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Emergence of the scale-invariant proportion in a flock from the metric-topological interaction

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ABSTRACT

Recently, it has become possible to more precisely analyze flocking behavior. Such research has prompted a reconsideration of the notion of neighborhoods in the theoretical model. Flocking based on topological distance is one such result. In a topological flocking model, a bird does not interact with its neighbors on the basis of a fixed-size neighborhood (i.e., on the basis of metric distance), but instead interacts with its nearest seven neighbors. Cavagna et al., moreover, found a new phenomenon in flocks that can be explained by neither metric distance nor topological distance: they found that correlated domains in a flock were larger than the metric and topological distance and that these domains were proportional to the total flock size. However, the role of scale-free correlation is still unclear. In a previous study, we constructed a metric-topological interaction model on three-dimensional spaces and showed that this model exhibited scale-free correlation. In this study, we found that scale-free correlation in a two-dimensional flock was more robust than in a three-dimensional flock for the threshold parameter. Furthermore, we also found a qualitative difference in behavior from using the fluctuation coherence, which we observed on three-dimensional flocking behavior. Our study suggests that two-dimensional flocks try to maintain a balance between the flock size and flock mobility by breaking into several smaller flocks.

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1. Introduction

In models of flocking, it is generally assumed that individuals, called 'agents' generally, interact with those inside a given neighborhood. One notion used to define such a neighborhood is metric distance: that is, an agent interacts with exactly those individuals within a particular distance of the agent. The prototype of the metric distance flocking model was proposed by Reynolds (1987). In his model, which was developed to explain various formations of flocks, each agent has a fixed interaction length and the interaction neighborhood is divided into three zones: the repulsion zone, from whose members the agent heads away; the alignment zone, whose members' heading the agent tries to match; and the attraction zone, toward whose members the agent heads. Vicsek's model, the self-propelled particle (SPP) system, can be considered as an abstraction of Reynolds's model (Czirok and Vicsek, 2006; Szabó et al., 2009; Vicsek et al., 1995). In contrast to Reynolds's model, Vicsek's model has only one area (the alignment zone) but includes external noise. The SPP model exhibits an alignment phase transition as the noise parameter or population density is varied. Although the SPP model is typically used to study physical phenomena, such as statistical mechanics and hydrodynamics (Buhl et al., 2006), density dependence of the phase transition has also been reported in studies of locusts (Parrish, 1999) and schools of fish (Bertin et al., 2006). Despite their focuses on different types of collective phenomena, these models are both based on the concept that each individual unit (particle, bird, fish, etc.) interacts *locally* in a given space and that global properties spontaneously emerge from these local interactions, rather than from a central control.

Collective behavior has been widely accepted as a good example of self-organization (Goldstone and Gureckis, 2009; Moussaid et al., 2009; Sumpter, 2006). Indeed, models based on metric distance have been successfully used to explain various forms of collective behavior. Couzin's famous simulation, for instance, not only showed various formations in schools of fish, but also the possibility of collective memory (effects from past formations) in schools of fish (Couzin et al., 2002). The virtue of this kind of model is that it represents the relationship between the parts and the whole

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system in an abstract way. Individuals interact and collective behavior emerges from the whole group. Although some models used for solving the equations governing agent motion also represent the type of formation (Dossetti et al., 2009; Strefler et al., 2008), this kind of method obscures the issue of the cognitive perspective of an agent's neighbors. Therefore, the metric distance model has been considered sufficient for modeling collective behavior sufficiently well until recently (Grégoire et al., 2001a,b; Grégoire and Chaté, 2004; Hemelrijk and Kunz, 2005; Hemelrijk and Hildenbrandt, 2008, 2011; Hildenbrandt et al., 2010).

Ballerini et al. (2008a,b) have empirically shown that birds do not interact with their neighbors according to metric distance but instead employ topological distance. The meaning of topological distance in that instance is that a bird interacts with its nearest seven neighbors, no matter how far away they are. The results of that research can be compared with other empirical results (fishes, birds, and elephants, for example, can count up to three or four (Agrillo et al., 2008, 2009; Feigenson et al., 2004; Hunt et al., 2008; Sugimoto et al., 2009)) and support the "magic number seven" hypothesis, which states that the limit of the cognition of an individual is concentrated around the number seven, plus or minus two (Miller, 1956). However, there is a difference between counting neighbors and keeping track of certain neighbors. These empirical observations suggest that limitations on animal cognition are an important factor in flocking behavior. A model based on metric distance, for instance, may ignore the limits on animal cognition because the abstract agent can interact with all nearby neighbors, no matter how many. Additionally, Ballerini et al. (2008a,b) simulated flocks formed under these two types of distance and suggested that a flock formed by topological distance is more robust to predator attacks than a flock formed by metric distance.

The problem with using topological distance, however, is the limit on information transfer. If each bird interacts with only seven neighbors, the speed and accuracy of the information transfer will be degraded for larger flocks. To move as a large flock, each agent in the flock must share information that is as accurate as possible across a domain whose typical size exceeds the allowed topological distance. Recently, Cavagna et al. have suggested the existence of a correlated domain with respect to fluctuation vectors in real flocks (Bialek et al., 2012; Cavagna et al., 2010). (In their model, an individual's fluctuation vector is determined by subtracting the average velocity vector of the flock from the individual's velocity vector.) Furthermore, they found that the size of the correlated domain was proportional to the flock size (Bialek et al., 2012; Cavagna et al., 2010), encompassing nearly 30% of the whole flock. It should be noted that the size of this correlated domain is much larger than both the metric and topological interaction distances. This suggests the occurrence of indirect information transfer, mediated by direct interactions between individuals who are metric or topological neighbors. By sharing information across a large area, the flock easily responds to external perturbation.

This discovery of a scale-free correlation (SFC) also suggests the dynamical nature of information sharing in a flock. The correlated subdomain can contract and expand with changing motion and flock shape because correlated domains are proportional to flock size. This raises the question: How does each bird evaluate the size and shape of the flock? It is not obvious that direct interaction leads to information sharing across large areas. Cavagna et al. explained this in the SPP model, which can generate SFC if an appropriate noise level is given. Generally, the correlated domain is larger for lower external noise. To generate SFC, each individual in the flock should have the ability to tune the noise (or degrees of freedom). In this study, the main aim is to consider how to reach and maintain the proper level of noise under various conditions. In other words, each individual should be thought of as actively adjusting its degrees of freedom (or noise) under uncertain conditions.

The role fluctuational coherence, which is observed with scale-free correlation, in collective behaviors is still unclear. For example, it is assumed that flocks of birds have the highest sensitivity to external perturbations when the flock is at a critical point. A large correlation domain inside of the flock allows easier avoidance of predator attacks at the group level. However, this argument holds only when each agent can move in three dimensions. How about two-dimensional cases? The situation is radically different when each agent is restricted to a plane, because predator attacks can come from the sky; for example, Asian soldier crabs (*Mictyris brevidactylus*) are preyed upon by birds such as sandpipers (*Scolopacidae*) (Takeda and Murai, 2004). When flocking behaviors are restricted to a plane, it is hard to avoid an out-of-plane predator attack by maintaining a single collective. With out-of-plane predators, the risk is not mitigated when agents maintain one collective. Therefore, agents limited to a plane need a different method of structuring correlation domains than agents with three-dimensional movement if SCF is to be achieved for the two-dimensional case.

In a previous study, we proposed a model that takes account of both the topological distance and the metric distance (Niizato and Gunji, 2011, 2012). By using both models for interactions, we express an ambiguity in interactions from the cognitive perspective: cognition as a class (this corresponds to the metric distance) and cognition as a collection (this corresponds to the topological distance). These notions will be discussed in the next section (or see Niizato and Gunji, 2011, 2012). Although we have used the metric-topological interaction (MTI) model in three dimensions to show the existence of SFC and some other nontrivial properties (Niizato and Gunji, 2012), it is still uncertain whether this model also holds in two dimensions. To address this, we first show that this model has a correlation domain with fluctuations, and that this model closely simulates real flocks and exhibits SFC for a wide range of parameter values. Then, we examine how this SFC is expressed when flocking behaviors are restricted to a plane. As a result, we find that a power law relation between the flexibility of flock movement and flock size. Our study suggests that SFC in two dimensions aids optimal sizing by adjusting between speed of information transfer and flexible movement as one flock.

2. Metric-topological interaction model

The MTI model was proposed to close the gap between the metric and topological distance models (Niizato and Gunji, 2012). The motivation for the MTI model is as follows. Topological distance is implicitly based on metric distance because an agent employs metric distance to recognize its nearest neighbors. Additionally, the notion of metric interaction is also an implicit assumption of topological interaction because the radius of each neighborhood has to be adjusted according to the number of agents present in the neighborhood. We re-interpreted these two neighborhoods as corresponding to notions of cognition as a class and cognition as a collection. To distinguish these notions, we can consider the cognitive context in which each agent interprets collective behavior. Although a population of individuals is understood and averaged by agents (cognition as a collection), these individuals are collected in terms of distance, which is evaluated by role (cognition as a class). Thus, one interpretation is that cognition as a class corresponds to metric distance interactions and cognition as a collection corresponds to topological distance interactions. These notions are not unnatural. For example, fishes may have two systems to recognize conspecifics. One is the system that distinguishes small numbers of objects (Agrillo et al., 2008), and the other is the system that distinguishes numerical ratios, such as 1:2 or 2:3

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