2015).

Our work in Chapter 4 manifests both collective responses by transition between states and the hybrid collective patterns where collective benefits emerge.
Physicists’ approach to Collective Behavior

Animal collective behaviors draw physicists’ attention with their vast complexity, emergent and synergistic nature, universality and dynamics. In general, a group of animal is categorized as an active system with agents continuously consuming energy from the environment and transforming it e.g. into work. The interactions between individuals depend on the group structure, i.e. the distribution of neighboring peers, and modify such structure at the same time. This feedback brings huge complexity and non-linearity to the system. Spontaneous symmetry breaking and emergent behavior hence arises. Despite the interests in complex system physics, the universality of collective behaviors is also intriguing. As described at the beginning of Chapter 1, collective behaviors recur across species and physical scales. Such universality suggests fundamental knowledge in underlying mechanisms beyond the biological meaning in certain animal groups. The cross-species characteristics also imply the relevance to other topics where physicists engage frequently, e.g. robotic systems.

In this chapter, we tackle topics in Chapter 1 from the physical aspects. Section 2.1 introduces active systems and active matters in general. This includes collective behaviors in synthetic active systems and how physicists study them. Section 2.2 describes the emergent behaviors in natural science, which are the origins of collective benefits in Section 1.2.1. Section 2.3 focuses on the social interactions. This includes agent-based modeling with the knowledge from Section 1.3, which confirms or reveals the connections between individual reactions for local interactions and the emerged group-level behaviors. Furthermore, the group consensus in Section 1.3.3 is addressed by information pathways and networks. Section 2.4 briefly discusses the group dynamics and sensitivity to environments (as in Section 1.4) with the concept of criticality. At the end, we conclude the benefits of conducting experimental studies on agent-based social models in Section 2.5. This is the approach which we apply in this work and will be discussed in detail throughout Chapter 3.
2 Physicists’ approach to Collective Behavior

2.1 Active Matters

Unlike in thermodynamic equilibrium states, groups of animals obtain energy from their habitats. Such energy is convert into activities e.g. change of positions, velocities or orientations. Thus, a group of animal actively vary in shape and internal configuration. Soft active systems consist of large number of active agents are referred to active matters. Collective animal groups, bacterial colonies, cellular tissues are all biological active matters. In the case of synthetic active matters, complex autonomous devices can mimic animal groups e.g. a swarm of drones. Or in micrometer scales, active particles powered by relatively high power compared to their inertia, friction and/or drag force easily. Due to the less requirements in space and energy supply, active matter is more frequently referred to systems of active microparticles. In the following part of this section, we review the macroscopic active matters and the systems of active particles and microswimmers. Due to the unique properties and relevance to Chapter 3, we introduce much in depth regarding the motion of microswimmers, i.e. the active Brownian motion, and examples of some basic interactions.

2.1.1 Macro-scale active matters

Swarms of cooperative robotic units are by definition active matters. Unmanned aerial vehicles, or commonly “drones”, in large scale light shows and other potential applications are examples for valuable collectively functioning in such macro-scale active matters (Tahir et al. 2019; Abdelkader et al. 2021). Decentralized control algorithms for not only aerial but also terrestrial, aquatic and outer-space robotic swarms are hence popular topics (Schranz et al. 2020).

Interestingly, robotic swarms also contribute to collective behavioral research (Horsevad et al. 2022), e.g. from collective escape (Min and Wang 2011) to emerging collective movement by individual activities and weak coupling (S. Li et al. 2019). Such experimental approaches can exploit the same environmental and physical conditions as real animal groups, but in exchange, are constrained by the large space requirement compared to most laboratory experiments and the need of recharging or wiring.

2.1.2 Active particles and microswimmers

Active matters composed of micron-sized active particles obtain opposite characteristics than their macro-scale counterparts: these particles acquire energy directly from their surroundings, but
usually are not capable of complex interactions e.g. with non-reciprocal responses or decision-making processes. Due to the relatively small and manageable size of such active matters, e.g. a conventional microscope slide, the energy source of the active particles is inserted directly through light, electric or magnetic fields, and/or the “fuel” is dispersed in the environment with sufficient concentration.

There are various kind of such synthetic active matters (Bechinger et al. 2016), most of them are suspensions in liquid. One well-established system is the dispersion of catalytic Janus particles in hydrogen-peroxide ($\text{H}_2\text{O}_2$) solutions (Paxton et al. 2004; Golestanian et al. 2005), where the heterogeneous rate of $\text{H}_2\text{O}_2$ decomposition at the particles surface results in propulsion. Particles like these, self-propelled without interaction with a boundary, are also named microswimmers. Another example is the Quincke rollers (Bricard et al. 2013), which are insulating particles in a conducting, e.g. ionic, fluid. When exposed to an electric field, the interplay between induced charge and electrostatic torque produces motion of an active roller. There are also bio-inspired active particles, e.g. helical rotor swimmers powered by magnetic field which resemble the corkscrew motion of bacterial flagella (Ghosh and Fischer 2009; Zhang et al. 2009).

The simplicity in active microparticles restricts their diversity in motion and manipulation. The difficulty to precisely manipulate systems under micrometer scale is a technical bottleneck in many cases. For example, either chemical concentration, electric or magnetic fields can be easily localized for individual particle control.

However, in Chapter 3, we introduce our experimental approach feasible of individual microswimmer manipulation in both speeds and directions with real-time feedback control. Such an unique system enables studies on agent-based social models.

### 2.1.3 Active Brownian motion and basic interactions

Most of the microswimmers or rollers obtain an intrinsic axis of symmetry which corresponds to the direction of their active motion. Such an axis hence defines the “forward” motion, or the particle orientation. The spontaneous motion of such microparticles is well captured by the active Brownian particle (ABP) model, which describes active Brownian motion as the combination of constant speed forward propulsion and both translational and rotational diffusion. The concept of ABP is commonly adapted to simulations of active matters (e.g. in Section 4.4) as well as agent-based social models (in Section 2.3.1).
Active Brownian motion  

Starting from the single particle diffusion, one can derive the overdamped stochastic Langevin equations of Brownian motion following textbooks, e.g. Nelson (2020). The overdamped condition reflects the low Reynolds number in the scale where Brownian dynamics are significant. We now consider a Brownian particle at temperature $T$ with translational and rotational diffusion coefficients $D_T$ and $D_R$ respectively. When this particle obtains constant propulsion of speed $v$ always in the direction of particle orientation $\hat{u}$, the equations of motion for such an ABP are

$$\frac{dr}{dt} = \frac{D_T}{k_B T} \zeta_T + v \hat{u} \quad \text{and}$$

$$\frac{d\theta}{dt} = \frac{D_R}{k_B T} \zeta_R \quad (2.1)$$

where $k_B$ is the Boltzmann constant, and the zero-mean stochastic processes $\zeta_T$ and $\zeta_R$ follow $\langle \zeta_T(t)\zeta_T(t') \rangle = 2D_T\delta(t-t')$ and $\langle \zeta_R(t)\zeta_R(t') \rangle = 2(k_B T)^2/D_R\delta(t-t')$.

Although the particle trajectory $r(t)$ is non-deterministic, its translational mobility can be quantified by the mean-squared displacement (MSD),

$$\langle \Delta r^2 \rangle = (4D_T + v^2\tau_p) t + \frac{v^2 \tau_p^2}{2} (\exp(-2t/\tau_p) - 1) \quad (2.3)$$

with the persistence time $\tau_p = 1/D_R$ for particle reorientation due to diffusion (Howse et al. 2007). Motion described by Equation (2.3) is diffusive under the limit $t \gg \tau_p$ with effective diffusion coefficient $D_{eff} = D_T + (v^2\tau_p)/4$. While at $t \ll \tau_p$, $\langle \Delta r^2 \rangle = 4D_T t + v^2 \tau_p^2 t^2$ exhibits a superposition of propulsion and diffusion. Diffusive and persistent motion reflect exploratory (ergodicity) and transporting (displacement) behaviors respectively. Understanding the time scales corresponding to different kinds of individual motion is crucial for emergent collective behaviors.

Basic interactions  

Interactions between synthetic active particles are typically reciprocal and non-selective, which compared to the biological and macro-scale active matters are basic. However, such interactions are not necessarily trivial to simulate or even to understand. The short range forces, e.g. phoretic, steric and hydrodynamic interactions, can sometimes be very complicated. Active particles powered by external field also experience interplay between the field, the environment, e.g. substrates and/or solutions, and the particles themselves. In Section 2.2, we revisit the potential of these basic interactions emerging into collective motions in synthetic active matters.
Emergent behaviors describe macroscopic properties which arise from a infinitely large ensemble of microscopic units which cannot be predicted from the knowledge regarding such units. In other words, a group-level behavior arises from complex interactions between members, e.g. a collective benefit in Section 1.2.1, is an emergent behavior. To help understanding the non-trivial connection between microscopic interactions and corresponding macroscopic emergence, in this section, we look at examples with microswimmers and active particles introduced in Section 2.1.

### 2.2.1 Cohesion by density-dependent mobility

Swarming ABP-like particles are reported in both simulations (Fily and Marchetti 2012; Redner et al. 2013) and experiments. Figure 2.1 shows the mechanism found in experimental work by Buttinoni et al. (2013). The spontaneous clustering is an emergence due to the significantly reduced mobility of particles at high density region, i.e. self-blocking. Because the persistent time is longer than the collision time for particle encountering, these particles are not able to detach from previous head-on collisions before more particles merge into the cluster by chance. Such imbalance in time scale emerges phase co-existence. These experiments also address the role of basic steric interactions in dense and collective systems.

### 2.2.2 Alignment by environment-mediated interactions

Flocks and vortices emerge in a group of Quincke rollers with confinements. A complex interplay between hydrodynamic and electrostatic interactions acts equivalently to collision avoidance
and local alignment under social interactions. Meanwhile, confinements or gravitational potential effectively applies tunable cohesive interactions to the systems. In a long runway, rollers flock (Bricard et al. 2013); in a circular arena, rollers mill (Bricard et al. 2015); as in a soft potential well, rollers swirl (Kokot and Snezhko 2018, as shown in Figure 2.2). Despite that such hydrodynamic interactions are characteristics of active rollers, the emergence of large-scale order through interactions with the environments is still a profound finding.

2.3 Modeling interactions and information pathways

Emergent collective behaviors are hard to unravel from either individual motion or collective patterns alone. Here, we provide two major aspects regarding the origins of cooperative movements: interplay between social interactions resulting in a non-equilibrium steady state and exchange of information realizing collective decision-making or group consensus.

In Section 1.3, we address the importance of agent-based modeling, which can reveal the causal relation between individual and group behaviors. The involved strategy is to start with minimal models (as discussed in Section 2.3.1), and compare with animal collective behaviors.

Meanwhile, Section 1.3.3 emphasizes the information sharing and processing in cooperative movements. This consensus is essential for collective groups to perform as one single entities. Studies in this aspect focus on the availability of information, e.g. perceived by other group members exclusively. The analysis often includes network science, as in Section 2.3.2.

2.3.1 Minimal social models

Collective social groups obtain two essential properties based on Section 1.1: cohesion and alignment. The minimal models implement these two social tendencies with distance-dependent weights.
2.3 Modeling interactions and information pathways

![Diagram](image)

**Figure 2.3:** Minimal agent-based models: **a** Vicsek model with neighborhood marked by blue dash-dot line. **b** Topological Vicsek model with $k$-nearest neighbors for $k = 4$. Numbers indicate topological distances in number order. **c** Vicsek model with finite vision angle. **d** Zone model with 3-zones of attractive (outer, in green), alignment (middle, in blue) and repulsive (inner, in orange) interactions. **e** Continuous weight model where the social forces are weighted with distance (lower inset; green: attractive, blue: alignment, orange: repulsive interactions). The weight functions are example adapted from Kunz and Hemelrijk (2012)

to reproduce collective states. The action corresponds to social tendencies can be generally described as the result of social forces affecting the motion of this individual, and it can be implemented with either direct social forces acting on the individual agent or steering social forces which apply torques to the forward moving agent. In this thesis, we mainly focus on the steering models as it reflects better to fast moving animals e.g. birds and fishes.

**Vicsek model.** Proposed by Vicsek et al. (1995), this model is not the first successful flocking model, but is the minimal model where global alignment emerges from local alignment. The original Vicsek model considers point-like particles which travel in constant speed and align to the mean velocity of all other particles within neighborhood of a fixed range. (shown in Figure 2.3a) The Vicsek model receives a lot of attention from the physical community e.g. regarding its phase transition behavior. However, the model is not biologically meaningful due to the over simplification. Still, we categorize the models with local alignment as Vicsek-like model in this thesis.

**Variances of Vicsek model.** While preserving the local alignment-only nature of the original Vicsek model, variations with the choice of local neighborhood for alignment already bring about discoveries in the nature of emergent collective behaviors. One example is the Topological Vicsek model where the topological distance, e.g. nearest-$k$ neighbors (Chou et al. 2012), replaces the met-
ric distance in the definition of neighborhood (Figure 2.3b). Such model is especially powerful in investigations with network connections (which we will revisit later). Another interesting variant is the Vicsek model with vision angle where circular sector replaces the full circle in the shape of alignment neighborhood (Figure 2.3c). Such models are capable of reproducing mills in addition to flocks due to the front-back symmetric breaking (Costanzo and Hemelrijk 2018).

**Zone model.** As one of the most famous Vicsek-like model to date, the zone models incorporate attractive, aligning, repulsive interactions to neighbors in different "zones" corresponding to the ego agent. Figure 2.3d demonstrates the typical configuration regarding these zones. This design reflects behaviors of group-forming animals: approaching distant conspecifics, align motion with group members and avoiding collision with members. Different parameters regarding ranges of zones and vision angle result in corresponding collective states in Section 1.1. When first introduced by Aoki (1982), behavior zones are seemingly an necessary simplification for computational reasons. As for Couzin et al. (2002), the non-overlapping zones help differentiate effects of each corresponding social interaction. The model also reveals hysteresis when changing parameters on-the-fly, showing memory effects in group formations.

**Continuous weight model.** Another type of Vicsek-like models with attraction, alignment and repulsion simply implements all three tendencies as social forces weighted by distances from neighboring peers to the ego agent. As expressed in Figure 2.3e, this model avoids the artificial sharp boundary between behavioral zones by continuous functions of weights, but the dependence of neighboring distances to behaviors is less trivial. Such models are usually aim for other crucial factors, e.g. group size or individual abilities (Kunz and Hemelrijk 2003), or application of data-driven modeling (Gautrais et al. 2012).

**Model with functioning.** Based on the above models, additional interactions are appended for group formation with functions. One of the most studied topic is collective escapes from predators (Inada and Kawachi 2002; Zheng et al. 2005; Y. Chen and Kolokolnikov 2014). For individual agent, the escape is an action of moving toward the opposite direction to the predator, i.e. selfish escape. This is implemented by repulsive reactions. When the interplay between social interactions and selfish escape occur, some studies refer such behaviors as cooperative escape (Zheng et al. 2005).

In Chapter 4, we propose a different approach where the response of the group base on the cohesive social interaction. Such a model enable collective decision-making and manifests collective benefits in group behaviors.
2.3.2 Swarm signaling network

The idea of information network connecting individual group members arise naturally if we consider the constrains of local information and interaction. To achieve cooperative or coordinated group formation or functioning, local information must spray out and reach all members. At the same time, intra-group information exchange should involve processing of such information, so a consensus resolves conflicting information.

Swarm signaling network (SSN) describes such information network with the following characteristics (Komareji and Bouffanais 2013).

**Dynamic graph.** SSN connections base on the relative positions of group member to each other, which vary in time. This is a propound different from typical network graph theories.

**Directed edges.** Connections in SSNs are often asymmetric. Furthermore, even in a pair of interacting agents, the interaction from one to the other is mostly non-reciprocal.

**Dynamic feedback.** The information flow in the connection is emitted by the motion of source node (agent) according to its received information. The motion alters connections due to the dynamic graph. Depending on the interaction, such feedback can promote or deteriorate collective order.

In Chapter 5, we discuss group consensus in a flocking group of microswimmers. The chapter provides more details regarding applications of SSN in studies of collective patterns.

2.4 Critical Phenomena

Collective behaviors are not limited to static patterns of group functioning but also the dynamics in transitions between different collective states. As discussed in Section 1.4, collective responses often involve rapid changes in order and/or pattern with high sensitivity to the corresponding external stimuli, e.g. predator attacks. Such high sensitivity and easy transition reminds the concept of criticality (Bak 2013; Muñoz 2018). Despite the fact that collective states are not thermodynamic states, the difference in symmetry and order suggests some similarities with phase transition and criticality. In fact, from the high susceptibility (Gómez-Nava et al. 2023) and the scale-free information proliferation (Cavagna et al. 2010) to hydrid collective states (Brattstrom 1998), such critical phenomena-like properties are wildly studied.

Although this thesis does not discuss further regarding criticality in collective behaviors, readers can refer to Löffler et al. (2021) for experimental work with similar approach.
2 Physicists’ approach to Collective Behavior

2.5 Toward experimental agent-based studies

Throughout this chapter, we discuss the current development in modeling social interactions of emergent collective behaviors in active matters. As a conclusion, experimental studies would benefit significantly if microswimmers can perform agent-based models. Such a system is an intelligent microrobotic swarm responsive to its surrounding, and at the same time, experiments can proceed in a typical laboratory environment.

A physical implementation of agent-based social models explores the nature of collective behaviors with, not only the social forces between the agents, but also the influences from physical interactions. As discussed in Section 2.2, real-world interactions can inspire mechanisms of emergent collective behaviors. Furthermore, unlike most numerical simulations where particle information are obtained precisely, experiments revisit the whole procedures of data collection and corresponding constrains much similar to that in field or lab studies of living systems. In the case of real collective animal groups, observational constrains limit the precision of individual spatiotemporal tracking, especially in crowded areas. Living animals perform complex motions where the heading directions, instantaneous velocities and the tangents of smoothed trajectories represent different kind of orientations. An experimental approach with active matter is capable of capturing such nature and inspire the studies of complex systems and animal behaviors.

Meanwhile, individual robotic agent also resembles the biological unit by going through the full perception-decision making-locomotion processes with each of the three stages accessible for data collection. In an experiment with living animals, manipulation and monitoring of such sensory inputs and corresponding decisions require complicated design and control of experimental conditions. Hence, studies of bio-inspired collective behaviors with microswimmer model systems can inspire and provide guidance to experiments with real animals where information within individuals are limited.
In this thesis, all presented works are experimental studies acting on synthetic microswimmers which performed motions according to the assigned social behavioral rules and, at the same time, interacted with their surrounding environments. These microswimmers are silica spheres, diameter $2\sigma \approx 6.3 \mu m$ with one hemisphere coated with 80nm carbon layer, i.e. a kind of Janus particles. When dispersed in a critical binary solution, such particles obtain self-propelled velocities and re-orienting torques corresponding to the light intensity and the gradient of this intensity applied onto the particle surfaces. With such an active colloidal particle (AP) system, we hence achieve real-time individual motion control for a swarm of microswimmers, up to 400 individuals, in a feedback loop setup where a localized laser pattern is projected to each microswimmer, at its position, according to its virtual perception and behavioral rules. It is worth noting that the propulsion of our microswimmers is bounded to the 2-dimensional (2-D) plane close to the horizontal substrate due to the significant size and density of the silica sphere. Such an active matter system with unique controls resembles microrobotic swarms described in Section 2.5, allowing implementation of agent-based models in real world experiments. The following sections introduce the motion of the microswimmer along with the propulsion mechanism, the sample preparation procedure, experimental setup and control protocol for simultaneous individual particle motion that applies to all experiments in this thesis. At the end, we discuss the common experimental conditions and strategies with such experimental approach, especially shared by Chapter 4 and Chapter 5.

### 3.1 The motion of the microswimmers

Our microswimmers, Janus particles with different absorbance on each hemisphere, self-propel by inducing concentration flow in a water/lutidine mixture which can be heated up to its critical point
locally with light exposure. Lutidine (2,6-Dimethylpyridine) is a water-soluble liquid at room temperature (NTP). However, as shown in Figure 3.1a, a water/lutidine mixture has a lower critical demixing point at temperature $T_c = 34^\circ C$ and mass fraction $w_c \approx 29$ wt.% of lutidine (Grattoni et al. 1993). When a particle with a temperature gradient on its surface heats up the surrounding water/lutidine mixture across $T_c$ locally and asymmetrically, this particle experiences diffusiophoresis due to the concentration gradient from the demixing region to the homogeneous region.

In our approach, the temperature gradient originates from the absorption of light, which is greater on the carbon cap compared to the non-covered silica. Such different absorption has a profound effect also on the AP appearance, as shown in Figure 3.1b. Under a homogeneous illumination condition, self-propulsion occurs with an offset intensity $I_0$ corresponding to the sufficient local heating for $T > T_c$ demixing region. The intensity to propulsion velocity relation (Figure 3.1c) then reaches a linear regime (area in cyan) where a relatively small demixing region at the carbon cap side pushes the particle toward the uncapped side. We hence define the cap-orientation by this cap-to-uncapped direction in 2-D observation. Outside of the linear regime, the propulsion velocity first saturates with higher intensity. Then, an even higher intensity results in a demixing region exceeding one hemisphere, which leads to the reversal of intensity-propulsion velocity relation and, eventually, the inverse direction of propulsion at intensity higher than $I_{rev}$ (Gomez-Solano et al. 2017). The three regimes of velocity-intensity relationship are useful in different scenarios: the linear regime provide easy control of variable speed. In the saturation regime, constant speed is most stable against intensity fluctuation. The reversal regime obtains the highest speed and
sensitivity to intensity of the three. Nevertheless, a single particle under constant intensity illumination travels steadily with constant propulsion speed in the direction of its cap-orientation. Such a motion can be hydrodynamically described in good approximation as a neutral squirmer or force monopole (Lighthill 1952). And with the presence of thermal noise, the particle behaves similar to an active Brownian particle (ABP).

Other than the ABP-like motion, our Janus particles also show phototaxis under intensity gradients (Lozano et al. 2016), which we exploit to achieve individual motion control. Both the difference in absorbance across different hemispheres of the particle and the spatial distribution of light intensity projected onto the particle can contribute to the spatial inhomogeneity in temperature. As a result, our APs perform self-propulsion with active reorientation when the projected light intensity is asymmetric in the axis of cap-orientation. Due to the positive relation between local intensity and propulsion, the APs turn toward the direction of lower intensity, i.e. negative phototaxis, when operating within the linear regime, in Figure 3.1b. Figure 3.2a demonstrate such active reorientation of an AP exposed to a static intensity gradient $\nabla I$ in the same direction of the cap orientation $\theta$ at $t = 0$. The time evolution of $\theta$ indicates a maximum angular speed $\omega_{\text{max}}$ at $90^\circ$ between $\nabla I$ and $\theta$. Furthermore, $\omega$ is well-predictable by the angle $\gamma$ from $\theta$ to $-\nabla I$, i.e.

$$\omega(\gamma) = \omega_{\text{max}} \sin(\gamma).$$

(3.1)
Lozano et al. (2016) provides details of active reorientation under illumination with gradient.

We exploit the above concept into individual steering control of particle motion by the application of a Gaussian laser beam, sized roughly \(3\sigma\) in diameter, to each of the APs. Figure 3.2b illustrates two types of such laser illumination which activate individual ABP-like motion (upper) and ABP-with-steering (lower) of our APs. The offset position of such laser beam to the center of the particle allows the carbon cap majorly exposed to an intensity gradient along the offset direction, and hence imposes reorientation toward the opposite direction of this laser offset. The reorientation strength can be estimated by the comparison to the rotational diffusion. Figure 3.2c provides a case of steering an AP in one constant direction (Bäuerle et al. 2020). Due to the rotational diffusion, the trajectories of APs are curvy, and the probability distribution of \(\gamma\) reveals the maximum reorientation torque of \(25k_BT\).

### 3.2 Microswimmer preparation

To fabricate the 6.3 \(\mu\)m Janus particles, we first prepare a monolayer of dry silica spheres out of a commercial product (microParticles GmbH) by evaporating a thin layer of aqueous suspension on a plasma-cleaned microscope slide. Both drop-casting and blade-coating techniques (Figure 3.3) are used in monolayer preparations and show consistent results in the final product of Janus particles. In the case of drop-casting, the appropriate concentration and evaporation conditions results in rather sparse monolayer of particles. As for blade-coating, a blade to which the droplet pins moves in the appropriate speed, so the surface tension drags particles downward, leaving the compact monolayer on the trace of the moving droplet. This dry monolayer is then coated with an 80 nm carbon film via carbon thread evaporation (Leica, EM ACE600). The microscope slide is, afterwards, dipped into purified water for several times where the surface tension releases single-side coated, i.e. capped, particles from the slide.

![Figure 3.3: Drop-casting (upper-right) and blade-coating (lower-right) for particle monolayer preparation. Both methods require dropping the suspension onto the substrate (left).](image)
3.3 Experimental setup

**Figure 3.4:** Flow cell of AP sample placed in the experimental setup (introduced in Section 3.3). The photo contains the quartz glass flow cell settled on a copper stage for temperature control and the green laser projected from the upper microscope objective for AP steering.

To prepare the sample ready for experiments, a small amount ($\lesssim 0.1$ µL) of Janus particle sediment in aqueous mixture is re-dispersed in 200 µL water/lutidine mixture with $\nu_{\text{Lut}} \approx \nu_c$. This mixture is loaded to a plasma-cleaned thin quartz glass flow cell with 200 µm spacing (Hellma Analytics, 137-0.2-40) and sealed with Parafilm for stability against evaporation and chemical contamination. Figure 3.4 shows one such cell placed in the experimental setup as introduced in Section 3.3. The whole preparation processes are at room temperature to insure the homogeneous mixture at all time. As the dispersion settling in the flow cell, the Janus particles quickly sediment to the lower substrate of the cell due to the size and density ($1.85$ g cm$^{-3}$) of the silica spheres. At the substrate, particles are stabilized by the intrinsic negative charges on the silica surfaces of the cell and particles themselves. Particles in this dilute and short gravitational length ($l_g = k_BT/(m'g) < 10$ nm) conditions form quasi-2D system in very good approximation which is suitable for observation with bright-field microscopy.

### 3.3 Experimental setup

The experimental setup operating on the Janus particle sample keeps the sample in a temperature close to but lower than $T_c$, projects a laser beam for particle motion control, and, at the same time, records the particle image with video microscopy. To fulfill all three functionalities, a copper stage connected to a thermal bath positions the sample cell in an optical setup as shown in Figure 3.5. A laser beam ($\lambda = 532$ nm; Laser Quantum, opus 532) tuned in intensity and polarization by a pair of $\lambda/2$ plate and polarizer cube enters a 2-axial acousto-optic deflector (AOD; AA Opto-Electronic, DTSXY-400-532), where the laser beam is deflected according to the desired position at the sample cell. A telecentric $4f$-telescope converges the AOD-deflected laser beam onto the back focal plane of an illumination objective (Nikon, T Plan SLWD 20x/0.3) where the illumination for observation
Figure 3.5: The schematic of the experimental setup. The optical setup incorporates steering (laser) and observational (LED) illumination. The sample cell (orange) sits on a temperature-controlled copper stage, on top of a piezo stage. Laser beam deflected by the AOD scans through multiple (in these example, 3) APs converges into the illumination objective which converts the deflection angle of AOD to the position of beam at the plane of the APs with the beam size of $3\sigma$. The LED provides the illumination for bright field microscopy. For the parts on the left, the setup is vertical in order to allow gravitational constrain of 2-D AP motion near the lower substrate inside the sample cell. This schematic is not to scale. The color of LED light is altered to yellow for clarity; the real LED emission is green for reduction of chromatic distortion between laser.
3.4 Simultaneous individual motion control

(\(\lambda \approx 528\) nm; Osram, SSL 80, LH CP7P) from a collimator also joins. This illumination objective focuses the laser beam below the lower substrate of the sample cell, so that the Gaussian beam profile at the height of the Janus particles is approximately \(3\sigma\) in diameter. Here, the laser intensity at the sample is very low (0.3 mW), shared by all particles; see Section 3.4 for details) compared to the typical optical tweezer, therefore no optical forces are either considered or observed. The imaging objective (Zeiss, LD Plan-Neofluar 20x/0.4) at the lower end of the sample cell collects the bright-field image for video microscopy with a corresponding tube lens and camera (Basler, acA2440-75um) while the residual laser coming through the objective is filtered out by an interference filter. In order to prolong the experimental duration in the case of collective moving APs, the copper sample stage is mounted on a two-axial piezoelectric stage (Physik Instrumente, U-751.24), providing the ability to “trace” the global motion of the AP group.

3.4 Simultaneous individual motion control

Continuous motion of multiple microswimmers requires a feedback control system to live-update the laser positions for each individual AP. Within such a feedback loop, a computer performs particle detection, steering aim computation and updates all laser positions to the AOD controller which scans all laser positions rapidly enough (\(\geq 250\) Hz) to achieve quasi-static illumination.

3.4.1 Laser scanning protocol

The protocol for rapid laser scanning consists of two time scales: the cycling period \(\tau_{\text{cycle}}\) for one scanning through all particles, and the illumination period \(\tau_{\text{laser}}\) for the laser beam staying at one particle. When the laser has stayed at the \(i\)-th particle for \(\tau_{\text{laser}}\), the AOD switch to position for the \((i + 1)\)-th particle. Such a transition require time \(2\sigma_w/v_{\text{sound}}\) where \(\sigma_w\) is the radius of the laser beam, and \(v_{\text{sound}}\) is the speed of sound in the AOD crystals which corresponds to the propagation of deflection angle. To ensure well-defined laser position at all time, we introduce a waiting time \(\tau_{\text{wait}} \geq 1.7\) \(\mu\)s between two laser positions according to the above estimation and our system parameters. This yields \(\tau_{\text{cycle}} \leq (\tau_{\text{laser}} + \tau_{\text{wait}})N\) for a total of \(N\) particles in control during the experiment. In reality, we fix \(\tau_{\text{cycle}}\) with a maximum number \(N_{\text{max}}\) of laser positions, i.e. \(\tau_{\text{cycle}} = (\tau_{\text{laser}} + \tau_{\text{wait}})N_{\text{max}}\). To resemble continuous illumination at multiple particles simultaneously, \(\tau_{\text{cycle}}\) should be sufficiently short, while \(\tau_{\text{laser}}\) should be reasonably long, otherwise the total waiting time deteriorates the duty cycle. All experiments in this thesis applied \(\tau_{\text{laser}} = 8\) \(\mu\)s and \(\tau_{\text{wait}} = 2\) \(\mu\)s. While \(\tau_{\text{cycle}} = 2\) ms and 4 ms in Chapter 4 and Chapter 5 respectively.
3 Experimental system for agent-based studies on collective behaviors

In Section 3.3, we introduced the laser beam size of $3\sigma$ in diameter, which makes the consideration of overlapping intensity pattern practical when scanning APs in a high-density area. In such a scenario, we apply intensity correction based on Gaussian beam profile, i.e. the intensity at $r$ with an Gaussian beam at the origin with peak intensity $I_0$

$$I(r) = I_0 \exp\left(\frac{-2r^2}{\sigma_w}\right)$$

(3.2)

With multiple beam, the increased intensity at the center of $i$-th beam due to overlapping is

$$\Delta I_i = \sum_{i \neq j} I_{0,j} \exp\left(-\frac{2d_{ij}^2}{\sigma_w}\right)$$

(3.3)

where $d_{ij}$ denotes the inter-beam distance. In the work of Bäuerle et al. (2018), an according reduced beam intensity

$$\hat{I}_{0,i} = \frac{I_{0,i}}{1 + \Delta I_i}^{1.4}$$

(3.4)

is sufficient for constant local intensity compared with non-corrected conditions. Such corrections regarding overlapping laser beams are also applied in all our experiments.

For even more details regarding laser scanning and AOD driving protocol, the readers are referred to Bäuerle (2020) which mentions an identical experimental system and corresponding protocol.

3.4.2 Feedback controls

On the computer side, the software-based feedback loop, running in Matlab, acquires the microscopic image from the CCD camera (e.g. Figure 3.1b), and extracts the centers of circular contours with the expected radii. After particle detection, the computer then uses these positions and orientations of particles to compute the aimed moving directions according to the social behavioral rules of interest. Such aimed directions are transformed into the next-moment laser positions according to the driving and/or steering mechanism (as discussed in Section 3.1) and then into AOD controller signals for the AOD driver.
3.4 Simultaneous individual motion control

Figure 3.6: Particle detection with circular shape and orientation estimation. a Bright-field microscopic image of APs, b The edge extraction with a gradient mask, c The accumulator of circular Hough transformation with the target radius of $10 \pm 1$ pixels. After a peak detection from c pinpoints the centers of APs, orientation estimation applies on the central area of these APs (red circles in d, with enhanced contrast inside these area) by the direction of intensity gradient.

3.4.3 Real time detection

The particle detection is through a shape detection targeting certain range of radius. Such detection is utilized by circular Hough transform (Yuen et al. 1990) with phase-coding (Atherton and Kerbyson 1999) to estimate the likelihood of a circle center at certain position (pixel in a digital image). First, edge extraction with a gradient threshold is performed as a pre-processing to reduce further computation loads. The edge image is than computed into the so-called accumulator, in which the local extrema denotes possible circle centers. The sign of a extremum corresponds to the direction of gradient, i.e. the contour from dark to bright or bright-to-dark. Finally, a peak finding process pick out such circle centers as the detected particle positions. We adopted such algorism from the build-in function `imfindcircles` of Matlab. The cap orientation is then estimated by the direction of intensity gradient, obtained from the principal component analysis, at the central region for each particle.

3.4.4 Laser intensity calibration

According to Section 3.1, the laser intensity determines the speed of a particle: a feasible experimental setup must be able to project well controlled intensity to the particles. In our approach, the laser intensity at any position within the field of view is calibrated by measurements with a photodiode at the focal plane when the AOD scans a grid of positions corresponding to the camera’s field of view. Such calibration constructs lookup tables not only for the positional dependence
3 Experimental system for agent-based studies on collective behaviors

![Image](image.png)

**Figure 3.7:** The cartoon expression of scattering calibration. This calibration probes the divination between particle position on bright-field image and the position in sample by scanning the laser beam in the grid (blue spots in "Image") at the particle in the image. From the back-scattering measured by a photo sensor, a fitted peak in scattering intensity corrects the particle position in image to the position reached by the laser beam.

but also for the AOD control of deflected intensity, which we apply to compensate the positional offsets.

### 3.4.5 Laser positioning calibration

The conversion from (aimed) laser positions to AOD signals is supposedly linear (Bäuerle 2020), however, the distortions in imaging system, i.e. the LED illumination optics, can implement position-dependent offsets between AOD signals and particle positions detected from images. With a sample containing no particles and the replacement of the bandpass filter with a polarizing filter, the preliminary calibrations measures the position of the laser beam by a 2-dimentional Gaussian fitting, directly obtaining the linear coefficients of AOD frequency signals to positions. This linear transformation is known to be insufficient to precise laser beam positioning which is crucial to AP steering. In experiments similar to Bäuerle et al. (2020), as well as in Chapter 4, the collective movements of the AP group is sensitive to global bias in individual motion, which corresponds to the laser precision down to the scale of \( \approx 50 \) nm. Compared with our field of view, this precision is 0.03% from the center to the edge.

In order to map the position in the sample to the bright-field image, we perform the, so called, scattering calibration. When the Gaussian laser beam illuminates around a micron-sized spherical object, the intensity of the scattered light peaks at the particle center. As expressed in Figure 3.7, the “scattering calibration” exploits such concept by scanning a grid of positions at a detected pristine silica particle in the bright-field image. A photodiode collects the back-scattered light at the fixed position. Then, a Gaussian fit to the spatial intensity distribution determines the laser position, and the AOD signal, corresponding to the image position. The calibrations in this thesis
were performed with uncoated silica particles ($2\sigma \approx 6.3 \, \mu m$) and piezo stage motion to probe the whole field of view with consistent back-scattering conditions.

3.5 Strategies with Feedback-controlled microswimmers

In this thesis, the driving and steering mechanism is the ABP-with-steering, where the forward motion along the cap orientation (ABP motion) combines with the active torque. Such motion corresponds to continuously moving agents in most of the agent-based social models. It is worth noting that ABP-with-steering is not the only achievable AP motion in our experimental approach. In Section 3.1, the case with laser beam at the geometric center of the AP results in ABP-like motion where the propulsion speed of each individual is manipulated by laser intensity. Bäuerle et al. (2018) and Lavergne et al. (2019) exploited such driving strategy to investigate activity-based behaviors. The decoupling of forward motion and reorientation can be achievable by e.g. implementing two laser beams with different intensity to one AP for steering. Such a strategy simplifies AP motion at each instance into four moves, i.e. turns, forward and inactive, which is advantageous to e.g. machine learning projects (Löffler et al. 2023). Nevertheless, in the following chapters, all experiments apply AP steering with an constant laser offset $1.8 \, \mu m \approx 0.6\sigma$ in the opposite direction from the geometric center of the AP.
4 Collective Benefits in Social Responses to External Threats

The term “collective benefits” describes the advantages that emerge when animals acting together in a group rather than behaving solitarily. This includes vital activities such as heat preservation, foraging, reproduction and predation avoidance. Hence, collective benefits are common reasoning for gregarious behaviors. As one of the most intensive scenario, collective benefits of animals responding to threats, either environmental or predatory, have received wide attention and frequent discussion, including e.g. the increased vigilance (Lima 1995) and the predator confusion effects (Neill and Cullen 1974). In this chapter, we present an experimental study exploiting the properties of a stationary collective state to implement a minimal social behavioral rule for reliable threat response which exhibits similar effects to the increased vigilance (C.-J. Chen and Bechinger 2022). Furthermore, our results suggest that building multi-functional swarms where each agent is only capable of one single function is achievable through simple social interactions.

4.1 Introduction

Many living species receive collective benefits that exceed the sum of individual abilities by arranging themselves into functional cohesive group. Such self-organizations can emerge without centralized control but as results of individual behaviors following social (interaction) rules. As discussed in Section 2.3, agent-based simulations with social behavioral rules have successfully reproduced collective patterns e.g. flocking, milling, swirling, swarming and even the v-shape formation in migrating birds. However, due to the fact that behavioral rules are purely individual-based, the connections between these rules and the group-level functionalities or performances remain unclear. To investigate how collective benefits and functions can be implemented, we study the scenario where an intelligent swarm of active colloidal particles (APs) responds to a suddenly
present threat. The behavioral rules of the AP behaviors does not encode solitary escape (i.e. repulsion) from the threat, but enable a collective decision making process by which the APs obtain consensus for group-level avoidance.

So far, the modeling of avoidance behaviors in social groups of animals has focused on the predator-prey interactions. Such studies consider prey agents performing behavioral rules e.g. regarding swarms or flocks before the introduction of the predator. The prey response to the predator is modeled as solitary escape, with which an individual aims to move, selfishly, in opposite direction from the predator. Once the group of prey agents encounters a predator, the overall behavior becomes a combination of social interactions and a prey-to-predator reaction, often leading to competitions between group cohesion and predator avoidance. Indeed, the high complexity of the interplay between social and selfish rules results in large variety of group formations, e.g. deformations, expansions or even splitting events, similar to animal groups in field and experimental studies (Inada and Kawachi 2002). In the case of a pursuing predator, the prey selection can also reveal the predator confusion effect while reproducing collective patterns occurs in live animals group (Zheng et al. 2005; Y. Chen and Kolokolnikov 2014). Despite such results, little has been discussed about the collective benefits which can emerge when prey agents stay cohesive and exploit the potential and flexibility of social interactions. Furthermore, the collective state of the prey group before and after the presence of the predator seldom varies in these models. The mechanism responsible for the transitions between functional collective states is still unclear.

In contrast to studies listed above where selfish actions are motivated by close encounter with the predator, cooperative collective movements occur in animal groups, e.g. fish schools move away from high temperature regions (Breder 1951) and avoiding shallow areas (Ward and Webster 2019). Another example is the group responses regarding early discovery of a still distant predator: certain animal groups react to the elevation of risks collectively, e.g. by the formation of rotational states (Rieucau et al. 2016). These observations corresponds to the cooperative group behaviors against a non-immediate danger with swirling or milling collective states. Such behaviors suggest potential benefits of collective responses against predation, which is in agreement with numerical simulations (Kunz et al. 2006; Wood and Ackland 2007; Couzin et al. 2002). Furthermore, by reacting as a whole collective, animal groups obtain enhanced responsiveness to a threat by effectively utilizing vigilant capabilities of all members into a single unit (Lima 1995). Group escape also enables more variety and complexity in their defense compared to scattered and being solitary (Pitcher and Wyche 1983; Tosh et al. 2009; Jeschke and Tollrian 2007; Penzhorn 1984; Hayward and Kerley 2005).
4.2 Social behavioral rules

In this chapter, we study the situation where a rotational stationary group, a swirl, responds collectively to a threat. As discussed above, the swirling collective state is an alert and cohesive group formation. Without any disturbance, a swirl is essentially stationary, which would make any directed response to the threat profoundly different, even triggering a transition between collective states. We model our APs to respond to the threat as part of a cohesive (swirling) rule rather than the conventional individual repulsion to the hazardous object, which leads to potential group splitting. In other words, the cohesion is not compromised for the response to the threat. Instead, all group members interact through this cohesive rule and, hence, can achieve emergent cooperative response.

The group-level behaviors of our APs provide clear evidence that precise and reliable escape motion can be encoded in a collective rule without any solitary repulsion. In such a collective rule, each individual in the group is only responsible of partial information regarding the location of the threat. The complete location information is recovered by the group’s internal dynamic, i.e. a collective decision making process. We also demonstrate that this combination of group escape and cohesion results in higher robustness against individual detection errors compared to solitary responses. Such results not only coincide with the increased collective vigilance but also compatible with the enhanced group cohesion under threat (Pitcher and Wyche 1983; Sosna et al. 2019). Additionally, the tolerance to individual misdetection suggests possible division of works for multifunctional group with single-functional agents, which is crucial to swarm microrobotic designs with limited individual abilities.

4.2 Social behavioral rules

The social behavioral (or interaction) rules determine the steering direction of each AP in three spatial conditions: extreme proximity to a neighbor, group behavior without threat and threat-altered group behavior. Such three conditions are perceived by the APs with non-obstructive vision. The vision horizon is assumed to be reasonably large so that it always encloses the whole group of APs and the threat, if presence. Figure 4.1 shows the three cases respectively. When an AP is too close to another AP, this pair of APs turns away from each other to keep their minimal clearance of $0.25\sigma$ (Figure 4.1c). With this minimal clearance, an AP interact with the whole group by approaching the group’s center of mass (COM) with a deviation angle $\Delta < 90^\circ$ to either the left (+) or the right (−). Such an indirect attraction yields the rotational motion around COM. To achieve collective motion, an AP applies the sign of $\Delta$ to best align with the closely surrounding neighbors within $R_0 = 25\ \mu m \approx 4\sigma$ as a local consensus (Figure 4.1a). As long as the estimation of COM
4 Collective Benefits in Social Responses to External Threats

Figure 4.1: Social behavioral rules for a threat responsive AP group. **a** In absence of the threat, an AP (in red) approaches the group’s COM with an angular deviation $\Delta$ (green arrow, solid if the direction is chosen) toward the direction closer to $\langle \hat{u} \rangle$, the mean orientation of neighbors within $R_o \approx 4\sigma$ (in blue). **b** In presence of the threat at direction $-\hat{e}_T$, an AP approaches COM with $\Delta$ deviating toward $\hat{e}_T$. **c** In the case of proximity, APs turn away to retain the clearance of 0.25$\sigma$. Adapted from C.-J. Chen and Bechinger (2022, CC BY 4.0).

is shared by all group members, this rule results in a stationary swirl (Bäuerle et al. 2020). Last, when a localized threat is present, the degree of freedom in the sign of $\Delta$ is inhibited; an AP at the direction $\hat{e}_T$ from the threat turns to the $\Delta$ with the larger angle from the direction to the threat, i.e. aligning to $\hat{e}_T$ (Figure 4.1b).

All three rules are completely social, meaning that the motion of one AP depends always on at least one other AP. Obviously, such rules only work when individuals stay in a group. In fact, we consider the scenarios where the individuals prioritize the integrity of a compact group. This is realized by the approach toward COM of all APs disregarding the presence of the threat. Note that depending on the value of $\Delta$ and the position of the AP in the group, both available choices of steering directions might lead to closer distant to the threat (as shown in Figure 4.1b). For an individual AP, the chance of moving towards the threat due to the rule is the compromise for group cohesion. However, an immediate advantage of such responsive rule is the reduction of necessary information regarding the position of the threat. Every individual AP only requires a binary information, whether the threat is at the left or right of COM from its own perspective. The reduction of sensory information can also means higher robustness in sensory error. In the second half of the Results section, we will come back to the collective benefits corresponding to
4.3 Experimental Results

4.3.1 Collective response to a static threat

Following the social behavioral rules, when a swirl of APs encounters a static threat outside of the group, it transforms into an arrowhead-shaped flock pointing and moving precisely away from the threat. Figure 4.1a shows a time series of snapshots with intervals 200 s regarding such transformation. As the static threat (demonstrated as a purple triangle) appears right after the first snapshot \( t = 0 \) s, the reorganization of group formation occurs along with the group’s escape motion. The density distributions in Figure 4.2b reveal the clear deformation of the AP group at the according threat-exposure time with the direction to the threat always downward. The group shape of an arrowhead remains stable once formed at \( t \geq 400 \) s. Remarkably, both Figure 4.2a and b demonstrate the geometrical shape of the group precisely correspond to the relative position to the sensory load and the collective decision making that regain the precise position of the threat in the group level.
4 Collective Benefits in Social Responses to External Threats

the threat, even though such precise information is never acquired by the individual AP to perform
the social behavioral rules. Not only that the group’s escape formation is highly responsive to the
threat, the motion of the group also exhibits rapid and efficient response. This is well captured by
the trajectory of COM distance to the threat $d_{\text{COM}}$ in Figure 4.2c. Almost immediately at $t \to 0 \text{s}$,
the slope of $d_{\text{COM}}$ increases to a constant velocity of $\approx 0.12 \mu m \text{s}^{-1}$. The direction of such COM
motion indicates an efficient escape motion as it aligns with the pointing direction of the group
formation, straight away from the threat. The rapid reorganization can also be quantified with the
rotational and polarization order of APs in the group, namely

$$O_R = \frac{1}{N} \sum_{i=1}^{N} \left( \hat{r}_i \times \hat{u}_i \cdot \hat{e}_z \right)$$

(4.1)

and

$$O_P = \frac{1}{N} \sum_{i=1}^{N} \left| \hat{u}_i \right| ,$$

(4.2)

respectively (C.-J. Chen and Bechinger 2022). Here, $N$ is the number of APs, $\hat{r}_i$ the unit vector
from the group center to the $i$-th particle, and $\hat{e}_z$ the unit vector perpendicular to the 2D plane
of motion. In Figure 4.2d, the finite $O_R$ and low $O_P$ at $t \leq 0 \text{s}$ is a typical signature of a swirl.
Upon the threat presents, the APs become polarized as $O_P(t \to 0)$ surges and $O_R(t \to 0)$ drops to
near zero accordingly: a clear indication of a flock. It is worth noting that $O_P$ drops slightly at
$t \approx 300 \text{s}$, where in Figure 4.2c, the slope decreases to $\approx 0.11 \mu m \text{s}^{-1}$. This reflects to the end of
the transformation where the group formation reaches a steady state (which we will revisit in the
following paragraph).

4.3.2 Structure-mediated group behavior

In order to understand the origin of the escape formation and the dynamics under the swirl-flock
transition, we evaluate the local vorticity $c(r)$ and visualize it in Figure 4.3, where the structure of
AP motion evolves in time. For a position $r$ from COM, the vorticity

$$c(r) = \frac{1}{N} \sum_{i=1}^{N} g(r - r_i) \frac{(r - r_i) \times \hat{u}_i^{\text{COM}}}{|r - r_i|} \cdot \hat{e}_z$$

(4.3)

measures the local degree of circular AP motion in the COM’s co-moving frame, with $r_i$ a vector
pointing to the $i$-th particle, $\hat{u}_i^{\text{COM}}$ its direction of velocity in the reference frame of COM and
4.3 Experimental Results

**Figure 4.3:** Local vorticity in the group’s co-moving frame and velocity in Lab-frame of APs within an escaping flock. **a, b, c** At $t = [0, 100, 300]$s respectively; upper part: Color maps of the spatially resolved AP vorticity motion in COM’s co-moving frame. The opacity refers to the local AP density. Lower part: Corresponding AP velocity direction indicated by arrows. Adapted from C.-J. Chen and Bechinger (2022, CC BY 4.0).

$g(r - r_i)$ a Gaussian weight with variance of $2\sigma$ to estimate the local contributions of this $i$-th particle (C.-J. Chen and Bechinger 2022). A local minimum (maximum) in $c(r)$ pinpoints the rotational center of surrounding AP motion in clockwise, cw, (counterclockwise, ccw) direction. In Figure 4.3, the opacity refers to the local AP density. At $t = 0$, the unperturbed swirl obtains a single vortex center, the blue cw spot in Figure 4.3a, close to COM. (The low opacity ccw rim is due to the finite size.) When the deformation responding to the threat starts (Figure 4.3b), APs at the right-hand-side of the COM-threat axis flip from cw to ccw motion, as the left-hand-side of the group remains unaffected. This eventually develops into two rotational centers in counter-directions (Figure 4.3c). The motion of COM during this transformation period arises from the deformation, i.e. the migration of the APs originally at the closer-to-threat end into the peripheral “wings” at both sides (Figure 4.4). After the formation of the arrowhead, the steady-state shape of group

**Figure 4.4:** The schematic of the flock structure. According to the AP density (the purple color map in the back) and dynamics, the escaping flock is composed with three regions: The dense central area marked by the red dash-dotted line and the peripheral “wings” extending backwards on two sides (enclosed by green dashed lines). The arrows indicates the general tendency of motion regarding APs in the two “wings”, while APs in the dense area obtain low mobility due to the crowdedness.
4 Collective Benefits in Social Responses to External Threats

Figure 4.5: Geometrical shape and mean escape speed of an AP group as functions of $\Delta$. a-d Probability distributions of APs in escaping flocks with $\Delta = [33.75^\circ, 56.25^\circ, 67.5^\circ, 78.75^\circ]$, respectively. Dashed lines correspond to the contours of [52%, 67%, 75%]. e The correlation between steady escape speed $v_{\text{flock}}$ (normalized by $v_{\text{iso}}$, the speed of an isolated AP) and $|O_R|$ before the threat appearing. f $v_{\text{flock}}/v_{\text{iso}}$ as a function of $\Delta$. The error bars are standard errors. Adapted from C.-J. Chen and Bechinger (2022, CC BY 4.0).

The collective escape behavior of APs has a strong dependence on the rule parameter $\Delta$ which can be well predicted by the unperturbed swirl behavior. The deviation angle $\Delta$ determines strongly the collective state of the AP group performing the swirl rules (Bäuerle et al. 2020). As it reflects to the tendency of circular motion around COM, a low $\Delta$ results in a swarm of no local order; a high $\Delta$ promotes high rotational order, i.e. $|O_R|$ close to 1. In this work, we explicitly apply the swirl condition $33.75^\circ \leq \Delta \leq 78.75^\circ$. Figure 4.5a-d shows the density distribution of the escaping flock with different $\Delta$. While the general shape of an arrowhead persists, the overall density is significantly lower with larger $\Delta$. This Density-$\Delta$ relationship coincides with that of a swirl. We can apply the understanding of AP motion and density from an unperturbed swirl to the two sub-
4.3 Experimental Results

swirl structure in the escaping flock, where the peripheral “wings” are expected to extend with the increasing $\Delta$, as the dense central area remains compact. In addition to the density, the efficiency of the according collective motion also obtains a good agreement: in a swirl, the magnitude of rotational order; in an escaping flock, the normalized escaping speed. Figure 4.5e shows such $|O_R|$, measured at $t < 0$ s, and the steady escaping speed $v_{\text{flock}}$ (normalized by $v_{\text{iso}}$, the speed of an isolated AP) afterwards. This positive correlation between $|O_R|$ and $v_{\text{flock}}$ further supports that the two sub-swirl structure inherits properties from the unperturbed swirl. In fact, Figure 4.5f reveals $v_{\text{flock}}$ as a function of $\Delta$ identical to $|O_R|$ reported in (Bäuerle et al. 2020). The $\Delta$ values leading to a more pronounced swirl behavior also promote the group’s escape motion. Interestingly, such consistency between collective states in their parameter dependency is rare. When two switchable collective states are facilitated by different rules or driven by different social forces, they often compete in relevant parameters. For example, in zone models (Couzin et al. 2002), milling or flocking behavior occurs in different combination of alignment and cohesion. Collective predator avoidance modeled by a repulsive reaction to the predator and attractive social interaction (Lee et al. 2006; Y. Chen and Kolokolnikov 2014) must balance between individual escape and group cohesion. In our rules, the flocking behavior arises from an altered structure of swirling individuals, so the general properties of the collective motion are preserved from the swirl-flock transition.

4.3.3 Threat-attentive and inattentive APs

With the collective swirl-flock transition responding to the presence of the threat, we further investigate the collective vigilance by implementing a fraction of APs which never detect the threat. As introduced previously, a key reason for an individual to act collectively rather than solitarily, hypothetically, comes from the emergent benefits. In models of collective detection e.g. the many-eyes hypothesis (Lima 1995), an increased vigilance of the group which exceeds the sum of individual capacity provides higher survival rate and/or less effort required to remain alert for an individual. Figure 4.6 demonstrates such effects in our collective escaping APs with a number of randomly assigned threat-inattentive APs, $N_{TI}$. We evaluate the group’s response as a function of $N_{TI}/N$ with two survival-essential quantities, namely the delay time $\tau$ for COM to accelerate to 50% of the maximum possible $v_{\text{flock}}$ and the steady escape speed $v_{\text{flock}}$. Figure 4.6c shows one example of the group’s COM speed $v_{\text{COM}}$ where $\tau$ and $v_{\text{flock}}/v_{\text{iso}}$ are marked in green and purple respectively. Remarkably, both $\tau$ and $v_{\text{flock}}$ deviates significantly only at $N_{TI} > 0.6$. In other words, APs whose individual detection rate exceeds 40% can perform group escape equivalent to APs with 100% detection rate. Such outcome clearly exhibits the benefit regarding the group’s total attention to threats achieved by cooperative behavior.
Figure 4.6: Group escape in presence of inattentive APs. a Time delay $\tau$ in the group’s respond to the threat and b normalized steady escape speed $v_{\text{flock}}/v_{\text{iso}}$ as functions of $N_{\text{TI}}/N$. c Definition of $\tau$ (green period), time for the escape speed of COM $v_{\text{COM}}$ to reach 50% of the maximal $v_{\text{flock}}/v_{\text{iso}}$ and steady escape speed $v_{\text{flock}}$ (purple dashed line) demonstrated with one experiment. d Normalized rate $f_{\text{col}}$ of an inattentive AP avoiding collision to an attentive AP. The error bars correspond to standard error. Adapted from C.-J. Chen and Bechinger (2022, CC BY 4.0).
4.3 Experimental Results

To enable this enhanced group vigilance, obviously, the social behavioral rules must provide an information pathway from attentive to inattentive APs regarding the collective escape. Such a pathway should obtain high influence and rapid transformation to its neighbors, so $\tau$ and $v_{\text{flock}}$ remain unchanged even with $N_{\text{TI}} = 0.5$. The local alignment rule (Figure 4.1c) cannot fulfill the above criteria because the mean orientation implies the majority of attentive APs in the neighborhood for an inattentive AP to receive the information regarding escape. In fact, such scenario only applies to, on average, less than $0.1N$. On the contrary, we find the clearance rule, for collision avoidance, playing an important role instead. When an inattentive AP is moving inconsistently with the threat response, its chance to encounter an attentive AP head-on is high. In such a case, the clearance rule, although being pairwise and reciprocal, sets the inattentive AP to a reversed direction, but not able to alter the behavior of the attentive AP, as they always turn back to the threat responding direction after the clearance is retrieved. As the result, the attentive APs keep on adjusting the orientation of the inattentive APs until the local alignment rule also agrees on the threat response, yielding the group consensus. The local alignment rule, thus, only reinforces the results from the collision avoidance, rather than flipping the behavior of the inattentive APs. Figure 4.6c shows the frequency $f_{\text{col}}$ of an inattentive AP avoiding collision to an attentive AP. As $N_{\text{TI}}/N$ increases, $f_{\text{col}}$ increases accordingly until it peaks at $N_{\text{TI}}/N \approx 0.6$ and then decreases with higher $N_{\text{TI}}/N$. This explains the threshold of $N_{\text{TI}}/N \approx 0.6$ in $\tau$ and $v_{\text{flock}}$. The non-monotonic relationship between $f_{\text{col}}$ and $N_{\text{TI}}/N$ fits to the simple argument of collision probability: for either $N_{\text{TI}}/N = 0$ or 1, the probability of an inattentive AP to encounter an attentive AP is zero, and a maximum probability should occur in the middle.

Despite the group’s COM motion being tolerant to $N_{\text{TI}}/N \leq 0.6$, the shape of the group reveals the effects of inattentive APs to the group. Figure 4.7a-d shows the density distribution of groups with $N = 85$ and $N_{\text{TI}} = [1, 20, 40, 60]$, respectively. The shape of the group varies from an escaping flock more to a swirl as the $N_{\text{TI}}/N$ increases. Surprisingly, even though the collective escape motion emerges from the group formation, the deterioration in the shape of the flock does not correspond to either $\tau$ or $v_{\text{flock}}$. To understand how the flock shape is decoupled with the COM motion of this structure-mediated escape motion, we look at the distribution of the inattentive APs and their dynamics with traces of 90s duration. Figure 4.7e-h shows the homogeneous distribution of inattentive APs in all groups, i.e. no signs of phase separation. At the same time, Figure 4.7i-k shows the dynamics of these inattentive APs: their motion is well integrated with that of the attentive APs when $N_{\text{TI}}/N \leq 0.6$. As for Figure 4.7l, where $N_{\text{TI}}/N \approx 0.7$, the motion of inattentive APs depends mainly on their close neighbors. In other words, there is no significance to clearly differentiate an inattentive AP from the attentive ones in an escaping flock of $N_{\text{TI}}/N \leq 0.6$. The behavior of the inattentive APs is averaged out into the stability of the special structure of the
Figure 4.7: Group shape and spatial distribution regarding inattentive APs. In a group with $N = 85$ and $N_{\text{TI}} = [1, 20, 40, 60]$ respectively, a-d the probability distributions of APs. Dashed lines correspond to the contours of [52%, 67%, 75%]. e-h AP positions with attentive and inattentive APs marked with open and filled circles respectively. i-l The corresponding 90s traces with attentive and inattentive APs in green and red respectively.
4.4 Supplementary numerical simulations

Apart from the major experimental study, we examine our findings with numerical simulations of the active Brownian particle (ABP) model with active torque and confirm qualitatively that the group’s escape motion is not system-specific to our experiment. The cooperative response by a group of APs demonstrate the performance of the social behavioral rules even in a physical realization. While it is practical to consider a complex environment where noise, interactions mediated by fluid, friction, etc. contribute significantly, sometimes an ideal system with only selective conditions helps us with unravelling the interplay between those complex interactions. We perform overdamped Langevin simulations of $N$ ABPs with active torque determined by the same social behavioral rules applied in the AP experiments. At the discrete time $t_i$, the position and orientation of a particle are

$$ r(t_i) = r(t_{i-1}) + \dot{\Theta}(t_{i-1})v_s T_i + \xi T \sqrt{T_i} $$

(4.4)
4 Collective Benefits in Social Responses to External Threats

<table>
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<th>Parameter</th>
<th>Value applied</th>
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<td>( \omega_{max} )</td>
<td>0.07 rad s(^{-1} )</td>
</tr>
<tr>
<td>( D_T )</td>
<td>0.014 ( \mu m^2 ) s(^{-1} )</td>
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<td>( D_R )</td>
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<td>( \sigma_s )</td>
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<tr>
<td>( \Delta )</td>
<td>56.25°</td>
</tr>
<tr>
<td>( N )</td>
<td>85</td>
</tr>
</tbody>
</table>

Table 4.1: The parameters applied in all presented numerical simulations.

with orientational unit vector \( \hat{\theta} = \hat{u}(t_i) = (\cos(\theta), \sin(\theta)) \) and

\[
\theta(t_i) = \theta(t_{i-1}) + \omega_{max} \sin(\Delta^\ast(t_{i-1}))\tau_s + \zeta_R \sqrt{\tau_s},
\]

respectively. Here \( \tau_s = t_i - t_{i-1} \) is the unit time interval, \( \omega_{max} \) the maximum angular speed, \( \Delta^\ast \) the steering direction (in angle) determined by the social behavioral rules, \( \zeta_T \) and \( \zeta_R \), zero-mean random processes with the variance \( \langle \zeta_T(t)\zeta_T(t') \rangle = 2D_T\delta(t - t') \) and \( \langle \zeta_R(t)\zeta_R(t') \rangle = 2D_R\delta(t - t') \) respectively. The sinusoidal form of steering angular velocity is based on the active reorientation under light gradient (Lozano et al. 2016). Parameters regarding particle motility are set according to the experimental results (C.-J. Chen and Bechinger 2022). The dependency of simulation results to \( 0.001 \text{ s} \leq \tau_s \leq 1 \text{ s} \) is insignificant. We choose \( \tau_s = 0.1 \text{ s} \) for all simulations. To model hard sphere-like interactions, we check for overlapping particles, i.e., inter-particle distances smaller than the particle diameter \( \sigma_s = 6.3 \mu m \) at the end of each iteration. These overlaps are recursively treated by shifting overlapping pairs of particles away from each other until the overlap vanish.

Numerical simulations reproduce the swirl and escaping flock corresponding to the presence of

![a](image1.png) ![b](image2.png)

**Figure 4.8:** An Escaping flock in the numerical simulation with a particle orientations indicated by arrows and b Color maps of the vorticity in COM’s co-moving frame.
4.4 Supplementary numerical simulations

![Graph](image)

**Figure 4.9:** Group escape with inattentive particles in simulations. With groups of $N = 85$ in simulations (Simu.) and experiments (Exp.), a time delay $\tau$ in the group’s response to the threat, b normalized steady escape speed $v_{\text{flock}}/v_{\text{iso}}$, and c normalized rate $f_{\text{col}}$ of an inattentive particle avoiding collision to an attentive particle as functions of $N_{\text{TI}}/N$. The error bars correspond to standard error.

(Simulations and experiments show) similar results to those of the experimental results, the geometrical shape of the flock corresponds to the direction of the COM motion. We find the two sub-swirl formation in c(r) (Figure 4.8), indicating that the same strategy for flock implementation in the social behavioral rules does not require the complex environment but can truly occur in a system of steerable particles. The increased group vigilance also applies to the simulations. Figure 4.9 shows the group response in $\tau$ and $v_{\text{flock}}/v_{\text{iso}}$ to the threat as functions of $N_{\text{TI}}/N$. When $N_{\text{TI}} \to 0$, the simulated group responds instantaneously. As $N_{\text{TI}}/N$ increases, $\tau$ also increases monotonically. The steady escaping speed stays rather constant at $N_{\text{TI}}/N \leq 0.6$. Such a threshold coincides again with the maximum $f_{\text{col}}$ between a threat-attentive and inattentive particle. Across our findings in experiments, we confirm, in these numerical simulations, both the transition between collective states and the collective benefits are independent of the details in particle-particle or particle-environment interactions. On the contrary, the occurrence of such group behaviors in a physical realization demonstrates the robustness of the underlying mechanism, i.e. the social behavioral rules, against the uncertainties and complexities in possible applications.

Despite the qualitative similarities, our simulations without short range particle interactions that APs in experiments inevitably experience, show significant differences in both the density distributions and the particle dynamics (Figure 4.10). Starting from the unperturbed swirl, the simulated group does not concentrate as much at the COM, although the overall physical size of the group is smaller than that in the experiments. Similarly, the escaping flock also obtain a smaller area...
compared with the AP group in experiments. The geometrical shape of the simulated escaping flock is a triangle: the “wings” that extend backward to the COM motion does not occur. Remarkably, such variations of group structure corresponds to the internal dynamics of particle motion. In experiments, the AP-AP interactions within the range of the clearance rule, e.g. phoretic and hydrodynamic interaction, arise from the steering and propulsion mechanism. These additional short range interactions prevent APs sliding and crossing each other in a distance of physical contact, i.e. surface-to-surface distance → 0. In Figure 4.10c, the traces of APs in an escaping flock show strong localization of AP in the central area, indicating the effects from such interactions. In the simulation (Figure 4.10d), particles sliding and squeezing through a dense area with only steric interaction are common. As a result, simulated particles “swim through” the group center when approaching it. In the swirl, this corresponds to the absence of high density at the center; in the escaping flock, this breaks the low mobility area at the COM-threat central axis, allowing particles diverging from the central axis earlier than APs in experiments. The lack of low mobility area not only prevents the backward extending “wings” on the sides, but also accelerates the COM motion: $\frac{v_{\text{flock}}}{v_{\text{iso}}}$ in simulations are ≈ 4 times of that in the experiments. Meanwhile, the pronounced localization of APs in the flock center suggests higher efficiency regarding collision avoidance in experiments than that in simulations. As we consider the clearance rule as the major information pathway between threat-attentive and inattentive APs, this yields variations in the dynamics of a simulated group’s response as a function of $N_{TI}/N$. Remarkably, the response time $\tau$ in simulations increases dramatically at $N_{TI}/N > 0.2$, while $v_{\text{flock}}$ still deviates at $N_{TI}/N > 0.6$. This less efficient swirl-flock transition is consistent with the information transferring through the clearance rule, which is less effective in simulations. Nevertheless, our numerical simulations elucidate the effects of social behavioral rules from complex physical interactions which is not system specific to our experimental approach.
4.5 Discussion

In this chapter, we present an experimental study of the response and escape of a socially interacting AP group to a suddenly appearing static threat. The social behavioral rule which facilitates the group’s response to the threat requires only the relative position of the group’s COM and the angular direction (left or right) from COM to the threat according to the individual perception of each AP. This largely reduces the information acquisition and processing for one individual, as the precise positional information is encoded in the group formation emerging from social interactions. As a result, the response of a single AP is not necessarily leading to a motion opposite to the threat, but in combination with the social interaction with their peers, the overall group’s response results in a collective threat avoidance motion. The profound benefit of such a collective escape behavior is that the group’s response to a threat hardly deteriorates even when a considerable fraction of group members does not respond to this threat.

Many other prey-predator social models mimic the individual response to a predator by a repulsive reaction which typically results in group expansion and/or splitting. Such behavior can be indeed part of a predator confusion strategy in case of a rapidly approaching predator (C.-J. Chen and Bechinger 2022). However, in the case of living animals, the general tendency of group cohesion either prevents group splitting by creating a vacancy around the predator (often called “vacuole”) within the group or, more importantly, promotes remerging and reformation into a new unified flock behind the predator (Pitcher and Wyche 1983; Carere et al. 2009). Although we motivate the social behavioral rules with the scenario of a distant or static threat, in Figure 4.11, we demonstrate the group response to a fast passing threat with a sequence of snapshots. The time interval is 100s.

Figure 4.11: Response of an AP group to a penetrating threat. Sequence of Snapshots where a rapidly approaching threat penetrates an escaping group. The time interval between each snapshot is 100s.
According to the interaction rule, the distance of the group to the threat does not affect the behavior of APs. In the case of Figure 4.11, the APs remain in a steady escaping flock until the threat invades the group where an extra clearance rule enforces APs to avoid contacts with the threat with highest priority. Still, the group formation varies significantly only after the threat passes the group’s COM. The group, then, deforms into a new flock in the corresponding new escape, i.e. threat-to-COM, direction. The cohesive rule of threat response inhibits group splitting and promotes remerging of transient fragments during the deformation, similar to animal groups closely encountered by predators. In short, although the passing predator is leading to a large deformation of the group, it immediately reshape after the predator dashed through.

The flock-like group configuration which generally forms during the cooperative escape is rather different from what is typically found in Vicsek (or related) models (Vicsek et al. 1995; Couzin et al. 2002). Opposed to flocking states with only small variance of the polarization within the group, the collective maneuver of our AP group emerges from the internal dynamics of two counter-rotating swirls (C.-J. Chen and Bechinger 2022). Such hybrid collective pattern, i.e. swirls in a flock, is only obvious in the co-moving frame of the entire group. The observation in lab-frame, on the contrary, indicates small deviations in AP orientations corresponding to their relative positions in group. Similar patterns are recorded e.g. in school of fish (Carvalho et al. 2007). Meanwhile, hybrid collective patterns are reported in field studies of wild animals (Brattstrom 1998). Our study suggests complex dynamical structure in moving collective groups where the true dynamics is entangled with the overall group motion.

Another important part in this work demonstrates the collective vigilance mediated by the social interactions. Interestingly, we find the clearance rule, which we implement mainly for collision avoidance, plays an important role. As an information pathway, the clearance rule outperforms the local alignment rule and explains the tolerance of group’s response with > 50% threat-inattentive APs. Since the collective escape motion is encoded in the group formation, the information passes from threat-attentive APs to inattentive APs is only 1 bit; this compensates the limited and imprecise information that the clearance rule can convey. The combination of pairwise interaction and binary information reminds us about the social contagion models. Indeed, the clearance rule may work effectively as simple contagion, while the local alignment rule is similar to a threshold model. However, it is worth noting that the information from either attentive APs or inattentive APs is equally influential. In the case of a more intelligent swarm, additional sensory cues might tune the influence difference between information and misinformation, ending up with more efficient and reliable social contagion. Nevertheless, our social behavioral rules demonstrate information sharing by a simple pairwise interaction from which the enhanced group vigilance emerges.
4.5 Discussion

The important role of the clearance rule in the group’s escape formation emphasizes the effects of short-range AP-AP interactions to collective behaviors. In our experiments, AP motion in the crowded area arises from not only the rule determined steering direction, but also, e.g. steric, hydrodynamic and phoretic, interactions mediated by the real world environments. Such interactions, in our case, strengthen the effect of the repulsive clearance rule, resulting in more efficient information transferring and more stable dynamic structure of the group formation. In real biological systems, complex short-range interactions also arise from both the environment, e.g. the aerodynamics around birds, and/or additional sensory cue, e.g. response to the mechanosensing of a fish’s lateral line. By the comparison to the active Brownian particle simulations, the findings in our experimental approach elucidate the essential roles of these short-range interactions and suggests social behavioral rule modeling to exploit the properties of such interactions.

Beyond its relevance for the understanding of collective response of living organisms to a threat, our results have also relevance to micro-robotic systems where the individual functionalities or sensory precision is limited (C.-J. Chen and Bechinger 2022). By encoding information into group structure or internal dynamics through appropriate social interaction, not only the work load of single individual is reduced, but also the overall tolerance of the group to individual missing or even false information (e.g. due to sensor failures or noise) is enhanced. Considering a swarm of several thousand interacting robots, such interactions can serve as error correction mechanisms and, hence, are essential for reliable and failure-resistant performance. Furthermore, the tolerance to individual misdetection can be exploit into the division of work loads, allowing individuals with single function other than performing the social interactions to form cooperative group which performs all individual functions as a single entity. This is particularly important in the case of designing robotic swarms with sub-groups optimized for different tasks or even when implementing hierarchy controls, where these interactions work as behavior sharing mechanisms for enabling group-level functions.
Between Perception and Attention in Collective Behavioral Rules

In collective social groups, interactions between individuals can achieve information sharing by e.g. forming swarm signaling networks (SSNs) where perception describes the possible signal intake and attention determines the actual connections. When modeling individual behaviors, perception is the input which contains information regarding object recognition, position, orientation, velocity, etc. Realistically, the type of information obtainable from the perception corresponds to its sensory origin, regarding both capabilities and constraints, e.g. range and obstruction. Once perceivable information is given, it is up to the individual whether to process, and then respond to, such signals. This is modeled as the attention. While perception and attention are essential factors for determining the SSN, social interaction rules which consider both effects are rare. In this chapter, we show how flocking behavioral rules obtain different group stability regarding individual capacity of attention under realistic perception. The results not only indicate a minimal attention capacity for stable flocking formation, but also provide evidences connecting perception models to geometrical models.

5.1 Introduction

Many animal groups organize into flocking formations where individuals obtain high degree of velocity alignment with each other. Such collective states are mobile and cohesive, providing collective benefits from energy saving (Fish 1999) to predation avoidance (Pitcher and Wyche 1983). The self-organization of group members into a flock requires information, regarding directions of individual velocities, sharing across the whole group. In the case where an individual only obtain local information from neighbors, a signaling network must connect all group members, so that information outside of the neighborhood can propagate. Such a swarm signaling network (SSN) (Komareji and Bouffanais 2013) is dynamic due to the variations of relative positions of members.
within the group which the connections in a SSN base on. This effect is most pronounced during collective turnings or group deformations. A group with insufficiently intra-connected SSN would risk breaking apart or losing the stability in group performance.

From the individual point of view, a flock member must perceive the information regarding directions of other members so that it can act correspondingly, both for group forming and passing information to others. Visual perception is especially useful in this case since the direction of motion can be estimated by the heading direction for most of the self-propelled objects. Vision also provides a perceivable range which defines the maximum physical length of a connection in the according SSN. With vision-like perception, a minimal model proposed by Vicsek et al. (1995), where point-like particles travel in constant speed and align to the mean velocity of all other particles within neighborhood of a fixed range \( R_o \), demonstrates global flocking behavior arising from local interactions. Further modifications for achieving more biologically relevant models implement repulsive, aligning and attractive interactions with different distance-dependent weights which reflect the behaviors of living animals (Aoki 1982; Niwa 1994). As discussed in Section 2.3.1, such models successfully reproduce flocks and other collective patterns reported in field and laboratory observations.

Despite the fact that these Vicsek-like models can qualitatively mimic collective patterns in animal groups, discussions regarding the neighbors of interaction (NIs) continue for reasons e.g. the fixed-range neighborhood encloses unrealistically large number of NIs in the case of a high density flock (Kunz and Hemelrijk 2012). The spatial distribution of NIs in respect to the ego agent also has significant effects on the emerging collective states. One example is the Vicsek model with a finite vision angle (Costanzo and Hemelrijk 2018), where by changing such vision angle alone, the group exhibits flocking or milling behaviors correspondingly. The importance of NIs can be understood from the SSN as the NIs essentially describes the directed edges from a node (individual). In a dynamic signaling network, such connections can characterize the network without explicitly looking at the complete network graph (Komareji and Bouffanais 2013). The state-of-the-art modeling of NIs considers the obstructed perception of nearer neighbors to the further ones (Kunz and Hemelrijk 2012; Strandburg-Peshkin et al. 2013). Such obstructions fully reconstruct the individual perceptions by taking into account the physical constrains of vision. This model better describes animal behaviors in groups (Strandburg-Peshkin et al. 2013) and reflects to applications in robotic swarm with machine vision.

Different from the above discussions where perception field determines NIs, attention, whose limit links to the total number of NIs, is also an important factor for realistic modeling. As we exploit the vision-like perception for its ability to extract heading directions of NIs, it is worth noting that

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the heading directions, compared to the positions, require an individual to pay more attention to each NI. Such attention is not infinite in capacity, suggesting an upper bound in the number of NIs. This limited number of NIs is found in animal groups. Studies reveal an average number of 6 to 7 NIs for flocking birds, which is not due to the number of perceptible neighbors, but rather to the limitation of processing the visual inputs (Ballerini et al. 2008). Similar to the physical constrains in perception, the attention limit also contributes significantly to the selection of NIs. Hence, understanding the minimal number of NIs which works for a stable flocking formation is helpful to the studies of animal collective behaviors and the design of cooperative robotic swarms.

So far, the research related to the number of NIs exploits the network theory and agent-based simulations with topological Vicsek model (TVM) (Chou et al. 2012; Komareji and Bouffanais 2013; Rahmani et al. 2020). By replacing the $R_o$ neighborhood with the topological neighborhood, which encloses a fix number $k$ of nearest neighbors, TVM results in SSNs composed of a fixed number of directed links. Studies with TVM provide insights regarding certain $k$ value corresponding to a maximum flock size of $N_c$ agents, i.e.

$$k \approx c \log N_c,$$

where $c$ is a system specific constant. Such predictions regarding $N_c$ result from the statistics of randomly generated $k$-nearest neighbor network graphs where $N_c$ nodes are connected. TVM with additional environmental cue, e.g. a hazardous site, reveals the trade-off between reactions to the environment and social interactions when the two behaviors require limited attention at the same time (Rahmani et al. 2020). Depending on the chance of encountering such cues, the limit in attention can be either enhancing or detrimental to the formation of cooperative social groups. Indeed, with TVM as a minimal model regarding a fixed number of NIs, simulation works show significance of limited attention to the behaviors of a group of social agents. However, the effects of limited attention in a more realistic perception are not yet investigated. In a local perception where neighbors obstruct each other and, hence, a fixed number of NIs at every instance is not guaranteed, the selection of NIs is the interplay between perception and attention. The minimal attention for a stable flock in such interplay can differ a lot from that in TVM.

In this chapter, we combine the limited attention and a Vicsek-like flocking model with obstructed visual perception in an experimental approach with a swarm of microrobotic active particles (APs). Our model consists of social behavioral rules regarding mostly aligning but also relatively weak attractive interactions along with collision avoidance at proximity. Such a model is both realistic, regarding group forming with real particles that are not point-like, and sensitive to the consensus in individual moving directions due to the insufficient attractive tendency between group members.
Figure 5.1: Social behavioral rules with obstructed perception. **a** The flocking rule determines the pairwise response to any of the neighbors of interaction (NIs) which is a combination of attractive, i.e. $\phi_{ij}$, and aligning, i.e. $\theta_{ij}$, steering as shown in Equation (5.2). The overall steering direction is a weighted sum of all pairwise responses (Equation (5.3)). The NIs are selected in the metric range $R_o = 50 \mu m \approx 8\sigma$ (blue circle) according to selection rule in **c**. **b** In the case of two APs with surface-to-surface distance shorter than $0.25\sigma$ (yellow circle), the clearance rule steers them away from each other. **c** The selection of NIs with ranged ($R_o$) and obstructed perception (cyan area) choose perceptible nearest neighbors of the number limited by attention $N_a$. If $N_a = 1$, only the orange solid line connects to NI; both orange solid and purple dash-dot lines for $N_a = 4$, and all green dashed, orange solid and purple dash-dot lines for $N_a \geq 8$.

The attention limit, modeled as the $N_a$-maximum nearest neighbors, determines the NIs within the obstructed perception. Depending on the NIs, the resulting SSNs provide different degrees of stability against noises in the real experiments which promotes group splitting.

Our experimental results demonstrate that a minimal attention for stable flocking formation exists in the case of realistic social groups and visual perception. Surprisingly, such a minimal attention sustainable for a stable flock corresponds to the spatial distribution of neighbors. When a $N_a$ value allows all closest surrounding neighbors as NIs, we discover strong suppression of potential group splitting events. We find such closest surrounding neighbors highly relevant to the Voronoi neighbors (Ginelli and Chaté 2010). The minimal $N_a$ is then equivalent to the maximum in number of Voronoi neighbors. Our results not only suggest a minimal attention predictable by spatial configurations, but also connect the obstructed perception to the Voronoi model, providing insights regarding attention and the modeling of NIs.
To study the effects of attention and realistic, i.e. obstructed and ranged, perception to the stability of flocking formation, we apply a social behavioral rule that is composed of weighted alignment and attractive interaction. Figure 5.1a shows the relevant quantities for a pairwise response of the ego AP $i$ to a perceptible neighbor $j$ (in the blue region), and the resulting steering direction of $i$ is

$$\Delta_{ij} = \theta_{ij} + (\phi_{ij} - \theta_{ij}) \exp(-0.01d_{ij}) , \quad (5.2)$$

where $d_{ij} = |r_{ij}|$. This facilitates alignment to close by NI and approaching to distant NI, i.e. $u^*_{ij} = \theta_{ij}$ for $d_{ij} \rightarrow \infty$, and $\Delta_{ij} = \phi_{ij}$ for $d_{ij} \rightarrow 0$. The overall steering direction for $i$ is the weighted sum of all pairwise responses,

$$\Delta_i = \sum_{j \in \{\text{NIs}\}} d_{ij}^{-1} \Delta_{ij} . \quad (5.3)$$

This inverse-distance weighting corresponds to the intensity of the sensory signal, i.e. the visual angle perceived from the ego AP. The NIs are selected in the vision-like perception field with the range of $R_o = 50 \, \mu m = 8 \sigma$ and the nearer APs obstructing the further ones. For simplicity, the obstruction occurs only when the AP center is covered by the visual angle of another nearer AP. Figure 5.1c visualizes such perception (light blue area), where the NIs are the perceptible closest $N_a$ neighbors due to the limited attention. To minimize particle collisions, the APs prioritize a clearance rule where they turn away from each other when their clearance is below $0.25 \sigma$ (Figure 5.1b, yellow region).

Our implementation of limited attention, by a maximum of $N_a$ closest neighbors, does not guarantee that the number of NIs equals to $N_a$, due to the possibility of not enough perceptible neighbors. For example, $N_a = 10$ in the case of Figure 5.1c still results in 8 NIs for $i$-th AP. However, some APs with more perceptible neighbors may obtain 10 NIs at the same time. The number of NIs depends explicitly on the spatial distribution of the neighboring APs. Meanwhile the clearance rule and the use of real particles, which occupy certain space, also shapes the perceptible neighborhood. Unlike the point-like particles, our APs obtain finite local density and are forbidden to simply crossing each other in the collision courses. As a result, the SSN in our experiments can deviate significantly from that obtained by TVM, in both numbers of connections and the spatial distribution of the flock members.
With $R_0 = 50 \mu m$, our social behavioral rules is clearly in lack of cohesive interactions which dominates in the long range interaction (Aoki 1982; Kunz and Hemelrijk 2012). Such attractive rules are responsible for group forming, and are usually given weights that ensures a single cohesive group. Here, as we are investigating the stability of the flocking groups, the cohesion is not enforced by rules. Instead, we start with a group of APs moving in the same direction. After 600s of collective “blind” motion, the APs start performing according to the social rules. The group stability corresponds to the evolution of group formation in time. Without the cohesive rule acting in long range, the group cohesion is expected to deteriorate due to the, both thermal and experimental, noise. The more stable of the system, the group can persist cohesion longer.

There are a few experimental details regarding individual or collective AP behaviors stated as below. If not stated otherwise, experiments were performed with $N = 36$ APs. To preserve a relatively constant $N$ during an entire experiment, soft repulsive boundaries are applied. And as introduced in Section 3.3, we trace the group, i.e. the center of mass considering all APs, motion by moving the observation field of view with a piezo stage holding the AP sample. This stage motion is later compensated to reconstruct the sample-frame AP trajectories, which is the frame of reference if not stated otherwise.

### 5.3 Experimental Results

#### 5.3.1 Flocks under limited attention

Flocking behavior in a group of APs highly depends on $N_a$: for small $N_a$, APs scatter into small groups with transient flocking, while for larger $N_a$, the group remains as large group(s) with more persistent flocking behavior. Figure 5.2a shows series of snapshots with 36 APs (initially at $t = 0$ s) and attention limits $N_a = [1, 8, 16]$ respectively. The snapshots are centered at COM of all APs. The colored traces are of 60 s duration. Within the first 350 s since the APs start performing the social rules at $t = 0$ s, group splitting has occurred. For the extreme case e.g. $N_a = 1$, the splitting is almost isotropic. The group of APs expands and fills the field of view with dynamic small flocks composed of 3 to 5 APs. As $N_a$ increases, splitting event reduces to the frequency that the generation of each new sub-flock is temporally differentiable. Flock merging also occurs, but promotes higher tendency of splitting again into sub-flocks with the size of the pre-merging ones. With a sufficiently large $N_a$, e.g. 16, the group remains as one single flock. Notably, there seems to be a maximum group size that a certain $N_a$ value corresponds to; this is especially significant in the range $8 \leq N_a \leq 16$ where steady flocks preserve for tens of minutes. We can therefore
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Figure 5.2: Flocking behaviors of APs with attention limit $N_a$. a Snapshots with 60s traces demonstrating three groups of 36 APs at time $t = [0, 350, 620, 830]$s from left to right. The three groups follows $N_a = [1, 8, 16]$ from top to down. The largest flocks in each snapshots are marked in orange, green and blue traces, respectively. For $N_a = [1, 8]$, the rest of the APs are marked in purple traces with the color maps on the right. The scale bar represents 40 $\mu$m. b The time series of number of APs in largest flock $N_{LF}$ for the three cases in a, with $N_a = [1, 8, 16]$ in orange, green and blue respectively.

define our flock stability by the maximal flock size that a group of APs could maintain throughout a particular time scale. Such stability quantifies the ability of the APs to resist group splitting. Here, we measure the largest flock size $N_{LF}$ based on the inter-AP distances and local density with DBSCAN (Ester et al. 1996) cluster analysis (DBSCAN, provided by scikit-learn (Pedregosa et al. 2011) in Python). As discussed in Section 5.2, alignment is the major social force which promotes group cohesion, hence, the polarization order of each flocks are general high, making such distance-based group size an sufficient indicator for flock stability. In Figure 5.2b, the time series of $N_{LF}$ corresponding to the snapshots in Figure 5.2a demonstrates not only the larger $N_{LF}$ but also less fluctuations with $N_a = 16$. In the case of $N_a = 1$, the group size is typically small, and the splitting-merging dynamics are rather frequent. On the contrary, in the case of $N_a = 1$, the group size is typically small, and the splitting-merging events are rather frequent. Since $N_{LF}$ clearly captures the effects of $N_a$ on flocking behaviors, we further apply the mean $N_{LF}$ at $t > 600$ s as our quantifier for flock stability.
5.3.2 Stability and connectedness

Figure 5.3a shows the mean $N_{LF}$ in respect to the $N_a$. The $\langle N_{LF} \rangle$ increases monotonically with $N_a$ and saturates at $N_a \geq 10$. Indeed, allowing more attention in the neighborhood enhances the stability of the flocks against group splitting. Meanwhile, the saturation of $\langle N_{LF} \rangle$ is an indication of the minimal $N_a$ for the flocking stability. Such a minimal attention is not significantly different from the discovery in bird flocks, which is 6 to 7 NIs, but in contrast with the network prediction from Equation (5.1), as these bird flocks consist of thousands of individuals rather than 36 APs in our experiments. (Further comparison with TVM and network analysis are presented in the next paragraph.) We try to understand these different results regarding the effects of $N_a$ on $\langle N_{LF} \rangle$ by looking into the group splitting events. Such events occur stochastically, triggered by the noise and enhanced by the clearance rule. Despite the randomness, group splitting events develop, originally, from a small subgroup of APs deviating their orientation from the rest of the flock. We can probe such partial collective turnings by averaging the deviations of AP orientations to the direction of COM motion within a reasonable response time and define individual events with a threshold. The

Figure 5.4: The partial collective turning event. One example of partial collective turning occurred in a group of APs with $N_a = 6$. The color code represents AP orientations. The time interval is 200 s. The scale bar represents 40 µm.
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**Figure 5.5:** The effects of $N_a$ on **a** mean and **b** maximal connectedness of APs. The outdegree $k_{\text{out}}$ and indegree $k_{\text{in}}$ are extracted from the social rule. $k_{\text{in,knn}}$ and $k_{\text{in,knn}}$ are estimations of indegrees with the assumption of topological model with no interaction range and with the range of $R_o$ correspondingly. The error bars are standard errors. The grey dashed lines are slope = 1 guidance.

frequency of such partial collective turning $f_{PT}$ is shown in Figure 5.3b.

In Figure 5.4, the temporal sequence of AP positions (in co-moving frame of COM) and orientations (color coded) demonstrate one event of partial collective turning. The subgroup of approximately 11 APs in the lower right turns away from the original group, and later divides into the second group. At the end of this splitting, both sub-groups exhibit flocking behavior. Although a partial collective turning event not necessarily develops into a group splitting event, it is still a direct measurement regarding the potential of splitting. In Figure 5.3b, the negative relationship between $f_{PT}$ and $N_a$ agrees with $\langle N_{LF} \rangle$ as a function of $N_a$. Moreover, the distributions of $f_{PT}$ converges to a small value at $N_a \geq 10$, which is a clear signal regarding suppression of partial collective turnings. Combining both Figure 5.3a and b, we can conclude $N_a \geq 10$ as the criterion for stable flocking in the presented system. However, the underlying mechanism of the strong suppression of $f_{PT}$ can only be studied by the interaction dynamics.

In TVM, network analyses reveal the interaction dynamics and predict the flock stability (Komareji and Bouffanais 2013). Figure 5.5 shows the mean and maximum connectedness in terms of outdegree $k_{\text{out}}$ and indegree $k_{\text{in}}$ following our interaction rules. The outdegree, which is the number of NIs in our case, is bounded by $N_a$. The maxima of $k_{\text{out}}$ (Figure 5.5b) indicates that there are always APs exploiting their full attention capacity in all experiments. However, the mean values of $k_{\text{out}}$ (Figure 5.5a) show clear deviations from $N_a$, especially at $N_a \geq 10$. Such non-fully loaded attention...
corresponds to the perception. There, the \( k_{\text{out}} \) represents the number of perceptible neighbors rather than \( N_a \), which is a profound difference compared to TVM. Another comparison between SSN of TVM and our experiments is the prediction of \( N_c \) through Equation (5.1). According to (Komareji and Bouffanais 2013), \( N_c = 30 \) yields \( k = 4 \pm 1 \) nearest neighbor connections, to ensure a fully connected SSN. Our experimental results show mean \( k_{\text{out}} = N_a = 4 \) where the steady flock size is significantly below 30. Such inconsistency with network analysis indicates a different cause of instability due to \( k_{\text{out}} < 10 \). In experiments, collective turning events occur with a subset of cooperative APs. (Figure 5.4) This group splitting originating from formation of a subgroup suggest insufficient inter-connections between the subgroup and the rest of the original group compared to the intra-connections within the subgroup, not necessarily a complete isolation as assumed in the case of Equation (5.1). Such imbalance between inter- and intra-subgroup connections can arise due to the anisotropic distribution of NIs (which we will revisit in Section 5.3.3).

The indegree \( k_{\text{in}} \) quantifies the influence of an AP to its neighborhood by the number of APs considering this ego AP as their NI. If a group of APs obtains higher \( k_{\text{in}} \) on average, the consensus, i.e. group-wise alignment, can be more easily reached. In principle, mean \( k_{\text{in}} \) should be quantitatively equal to mean \( k_{\text{out}} \) for a typical network, but due to the clearance rule, where the involved APs only obtain \( k_{\text{in}} \) but not \( k_{\text{out}} \), these two quantities are inequivalent. Again, we find the change of slopes in the \( k_{\text{in}} \) to \( N_a \) correlation at \( N_a = 10 \) for both mean and maximum of \( k_{\text{in}} \). The reduced increment of connectedness with the \( N_a \) at \( N_a \geq 10 \) suggests two categories of neighbors as show in Figure 5.6: Category 1, the closest surrounding neighbors, are always accessible as NIs. These are the neighbors which surround and cage the ego AP. The number of such closest surrounding neighbors should be around 9, which is the mean \( k_{\text{out}} \) at \( N_a = 10 \). Category 2, the neighbors at further distances, are frequently either obstructed by Category 1 or moving out of the perception range. The chance for a Category 2 neighbor to be one NI is probabilistic and, hence, proportional to \( N_a - 9 \).

\[\text{Figure 5.6: Schematic of the two categories of neighbors. Category 1, the closest surrounding neighbors, are marked and connected in purple. Category 2, which are perceptible from the spacing of the closest surrounding neighbors, are marked and connected in green.}\]
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As we propose the two categories of neighbors according to the perception, Figure 5.5 also checks the estimations of connectedness with different types of perception rules. This is achieved by taking the positions of APs and apply the accordind perception rules to determine the estimated NIs. With a knn model, i.e. TVM, the attention of \( N_a = k \) NIs is always fully loaded, and the corresponding \( k_{\text{in}} \) is the highest. The mean \( k_{\text{in}} = N_a = k_{\text{out}} \) coincides with other conventional TVM simulations (Komareji and Bouffanais 2013). The connectedness, both \( k_{\text{in}} \) and \( k_{\text{out}} \), has a linear correlation with \( N_a \). The TVM only facilitates Category 1 neighbors. If we further consider the metric perception range, the mknn model expresses a change of slope in connectedness-\( N_a \) relationship at \( N_a \geq 12 \). The differences between mknn estimations and experimental connectedness indicate the effects of perceptual obstruction in NIs. Such differences confirm that the closest surrounding neighbors of around 9 APs originate from the obstructed perception in our rules.

5.3.3 Spatial distribution of NIs

The results of Figures 5.3 and 5.5 along suggest that the complete coverage of the closest surrounding neighbors suppresses the partial collective turning events within a flock. Notably, the closest surrounding neighbors are not a set of neighbors defined by their number, but by their spatial distribution in respect to the ego AP. Figure 5.7a shows the angular distribution of NIs in respect to the orientation of the ego AP. The gaps between curves are recaps of mean \( k_{\text{out}} \) (in Figure 5.5a). In addition, we find \( \langle N_\delta \rangle \geq 1 \) for \( N_a \geq 10 \), which is equivalent to at least 1 AP in every \( [\delta - 22.5^\circ, \delta + 22.5^\circ] \). Such results suggest the closest surrounding neighbors of around 8 APs. With the full coverage
of these 8 closest surrounding neighbors, the spatial distribution of NIs is rather isotropic, which well explains the suppression to \( PT \). As discussed previously, the partial collective turning occurs with an imbalance between inter- and intra-connections of subgroups. Such an imbalance can hardly arise if all APs are isotropically connected. Interestingly, to cover all 8 closest surrounding neighbors, requires \( N_a \geq 10 \) corresponding to mean \( k_{out} \geq 9 \). The need of more NIs to include all closest surrounding neighbors coincides with the non-even angular distribution of NIs (which we discuss in the following paragraph).

From Figure 5.7a, it is notable that the shape of the distributions varies significantly from \( N_a = 8 \) to 10. Figure 5.7b shows separately the probability distributions of NIs \( P(\| \delta \|) \) with \( N_a \leq 8 \) (top) and \( N_a \geq 10 \) (bottom). For \( N_a \leq 8 \), \( P(\| \delta \|) \) are frontal centered. We understand such frontal preference by considering the “nearest neighbor” rule. As an AP travels, it approaches neighbors in the direction of orientation, increasing the chance of NI selection for neighbors in the front. Due to the obstructed perception, such a frontal preference is most significant between the closest surrounding neighbors. For \( N_a \geq 10 \), \( P(\| \delta \|) \) are double-peaked distributions. Once all the closest surrounding neighbors are included as NIs, further NIs are only accessible through the spacing between the closest surrounding neighbors, which is mainly probabilistic. Moreover, this probability for one AP to occur at the perceptible directions is mostly depending on the AP density at such directions. In other words, the double-peak distributions in \( P(\| \delta \|, N_a \geq 10) \) correspond to the elongated geometry of the flock as shown in Figure 5.2a. With the assumption of the closest surrounding neighbors (Figure 5.6), we explain the origin of the two different distributions in NIs as shown in Figure 5.7b. Meanwhile, the two distributions can also predict the flock stability. Simulation studies report that frontal perception, e.g. finite vision angle of 180°, promotes group turning in Vicsek-like models (Costanzo and Hemelrijk 2018). Combining the anisotropic NIs associated to the collective turnings, the frontal centered NI distributions are expected to cause higher \( f_{PT} \) than the more symmetric double-peak distributions.

So far, we show evidences of the closest surrounding neighbors of around 8 APs in our experiments. Here, we try to address the closest surrounding neighbors to the Voronoi neighbors (Ginelli and Chaté 2010). Given a set of points, the Voronoi tessellation divides space into cells, each enclosing a single point, and the distance to such a point within the corresponding cell is the minimum among the distances to all points. Figure 5.8a gives an example with one AP flock in our experiments. Such a diagram is used in modeling NIs to prevent arbitrary parameters e.g. metric range or number of nearest neighbors (Ginelli and Chaté 2010; Gautrais et al. 2012). By definition, the APs in the neighboring Voronoi cells, i.e. the Voronoi neighbors, of the ego AP are always safe from obstruction, but not vice versa. This makes the Voronoi neighbors the lower bound of the
5.4 Discussion

In this chapter, we study experimentally the effects of limited attention to the stability of a group of APs performing a Vicsek-like flocking model. Since the perception obtained by the APs are obstructed by each other, the attention limit $N_a$ is only an upper bound of the number of NIs. When $N_a$ allows all the closest surrounding neighbors as NIs for all APs, the potential group splitting events are largely suppressed. The minimal $N_a$ which satisfies such a criterion can be well estimated by the Voronoi tessellation. Our results connect the effects of attention to the spatial distribution of flock members and, at the same time, provide a mathematical method to estimate the minimal attention accordingly.

Compared with the conventional implementation of attention by the topological Vicsek model, attention under perceptual limits also show tendency for smaller group forming with small $N_a$ and

![Figure 5.8: The Voronoi neighbors and their number statistics.](image)
alignment across more APs with larger \( N_a \) (Komareji and Bouffanais 2013; Brown and Bossomaier 2017). However, in TVM, the agents are point-like particles: there are no limits in local density and no obstruction between agents in a crowded neighborhood. A compact super set of agents, once formed, can only obtain connections between each member regarding alignment information, even for members at the periphery (Brown and Bossomaier 2017). A SSN consisting of such super sets is fragile if the noise of the system is capable of diverging one of these subsets temporarily. As a result, TVM with \( k \)-nearest neighbors and relatively low noise in the system tends to form small flocks of \( k \) agents, where all flock mates are mutually interconnected. Similarly, small flocks of \( \approx N_a + 1 \) APs occur with \( N_a < 4 \) (Figure 5.9), where the NIs can still distribute all on one side of, rather than surrounding the ego AP. This ensures the local high density, so that under the “nearest neighbor” rule, it is unlikely for any of the flock mates to change its NIs. Such small flocks rarely occur with larger \( N_a \) as the closest surrounding neighbors at opposite ends are hardly NIs of each other. In general, the SSN in our experimental system tends to expend more isotropically. This prevents partial collective turnings or isolation of small groups.

Our rules incorporate the obstructed vision-like perception, which is reported, in experiments, to outperform either the metric or the topological models for NIs in semi-2D systems (Strandburg-Peshkin et al. 2013). In contrast to the current focus on obstructed perception e.g. regarding collective detection (Davidson et al. 2021), here we study the selection of NIs not only based on perception but also the attention. Interestingly, the minimal attention regarding flock stability occurs when the effects of obstruction become significant with increasing \( N_a \). Such effects of obstructed perception help us identifying the closest surrounding neighbors as the criterion for flock stability. In addition, we consider this obstruction constructive to the stability of the flock. The angular distributions of NIs in Figure 5.7b are more symmetric with the effects of obstruction, suggesting more resilient to partial collective turnings. Meanwhile, the average number of perceptible neighbors
5.4 Discussion

Figure 5.10: Complex group behaviors with $N_a < 10$. a-f Trajectories on top of snapshots where two AP flocks with $N_a = 8$ interacted with each other. The time intervals are 100 s. The trajectories are 60 s. In d and e, a transient rotational motion within the joint group occurred. saturates due to obstruction at $N_a > 10$ (Figure 5.5), indicating that most of the group members obtain spare attention capability. This is beneficial for groups obtain higher attention capacity but deal with tradeoff between social and e.g. environmental cues (Rahmani et al. 2020).

For the comparison with other SSNs, both the topological and Voronoi model target selection of NI rather than perception. The topological model has been suggested for collective behaviors in 3D systems, e.g. flocks of birds (Ballerini et al. 2008), where obstructions is less significant due to the relatively low density. The Voronoi model is widely considered in behavioral studies of fish in 2D (Gautrais et al. 2012). Our results show that the majority of NIs in the obstructed perception overlaps with the Voronoi neighborhood. And the minimal attention for flock stability reflects to the maximum number of Voronoi neighbors. Such a finding explains the, in generally, less NIs in Voronoi models but still feasible of capturing the collective behaviors. As a remark, it is more nature to consider the obstructed perception than the computationally expensive Voronoi tessellation when modeling individual behavior.

Our model, a Vicsek-like flocking model with relatively weak attractive interaction, exhibits complex inter- and intra-flock dynamics. Such behaviors mostly occur with $N_a < 10$. In the case of $N_a < 4$, multiple small flocks consisting of $\leq 5$ APs form and travel in directions which constantly vary. Such small flocks have no tendency to approach each other, but when they are in proximity,
they interact by exchange of members or transient merging. This is similar to the “miniflocks” in starlings under low predation risk (Carere et al. 2009) where the need of social attention regarding predation avoidance is low. In the case of $4 \geq N_a \geq 8$, the APs split into two to three flocks. The density of such flocks are lower than the cohesive single flock obtained with $N_a < 10$, and sometimes, one of such flock can further split. These loose flocks are similar to slowly dislocating foraging school of fish (Carvalho et al. 2007) where individual foraging and social alignment is in balance. With such intermediate social attention, rotational group formation arises ephemerally (Figure 5.10). The generation of rotational group by an alignment rule is achievable with Vicsek model and a visual angle $< 180^\circ$ (Costanzo and Hemelrijk 2018). We connection such finite visual angle to the frontal preference of NIs for $4 \geq N_a \geq 8$, and because of the insufficient strength of the frontal preference, the rotational formation is quite unstable. Last, the stable flocks with $N_a < 10$ corresponds to the fast moving animal groups which are usually exposed to high risk level (Carvalho et al. 2007). In such cases, the attention for social interaction is crucial for not only group coherent but also the behavior vigilance for collective detection of the threat. Interestingly, many of this living groups exhibit an elongated geometry in the direction of group motion (Carvalho et al. 2007; Carere et al. 2009), which coincides with our experimental results.

Following the discussion above, when modeling the social interactions in real living systems, the alignment order is not always optimized. Collective animal groups constantly change headings and even transit between collective patterns, e.g. from swarm to flock or temperate group splitting, to respond to the environments. This high diversity of collective motions suggests that collective animals might spend less attention than the minimal $N_a$ that promotes high flocking stability. For example, studies report NIs of 6 to 7 neighbors in flocks of starlings (Ballerini et al. 2008), which exhibit highly dynamic formations. With an additional attractive interaction rule which dominates for long inter-agent distances, e.g. attraction zone in zone models (Aoki 1982; Zheng et al. 2005), the slightly unstable flocking conditions, found in this work, would enable complex collective patterns responsive to perturbations, while the attractive rule ensures group cohesion or re-merging after temperate splitting.
Conclusions

In this thesis, I present experimental studies of collective behaviors with an active colloidal model system based on animal behavior-inspired social interactions. This model system consists of feedback-controlled light-steerable colloids as robotic agents which perform motion regarding forward propulsion and reorientation according to behavioral rules and individual perceptions. The capabilities of manipulating and acquiring individual perception and decisions of motion unravel the complex structures of the collective groups and their relation to the individual behaviors of group members.

In the first experimental work, we target the connection between cooperative motion of individuals and the group-level performance in the case of a threat-avoidance scenario. Our model, based on the swirling social behavioral rules, facilitates group response without explicitly modeling individual escape. In fact, even the relative position of the threat from the perception of the individual is reduced to binary information. Still the group transform from the stationary formation of a swirl into an escaping flock fleeing precisely opposite to the direction of the threat. Such behavior model exploits the emergent properties of social interactions to determine the spatial information of the threat through a collective decision-making process. Further analysis shows this collective decision-making originating from the dynamical structure of the group, which, in our experiments, can tolerate individual misdetection rate to the threat up to 60%. This findings suggest that group cohesion enables collective benefits e.g. enhanced vigilance via group structures.

The misdetection and presence of the threat is implemented by directly manipulating the perception of the robotic colloid, allowing in situ control and recording of the behavioral model inputs. While the particle motion is still bound to physical interactions between the particle steering mechanism and the surrounding environment, the behavior of the robotic colloid is not deterministic to the model outputs alone. With such accessible information in the realistic system, we reveal the major information sharing mechanism which is interesting in both the studies of functioning
6 Conclusions

and decision-making of collective groups. In the end, we provide a profound example of collective benefits which reflects to vital response to the environment of animal groups. Such an example contributes to both “why” and “how” gregarious animals perform cooperative movements.

In the second work, we investigate further the information sharing and group consensus with a flocking model where direct information transferring is limited by both realistic perception and finite attention capacities. Effects of limited attention has been previously studied with network analysis, but not with the considerations of the physical constrains in groups of real agents, which occupy space, obstruct other peers behind them and can only perceive peers within certain range. Our experimental approach incorporates all these factors, and finds the crucial connection between information network and the spatial distribution of group members. When the attention capacities allow an rather isotropic close ring of neighbors as the neighbors of interaction, the group consensus is significantly strengthened. The number of such closest surrounding neighbors can be estimated by the maximum Voronoi neighbors.

This unique correlation between signaling networks and real-space configurations is a profound characteristic of animal collective behaviors. In our experiments, the flock of robotic colloids form swarm signaling network which exchanges the moving directions by mimicking the motion of neighboring peers, i.e. local alignment. Unlike most of the network figures where fixed network topology determines the performance, the swarm signaling network is connected based on the positions of the individuals. Such positions vary in time according to the information, i.e. direction to align with, flowing in the network. As a results, selective connections with anisotropy enhances fluctuations in a local subnetwork and, eventually, promotes isolation and group splitting. Such findings suggest that the geometry in real space is more crucial than the simple parameter of number of connections in swarm signaling networks.

In both of the presented works, we report important findings and aspects regarding information sharing and cooperative movements of collective robotic swarms of colloids. These works not only connect to the studies of animal behaviors, but can also inspire the design of robotic systems. The collective threat-avoidance model provides an example regarding the division of workloads, where each group member only process the binary information of the position of the threat. As the complete spatial information is resolved by intragroup dynamics, such sensing and navigation task does not require all group member to participate in. The overall functions of the group is increased without enhancing individual capabilities. The flocking model with attention limits indicates the important factors for robotic agents to move in steady formations. The essential information from neighboring peers should distribute isotropically for an individual to stabilize its motion for a group. Furthermore the number of such neighbors can be estimated with Voronoi tessellation of
the spatial distribution of the group formation. While many of the swarm robotic design is inspired by nature, our studies with real world experiments can also contribute.

As an outlook, the potential of experimental studies on animal collective behavior remain abundant. These collective patterns occur across a wild range of scales and environments. On one hand, it would be beneficial to set up experimental systems in different length scales to fully exploit the advantages of investigations in real world. On the other hand, the demonstrated works with robotic microswimmers have not yet exhaust the possibilities in such system. Collective behaviors of microbes also exhibit high diversity and complexity. Due to the recurring viscoelastic environments of such entities, corresponding simulation studies are still rare or with much simplification. Extending our experimental approach into viscoelastic system would contribute significantly to our understanding and related applications.
References


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