Excerpt from

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1. Introduction

Collective animal behaviour is a fascinating field that analyses how simple actions of an individual influence the complex global dynamics of a group. Aristotle once stated: "The whole is greater than the sum of its parts."—a statement that describes the essence of collective animal behaviour. Typical examples are flocks of birds, schools of fish, swarms of insects, and herds of ungulates; phenomena that can be easily observed in nature. Results from studies of collective animal behaviour are useful for scientists from many different research fields—biology, physics, medicine, to computer science, and control theory [9, 25, 28, 39, 41, 43, 44]. Since humans behave similarly as groups of animals in a wide repertoire of situations (e.g. traffic jams and behaviour at large-scale events, such as sport games, and music concerts) collective animal behaviour is also interesting from the social studies perspective [37, 39, 44].

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With computational models it has been demonstrated that complex collective animal behaviour can emerge if individuals follow simple rules or *drives*. The first attempts at modelling collective animal behaviour via individual-based models were made in the 1980s. Aoki [1] proposed a bottom-up approach to the simulation of schooling mechanisms in fish. Reynolds [34] presented the first computer model for procedural animation of flocking birds. Heppner & Grenander [18], working on a similar project, modelled the behaviour of birds with stochastic non-linear differential equations. These and subsequent individual-based models [8, 11, 12, 19, 25, 32, 35, 39, 40] typically describe the artificial animals (*animats*) through perception, drives and action selection [24]. They differ in the way they implement individual parts, but in most models the behaviour is a constant blending of three drives called *cohesion*, *separation*, and *alignment*.

Cohesion denotes the attraction toward other individuals and is usually modelled as the tendency to move towards distant individuals when there are none nearby. Separation models the tendency to move away from neighbours that are too close, to avoid collisions. The third drive–alignment–models the tendency to synchronize velocity (direction and speed of movement) with nearby neighbours. As a perfect synchronization of movements will prevent collisions and dispersion the alignment drive can be interpreted also as a passive form of avoidance and attraction, and due to this some models concentrate exclusively on the alignment drive [41].

Most of the models encode the drives by means of equations, where for example cohesion is typically encoded as a force vector directing the animat towards the centroid of nearby neighbours [25, 40]. Some models, however, encode the drives by means of fuzzy rule-based systems to facilitate the use of expert knowledge in the construction of additional drives [10, 11, 13, 26].

Perception and the act of filtering out only the most important information about the surrounding environment is typically modelled either as *continuous* or *zone-based*, and *metric*, or *topological*. In the case of a continuous perception, all drives are computed based on the same set of nearby neighbours [18, 26, 34], whereas in the case of a zone-based perception, specific drives take into account only neighbours that are within a specific zone [1, 8, 14, 15]. While most models use a *distance-limited* (metric) perception, where the set of individuals with which an animat interacts is limited by distance, some studies suggest that interaction is *number-limited* (topological) [2]. In this case an animat interacts with a specific number of closest neighbours, regardless of their distance. Research suggests that in the case of topological perception, which is also spatially balanced, groups are more stable then in the case of a metric perception, and more resilient to external perturbations [5].

A combination of the metric and topological perception, where animats perform a double evaluation of their drives (one with metric, one with topological perception), was, on the other hand, proposed by Niizato & Gunji [29]. This *metric-topological* perception generates inherent noise and prevents the collapse of the group, while producing a scale-free correlation [30, 31]. However, Viscido, et al. [42] and Hemelrijk & Hildenbrandt [16] suggest that there is a strong influence of the number of influential neighbours on the properties of the group. Shang & Buffonais [36] suggest that interaction with approximately 10 closest neighbours speeds up the rate of convergence to consensus, irrespective to the group's size. In addition, a recent study by Hemelrijk & Hildenbrandt [17] suggests that there may be differences in topological range for avoidance versus attraction and alignment, thus also providing further evidence for the use of zone-based perception. Indeed, the study was able to reproduce empirical data from physicists in Rome [6] by assuming that individuals avoid a single closest neighbour only and align with and are attracted to their seven closest neighbours. Similarly, but with continuous metric perception, where the probability of interaction between two individuals was inversely proportional to their distance, Bode, et al. [4] were capable of replicating the anisotropic nature of interactions observed in an older empirical study by the same group of physicists in Rome [2, 3].

In the case of individual-based models that use fuzzy rule-based systems to encode the drives [10, 11, 24, 26] perception can be viewed as a mixture between a continuous and a zone-based one, regardless if it is implemented as metric or topological. In other words, even if all drives are computed based on the same set of nearby neighbours, the use of rules that take into account their distances, allows to achieve a similar effect as a zone-based perception (i.e. rules of individual drives can be used to create either strong, blurred or non-existing inter-zone boundaries).

Recently, researchers are concentrating on *visual* perception. For example Lemasson, et al. [27] investigate motion-guided attention. Other studies either concentrate on taking into account visual occlusion regardless if perception is implemented as continuous or zone-based, metric or topological [10, 11, 20], or select the interacting individuals [38] or compute drives [7, 33] based on the occupied angular area on the retina of the observed animat. Larsson [21–23], on the other hand, proposes a multi-sensory approach to perception.

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