FLOCK MEMBERS EXPERIENCE GAS PRESSURES HIGHER THAN LONE INDIVIDUALS

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ABSTRACT

Local interactions between flock members in absence of centralized control generate collective dynamics characterized by coherent large-scale patterns. We investigate whether aggregates of individuals like birds, swarms and fishes behaving in concert with their neighbors may modify the physical properties of the fluid medium in which they are embedded. Using the K-Nearest Neighbours algorithm to simulate collective animal behavior, we showed that the occurrence of collective dynamics can modify the physical parameters of the phase space in which the interacting individuals' trajectories take place. This means that lone individuals experience the nearby fluid medium (i.e., the air in case of birds/insects and the water in case of fishes) differently from flock members. In particular, our framework suggests that a bird belonging to a group and acting collectively with its neighbours perceives the nearby atmosphere as denser, compared with an isolated bird.

Keywords: Collective behavior; topological distance; flow.

INTRODUCTION

Collective animal behavior emerges from simple local rules of interaction among neighbor individuals in absence of centralized control (Ballerini et al., 2008; Cavagna et al., 2010). Self-organized global order consists of coherent and collective large-scale patterns generated in large interacting systems (Bialek et al., 2012; Mora et al., 2016). Scale-free changes in the behavioral state of one animal affect and are affected by those of all other animals, no matter how large the group is (Cavagna et al., 2019). Numerical models as well as experimental findings suggest that the mechanism of group formation is universal, transcending the detailed nature of its components (Attanasi et al., 2015; Hughey et al., 2018). Computational models assessing collective animal behavior like bird flocks are based on a few empirical rules (Reynolds 1987):
1) Attraction among individuals grants cohesion of the aggregation, ensuring that no bird remains isolated.
2) Short-range repulsion zone of the order of the wingspan prevents dangerous proximity and avoids collisions, thereby preserving individual integrity (Ballerini et al., 2008).
3) Alignment of the velocities allows birds to fly in the same direction, keeping similar speed and direction.
4) Noise must be kept into account when drawing the proper equations (Giardina 2008).

The experimentally assessable interacting flock members' physical features include shape, movement, density and structure, as well as subtler features such as directional polarity, average group speed, marginal speed, changes in flock shape, local density-density correlations, information transfer, topological distance, bearing angle, distance to nearest neighbors, two-points correlation function, coexistence of multiple timescales, etc. (Cavagna et al., 2022; Bialek et al., 2012; Chen et al., 2023).
Here, using two-points correlation function, we asked whether lone individuals might experience physical forces differently from groups of interacting individuals. We exploited the K-Nearest Neighbors (k-NN) algorithm to evaluate whether increases in the number of interactions among neighbour individuals lead to physical changes in the surrounding environment. In particular, we investigated whether lone birds experience the air masses surrounding them differently from birds belonging to flocks.

k-NN ALGORITHMS AND COLLECTIVE BEHAVIOUR

To evaluate the interactions among individuals during collective behavior, we focused on the K-Nearest Neighbours algorithm, also known as KNN or k-NN (Cover and Hart, 1967; Holmes and Adams, 2003). It is a nonparametric, supervised learning algorithm that uses proximity to catalogue the grouping of individual data points in a phase space (Rajagopalan and Lall, 1999). It is usually used as a classification algorithm based on the assumption that similar points can be found near one another (Bang-Jensen et al., 2004). It does not require prior assumptions as to the form of the variables' joint probability density function (Rajagopalan and Upmanu, 1999).

We coloured each point of the two-dimensional plane with the class that would be assigned to it using the k-NN algorithm, so that the 0/1 values were conventionally color-coded red and blue. In terms of collective animal behaviour, the 0/1 values had the following meaning:

1) The 1-valued blue shapes stood for the space occupied by interacting flock members.
2) The 0-valued red shapes stood for the space occupied by the fluid medium (either gaseous in case of birds or insects, or liquid in case of fishes) surrounding the interacting flock members.

To provide a few examples, the blue shapes might stand either for bird flocks, or mating swarms of mosquitoes and midges, or for a school of fish, while the red shapes might stand for the surrounding air or water provided with physical parameters like pressure, density, temperature, local turbulence, etc.

We performed a k-NN algorithm simulation on an original picture depicting red and blue shapes (**Figure**). We run the Stanford Vision and Learing Lab's interactive K-Nearest Neighbours Demo (http://vision.stanford.edu/teaching/cs231n-demos/knn/) using the following parameters:

a) Number of points: 60 (corresponding to the number of individuals is a flock).
b) Metric: L1 norm (Lasso regression).
c) Number of neighbors (K) =1-7.

As far as we are concerned with collective animal behaviour, the k-NN algorithm's most relevant parameter is the K value, i.e., an arbitrary number defining how many neighbours will be checked to determine the classification of a specific query point, i.e., a single individual (Lipsky and Porat, 2008). The number of neighbours K entails the similarity between a single point and the surrounding ones such that the higher the K, the higher the number of assessed correlations between adjacent points. The higher the number K, the higher the likelihood for neighbor individuals to perform the same physical movements (Patwardhan et al., 2023). In biological terms, this means that the higher the number K, the more the single individuals like birds, insects and fishes will behave in concert with their neighbors, displaying the same physical features like speed, or polarization, or direction, or bearing angle, etc. When the minimum default value of 1 is assigned to K, only one neighbor is used for the prediction and the instance will be assigned to the same class as its single nearest neighbor. In turn, when K corresponds to the maximum number of available data points, all the individuals in the flock are used for prediction.

We ended up selecting a number K corresponding to odd numbers between 1 and 7 for two reasons. First, it is recommended to have an odd number for K to avoid ties in classification. Second, it has been established that every bird in a flock interacts on average with a fixed number of six to seven nearest neighbors, independent of density fluctuations (Ballerini et al., 2008; Bialek et al., 2012). This interaction with the 6-7 closest neighbors does not depend on the metric distance or a fixed-size neighborhood, but rather on the topological distance (Niizato et al., 2014; Kumar and De, 2021). In brief, the best way to assess any change in physical parameters during collective animal behavior is to evaluate what happens to the surrounding environment when 6-7 neighbor individuals act collectively.

The **Figure** suggests that the higher the K, the more the blue shapes are extended. In turn, the higher the K, the more the red shapes shrink. The red surface covers 40.625% of the total surface of the original two-dimensional picture, while it covers 28.125% of the total surface of the picture corresponding to K=7. This suggests that the stronger the physical correlation among neighbors, the smaller the surface occupied by the nearby physical environment.

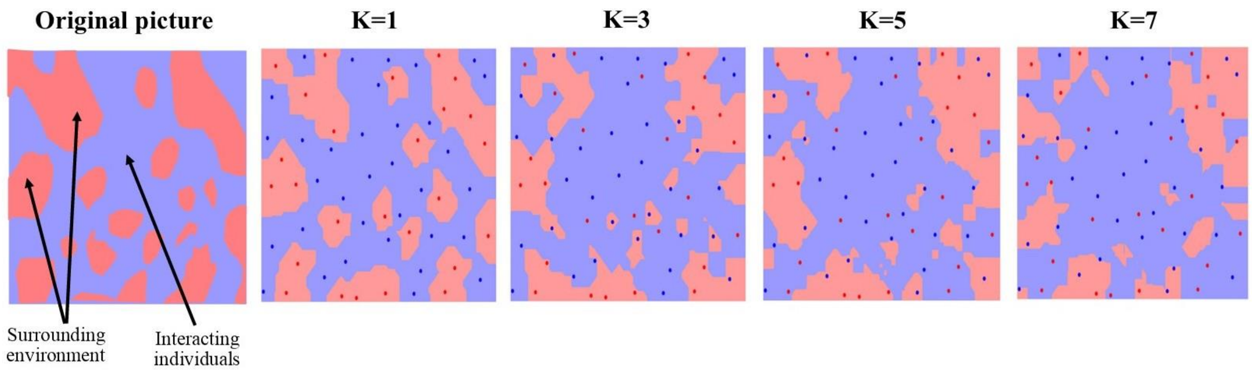

Figure. K-Nearest Neighbours algorithm's processing of a two-dimensional phase space consisting of shapes of different colors, standing for interacting flock members performing collective movements (blue) and the surrounding fluid medium (red). As the number of neighbours K increases, the surface of the red shapes decreases and the surface of the blue shapes increases.

ENERGY & PRESSURE DURING NEIGHBOURS INTERACTIONS

Once established that increases in K lead to shrinking of red shapes and dilation of blue shapes, the next step is to look for k-NN algorithm's feasible physical counterparts. By a physical standpoint, the blue shapes might represent individuals performing collective movements, while the red shapes might represent fluid objects mixed with these individuals. The red shapes might stand for fluid physical systems (henceforward FPS) surrounding the flock members. FPS are provided with experimentally quantifiable amounts of energy, volume and surface. To give an example in terms of collective animal behavior, the blue shapes could stand for bird flocks flying in the air. The air (corresponding to the red shapes) could be supplied with physical features such as friction, variation in pressures, density, etc.

Our k-NN simulations suggested that increases in K lead to decreases in red shapes' surfaces. This means that the larger the aggregates of individuals with the same behavior (blue shapes), the lower the surface of the nearby FPS (red shapes). The FPS' surface tension can be experimentally calculated and expressed in energy per unit area (J/m^2). If the energy endowed in FPS is preserved, decreases in surface lead to increases in surface tension. The layout holds not just for the two-dimensional phase space described in the original two-dimensional picture, but also for three-dimensional phase spaces. In three-dimensional phase spaces, the higher the number K, the smaller the FPS' volume. The pressure exerted by FPS can be experimentally calculated and expressed in $P = J/m^3$, corresponding to the fixed amount of energy J stored inside FPS per unit volume. If the amount of energy stored in FPS is kept constant, increases in K lead to decreases in FPS volume. Therefore, the pressure inside three-dimensional FPS increases when K increases.

Boyle's law suggests that the pressure is directly proportional to the density of any fluid object (Webster 1965). If the temperature is kept constant, increases in pressure lead to increases in fluid object's density. Therefore, increases in number K lead also to changes in FPS' density. This means that flying flock members behaving collectively experience an atmosphere that is denser, compared with the atmosphere experienced by lone birds.

Summarizing, by the standpoint of a flock with collective movements, our framework suggests what follows: when interactions among neighbors strengthen, the density, the pressure and the surface tension exerted by the nearby air are perceived as increased by every individual belonging to the group.

CONCLUSIONS

We argued that collective dynamics modify the physical parameters perceived by neighbor flock members, depending on the amount of their aggregation. A bird acting collectively with other 5-6 birds will perceive a given pressure from the surrounding air, while a lone bird will perceive a pressure that is lower. We contend that the k-NN algorithm is not just a methodological device for objects classification, but rather displays a physical counterpart too. The higher the similarity between a single point and the surrounding ones (expressed by higher values of K), the more the fluid objects embedded in the phase space are shrunken. Being the red shapes physical fluids that encompass an amount of energy and exert a certain pressure, increases in K lead to increase in the pressure exerted by the red shapes on the blue shapes. We suggest the possibility to introduce a relative physical quantity, namely the k-nearest neighbours pressure, i.e., a change in pressure depending on the relationships among the flock members in the phase space.

Compared with lone individuals, the perception of physical parameters varies by the standpoint of a bird belonging to a flock. This claim could be generalized by other types of collective movements in which physical parameters such as volumes, surfaces, magnetic field's density, etc., can modify. For instance, different degrees of biological aggregation, such as cell–cell adhesion processes or clusters of migrating cells, may lead to changes in volume energy densities (Cox and Smith, 2014). Another feasible example of highly varying biological aggregation might consist of oral biofilms harbouring microbial clusters interspersed with salivary fluid (Perez-Tanoira et al., 2019; Simon-Soro et al., 2022; Martínez-Hernández et al., 2023). Interacting individuals displaying collective behavior must be regarded not just as passive objects inside energy fields' gradients, but rather in terms of active agents able to modify the energy gradients surrounding them.

Our insights might contribute to explain unusual features of flocks' self-organized processes. To provide an example, the energy required to compress a gas to a certain volume can be calculated by multiplying the difference between the gas pressure and the external pressure by the change in volume, such that:

$$(Pi - Pe) \times \Delta V$$

This means that the pressure exerted by flock members contributes to increase the pressure inside FPS, with effects on the flocks' dynamics. Yet, the fact that the density within the flock is nonhomogeneous, as birds are packed more tightly at the border than the center (Ballerini et al., 2008), might be explained by the fact that the pressure exerted by the surrounding air is higher on the boundary of the aggregation. In close similarity with the complex patterns displayed by birds' collective escape under predation (Papadopoulou et al., 2022), it could be hypothesized that the closer the high-

pressure FPS is perceived by the flock members, the higher the frequency of their collective turning maneuvers. Further, it could be hypothesized that nearest neighbors are more likely to be found on the sides rather than in the direction of motion (Giardina 2008) in order to avoid the increased pressure caused by the surrounding FPS.
In conclusion, we suggest that the very collective dynamics among neighbor flock members could modify the physical features of the nearby environment.

STATEMENT

The author warrants that the article is original, does not infringe on any copyright or other proprietary right of any third part, is not under consideration by another journal, and has not been previously published.
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