Simulation of biological systems: Swarm intelligence

Aurélie Maillard

1 Modelling collective behaviour

1.1 Features of collective behaviour

Collective behaviour has been defined in many ways, but some features are recognized as essential:

- Collective systems operate without central control. The group level behaviour and properties arise spontaneously from the local behaviour of the individuals in the group, and no individual directs the behaviour of others.
- The individuals interact with one another, but because individuals typically do not have global knowledge about the whereabouts and behaviour of all the others, these interactions are local.
- Collective behaviour in nature always performs some biological function.

1.2 Concept of self-organization

The central tenet of self-organization is that simple repeated interactions between individuals can produce complex adaptive patterns at the level of the group. The suggestion is that biological structures can be explained in terms of repeated interactions between the animals and their environment, without invoking individual complexity.

1.3 Example of self-organization: Couzin et al. model

Couzin et al. present a self-organizing model of group formation in three-dimensional space, and use it to investigate the spatial dynamics of animal groups such as fish schools and bird flocks.

1.3.1 Behaviour rules

The behaviour of individuals is resulting from local repulsion, alignment and attractive tendencies based upon the position and orientation of individuals relative to one another.

N individuals with position and unit direction vectors are simulated in continuous three-dimensional space. In each time step, individuals assess the position and/or orientation of neighbours within three non-overlapping behavioural zones: zone of repulsion (ZOR), zone of orientation (ZOO) and zone of attraction (ZOA). This information is used to determine a desired direction for each individual for the successive time step using the following behaviour rules:

- **Rule 1:** Each individual attempts to maintain a minimum distance from others between themselves and others at all times within ZOR. The ZOR can be interpreted as individuals maintaining personal space, or avoiding collisions.
- **Rule 2:** If individuals are not performing an avoidance manoeuvre (no neighbours are within the ZOR) they tend to be attracted towards other individuals within the ZOO (to avoid being isolated) and to align themselves with neighbours within the ZOA. The attraction represents the tendency of organisms to join groups and to avoid being on the periphery, whereas the orientation allows collective movement by minimizing the number of collisions between individuals.

1.3.2 Analysis of the model

To understand the influence of individual differences on spatial position within a group, we investigate the consequence of variation in speed, turning rate, error and size of zones among individuals within a group. For each combination of parameters, individuals start with random orientations and at random positions within a sphere in which each can detect at least one individual.

Two global properties of the model are calculated from the integrated trajectories of all the individuals. Group polarization p_{group} measures the degree of alignment among individuals within the group. Group angular momentum m_{group} measures the degree of rotation of the group about the group center.

1.3.3 Results and discussion

Four collective dynamic behaviours As the width of the behavioural zones changes, the collective behaviour of the system exhibits sharp transitions between four collective dynamical behaviours:

- **Swarm:** An aggregate with cohesion, but a low p_{group} and low m_{group}. This occurs when individuals perform attraction and repulsion behaviours, but little or no parallel orientation.
- **Torus:** Individuals perpetually rotate around an empty core (milling). The direction of rotation is random. p_{group} is low, but m_{group} is high. This occurs when Δr_o is relatively small and Δr_a is relatively large.
- **Dynamic parallel group:** The group exhibits high p_{group}, but low m_{group}. This type of group is much more mobile than the swarm or torus, and occurs at intermediate values of Δr_o with intermediate or high values of Δr_a.
- **Highly parallel group:** As Δr_o increases, the group self-organizes into a highly aligned arrangement (very high p_{group}) with rectilinear movement (low m_{group}).

Our model exhibits several collective behaviours, with sharp transitions between them. Small changes in individual responses result in large changes in group properties and organization. The model predicts that animal groups, such as fish schools, change rapidly between these states since intermediate group types are relatively (dynamically) unstable. Biologically the transitions are important in allowing animal groups to change from one type of group structure to another in response to internal or external stimuli. The tendency of individuals to align with one another within the parallel group types is important in allowing the group to transfer information.

Self-sorting Differences in speed, turning rate and size of zones all influence the distribution of individuals relative to either, or both, the center and front of groups. For example, speed is strongly positively correlated with being at the front of the group, showing that faster individuals tend to occupy positions near the front of moving groups. Faster individuals also tend to be further from (negatively correlated with) the group center.

Behavioural and/or motivational differences between organisms may have an important structuring influence when animals aggregate. Individuals may change their position relative to others within groups based upon internal state. Individuals can modify their position within groups by several potential self-organizing mechanisms. This sorting depends on the relative difference between individuals. If individual differences in behaviour are intrinsic, the system will reassemble forming the same configuration after perturbation from that state. Individuals with similar behaviours tend to become aggregated within the group.

2 Swarm intelligence algorithms

Swarm intelligence algorithms are defined as algorithms that are based on and inspired by the swarms of the nature, like swarms of birds, animals and insects.

There are many reasons for such popularity and attention, and two main reasons are probably that these SI-based algorithms are flexible and versatile, and that they are very efficient in solving nonlinear design problems with real-world applications. Bio-inspired computation has permeated into almost all areas of sciences, engineering, and industries, from data mining to optimization, from computational intelligence to business planning, and from bioinformatics to industrial applications.

2.1 Examples of SI-based algorithms

- Ants- and bees-inspired algorithms are particularly suitable for discrete optimization problems (combinatorial optimization such as routing and optimal paths).
- Particle swarm optimization proves efficient in solving business optimization problems.
- Firefly algorithm can efficiently solve NP-hard scheduling problems.

There are many other SI-based algorithms, which may be equally popular and powerful and these include Tabu search (Glover and Laguna, 1997), artificial immune system (Farmer et al., 1986), wolf search algorithm and others.