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An index for quantifying flocking behavior

Vicenç Quera, Salvador Herrando, Francesc S. Beltran, Laura Salas and Meritxell Miñano

Grup de Conducta Adaptativa i Interacció, Universitat de Barcelona

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Abstract

One of the classic research topics in adaptive behavior is the collective displacement of groups of organisms such as flocks of birds, schools of fish, herds of mammals and crowds of people. However, most agent-based simulations of group behavior do not provide a quantitative index for determining the point at which the flock emerges. We have developed an index of the aggregation of moving individuals in a flock and have provided an example of how it can be used to quantify the degree to which a group of moving individuals actually forms a flock.

Measuring flocking behavior:

An index for quantifying the coordinated movement of individuals

Moving in a coordinated way is common behavior throughout nature. Flocks of birds, schools of fish, herds of mammals and even crowds of people are systems composed of a certain number of individual entities that coordinate their movements in order to achieve coherent displacement. All these systems share common properties that have been studied using mathematical models (Okubo, 1986; Tanner, Jadbabaie & Pappas, 2003) and rule-based models (Aoki, 1982; Huth & Wissel, 1994). The latter implement rules that generate complex behavior and use agent-based computer simulation to create an artificial world where virtual agents react in accordance with the signals of the environment and act by following simple low-level rules in order to achieve an established goal (Maes, 1997).

In accordance with the framework proposed by the adaptive-behavior approach (Meyer & Guillot, 1991), the complex behavior patterns observed in organisms are the result of those organisms' reaction to changes in their environment. Such reactions are guided by sets of simple low-level rules that result in the emergence of complex higher-level behavior (Beer, 1990; Brooks, 1991; Holland, 1995). In a seminal paper, Reynolds (1987) postulated an explanation for steering in artificial birds (named boids) guided by three rules applied to each individual: (a) each boid attempted to avoid collisions with its neighbors, (b) each boid attempted to stay close to its neighbors, and (c) each boid attempted to match the velocity of its neighbors. These rules were based on the neighbors' local behavior and did not include centralized coordination, but produced collective motion along a common heading (Werner & Dyer, 1992; Zaera, Cliff & Bruten, 1996; Camazine et al, 2001).

Based on Reynolds' approach, agent-based simulation has been used to study the collective displacement patterns of a wide range of organisms, exploring factors such as the relationship between group behavior and low-level rules, body characteristics and the group's environmental setting (Inada, 2001; Kunz & Hemelrik, 2003; Oboshi, Kato, Mutoh & Hito, 2002). Moreover, this approach is also applied to human displacements in order to understand and predict pedestrian flows and the movement of crowds of people (Schreckenberg & Sharma, 2002).

However, when flocking behavior is studied using agent-based simulation, flock detection is sometimes carried out merely by observing the changes in the agents' locations over time on the computer screen. Indicators based on the degree of parallelism of the agents' orientation (e.g., polarity, often calculated as an aggregation of the deviation of each agent's orientation from the average orientation) or those based on measures of inter-agent distance (often aggregations of nearest neighbor distance or distance to the flock center) have been used to analyze flock behavior (Kunz & Hemelrik, 2003; Parrish & Viscido, 2005). Other proposed indicators show properties of flock stability, shape or trajectory, but there is no simple index integrating different measures that indicates the degree of flocking behavior as a whole and that is easily applicable to agent-based simulations (Zaera, Cliff & Bruten, 1996).

Therefore, in order to objectively measure flocking behavior, we defined an index of the degree to which a set of agents actually forms a flock. A moving group as a whole is considered a flock when all the agents have similar headings and the distance between them is low enough; the heading of an agent at time t is defined as the vector connecting its location at t-1 with its location at t. For agents i and j at time t, we define an aggregation index as follows:

$$f_{ij}(t) = H(\Delta\alpha_{ij}(t)) \cdot Z(d_{ij}(t))$$

Their aggregation is the product of H, a function of the difference between the agents' headings at t ($\Delta\alpha_{ij}$ (t)), i.e., the difference, in degrees, between the vectors defining their headings, and Z, a function of their distance at t (d_{ij} (t)):

$$H(\Delta\alpha_{ij}(t)) = 1 - \frac{\Delta\alpha_{ij}(t)}{180°}$$

$$Z(d_{ij}(t)) = 1 - \frac{1}{1 + \exp\left[-\gamma \cdot (d_{ij}(t) - \delta \cdot m)/m\right]}$$

Both functions can yield values of between 0 and 1. Function H is equal to 1 when the agents' headings are identical, i.e., $\Delta\alpha_{ij}$ (t) = 0º, and is equal to 0 when the two agents face opposite directions, i.e., $\Delta\alpha_{ij}$ (t) = 180º. Function Z is the inverse logistic function ($\gamma > 0$, $0 < \delta < 1$; $m > 0$); it tends toward 1 when the distance between the two agents is close to 0 (in which case the exponential function yields a high value), and it tends toward 0 when the distance is great (in which case the exponential function yields a value close to 0). Thus, at time t, the aggregation index for agents i and j approaches 1 only when both H and Z approach 1, and approaches 0 when either H or Z approaches 0. Therefore, the more agents face similar directions and the closer they are, the greater their aggregation index; on the other hand, if the agents have identical headings but are far away from each other, or if they are close to each other but their headings are opposite, their aggregation index is low.

The inverse logistic function is used to ensure that, when the distance between agents is either small or great, smooth changes in distance cause smooth changes in function Z; however, when the distance reaches a critical value, a smooth change in distance causes a big change in Z. Figure 1 shows three inverse logistic functions for specific parameters $\gamma = 5$ (flattest curve), $\gamma = 10$ and $\gamma = 20$ (steepest curve); for the three curves, $\delta = 0.5$, $m = 20$. Note that Z decreases as the distance increases, and that the sharpest descent occurs for distances of around $\delta \cdot \underline{m} = 10$. The greater the γ value the more abrupt the descent. On the other hand, the distance at which the abrupt change occurs can be adjusted by changing the δ value; e.g., if $\delta = 0.8$ and $m = 20$, the critical distance is 16. Parameter $\underline{m}$ is the maximum interagent distance that is judged to define them as a group, given the dimensions of the world. Then given $\underline{m}$, setting δ at 0.5 sets the changing point at $\underline{m}/2$. Given that extreme γ values produce radical discrimination or no discrimination at all, it would seem reasonable to assign it medium-range values.

A global aggregation index or flocking index for all the agents present is defined as the arithmetic mean of the $\underline{f}_{ij}(t)$ indices, N being the total number of agents:

$$F(t) = \frac{1}{N(N-1)/2} \sum_{i<j} f_{ij}(t)$$

Values of $\underline{F}(\underline{t})$ range between 0 and 1; when $\underline{F}(\underline{t}) = 1$, the agents move in a coordinated and compact fashion in the same direction, and when $\underline{F}(\underline{t}) = 0$, they are scattered and move in a disorderly fashion. Thus, $\underline{F}(\underline{t})$ can be evaluated at each time unit $\underline{t}$ by computing the distances between the agents and the differences between their headings; values of $\underline{F}(\underline{t})$ are a time series that indicates when the agents move as a flock and whether the flock is maintained over time. If the agents' behavior is governed by some rules that make the flock emerge from initial disorderly movement, then an abrupt increase in $\underline{F}(\underline{t})$ indicates such a phase transition.

Yet a group of agents moving randomly and not in a coordinated way might theoretically result in $\underline{F}(\underline{t}) > 0$. Therefore, in order to evaluate $\underline{F}(\underline{t})$ appropriately, we need to know the distribution function of the index for specific N, $\underline{m}$, γ, and δ values in case the agents have random locations and headings. The distribution function can be estimated by assigning random coordinates and headings to the N agents repeatedly and independently many times (say, 10,000 times), and by calculating $\underline{F}$ each time; by averaging the Fs, an estimate of their mathematical expectancy (E[F]) can be obtained. Thus, the index can be converted into a Cohen's (1960) kappa coefficient:

$$\kappa_F(t) = \frac{F(t) - E[F]}{1 - E[F]}$$

In other words, at each time step, the difference between the obtained F(t) and its expected value in the case of random movement is divided by the maximum possible difference. Therefore, kappa can be viewed as the degree to which agent interaction actually causes a flock: a flock exists when $\kappa_F(t) > 0$ (i.e., the agents' headings are similar and their distances are shorter than in the random case), and the closer $\kappa_F(t)$ is to 1, the more defined the flock is (i.e., the more similar the agents' headings are and the shorter the distance between them). Converting F into a kappa coefficient makes it easier to interpret, because while actual values of F depend on the number of agents and the size of the world in which they move, kappa can be viewed as a sort of standardized index, making it possible to compare flocks with different group and world sizes.

We will show that $\kappa_F(t)$ makes it possible to distinguish between different kinds of flocking behavior (i.e., compact, disperse, etc.). Using agent-based simulation, we will generate groups of agents that act according to specific low-level rules of interaction (see below), and will check if the apparent flocks shown on the computer screen match the results indicated by $\kappa_F(t)$ over time.

Method

In order to show that the index $\kappa_F(t)$ distinguishes between flocking and non-flocking behavior, and between different kinds of flocks, we generated flocks using an agent-based software, P-flock, written in Borland C language. It is based on P-space, a program that simulates spatial behavior and has been presented elsewhere (see Quera, Beltran, Solanas, Salafranca & Herrando, 2000; Quera, Solanas, Salafranca, Beltran &

Herrando, 2000; Beltran, Salas & Quera, 2006)[1]. In P-flock, agents move on a two-dimensional torus world sized 120 x 90 cells; each cell can only be occupied by one agent at a given time step. Agents have a scope of attention (a circular sector which is defined as an area to which the agent pays attention at time t, so that only the other agents within that area are taken into account) and move according to a general rule: each agent moves within its local neighborhood of cells in order to minimize its local dissatisfaction. At each time unit, agent dissatisfaction depends on the discrepancy between the real distances it actually maintains from the other agents and the ideal distances it wants to keep from them. Thus, at each time unit, an agent moves to that location within its current neighborhood for which its dissatisfaction is minimum. Ideal distances change dynamically, and their change is caused by the outcomes of the interactions between the agents.

The model describing how ideal distances change is a set of low-level rules, which we call the Flock Synthesis Rules (FSR). According to this model, agent i initially moves without bearing in mind any other agent j, until its real distance from agent j is less than some critical value A. When this value is reached, the FSR are activated in agent i with respect to agent j; from that moment on, the ideal distance experiences two different kinds of change: smooth and abrupt. A smooth change is caused by agent i adapting to agent j's movements, which may cause the ideal distance to increase or decrease by constant amount C at each time step; an abrupt change can occur when the ideal distance remains constant during a certain time period B, in which case the ideal distance is increased by a large amount, and later on it will be decreased to the value it was prior to the change. Smooth changes in the ideal distance are governed by discrepancies between what agent i predicts regarding its future real distance to agent j and the actual change in real distance once both agents have moved.

Table 1 details how decisions regarding the increase or decrease in the ideal distance are made at each time step; these decisions are made for each agent i with respect to each other agent j if the FSR are activated for agent i towards agent j, and if agent j is within the scope of attention of agent i (i, j = 1 to N).

In a set of simulations, we defined N = 20 agents and initially assigned them random coordinates and headings. The agents' scope of attention was set at 180º and the parameters for calculating the F index were set at $\gamma = 10$, $\delta = 0.5$ and m = 20. The scope of attention and world settings remained constant for all conditions. We varied parameters A, B and C of the FSR systematically through three conditions: A = 60, B = 6, C = 0.01; A = 6, B = 6, C = 0.01; and A = 6, B = 100, C = 0.01. These conditions were chosen because previous simulations showed clear differences in the behavior of the agents on the computer screen. The three conditions produced, respectively, a compact flock (the agents remained very close to each other and had approximately the same headings), a scattered flock (the agents remained at greater distances from each other than in the preceding condition but had very similar headings) and no flocking behavior. We compared the flocking behavior observed on the computer screen and the F(t) index. For each condition we ran program P-flock for 20,000 time steps. At each time step of the simulation, the program calculated both F(t) and its corresponding $\kappa_F(t)$.

Results and discussion

In the first condition (A = 60, B = 6, C = 0.01), the agents remained very close to each other and had approximately the same headings throughout the simulation. Correspondingly, kappa reached values near 1 almost from the beginning of the simulation. In the second condition (A = 6, B = 6, C = 0.01) the agents remained at greater distances from each other than in the preceding condition but had very similar headings; in this case, kappa values oscillated in a range of medium values (approximately between 0.30 and 0.60) from time unit 4,000 onward. Finally, in the third condition (A = 6, B = 100, C = 0.01) no flocking behavior was observed on the computer screen, i.e., the agents remained far away from each other and their headings did not appear to be coordinated; accordingly, kappa values remained very close to zero throughout the simulation (see Figure 2). Snapshots of the group of agents as observed on the screen can be seen in Figure 3.

We have presented a simple and potentially useful index for measuring flocking behavior. The results provide an overview of its aim and usefulness: the F index (converted into a Cohen's kappa index for ease of interpretation) has proved to be sensitive to the different flocking patterns that can be generated by our FSR model, since it reached nearly the maximum value (around 1) for a compact flock, medium values (around 0.5) for a scattered one, and minimum values (around 0) when no flocking behavior was apparent. The index can therefore be effectively used to quantify the aggregation of moving individuals as the degree to which they move along a common heading while keeping the distance between them short. The index can also be useful to compare the data from different flocking-behavior studies.

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Footnotes

1. Both P-flock and P-space can be downloaded from www.ub.es/comporta/gcai/Paginas/gcai_Downloads.htm

Table 1

Decision table describing smooth changes at the ideal distance, in accordance with the Flock Synthesis Rules

Agent i's prediction at t of its real distance to agent j at t+1	Outcome at t+1 after both agents i and j have moved	Smooth change in the ideal distance of agent i with respect to agent j at t+1
Approach: Real distance at t+1 will be less than at t, because agent i is moving towards agent j's current location at t.	Actual approach > predicted	Ideal distance decreases; prediction is positively rewarded
	Actual approach = predicted	Ideal distance does not change
	Actual approach < predicted	Ideal distance increases; prediction is negatively rewarded
No change: Real distance at t+1 will be equal to that at t, because agent i is not moving.	Real distance has changed	Ideal distance does not change
	Real distance remains the same	Ideal distance is increased or decreased, with probability 0.50
Distancing: Real distance at t+1 will be greater than at t, because agent i is moving away from agent j's current location at t.	Actual distancing > predicted	Ideal distance increases; prediction is positively rewarded
	Actual distancing = predicted	Ideal distance does not change
	Actual distancing < predicted	Ideal distance increases; prediction is negatively rewarded

Figure Captions

Figure 1. Inverse logistic function used to calculate aggregation index F. It describes the effect of the real distance d between two agents on the Z(d) function. The curves correspond to parameters $\gamma = 5$ (flattest curve), $\gamma = 10$ and $\gamma = 20$ (steepest curve); for the three curves, $\delta = 0.5$, $m = 20$.

Figure 2. Evolution over time of aggregation index F (converted into a kappa coefficient), for each of the three simulation conditions under the FSR model: (a) A = 60, B = 6, C = 0.01; (b) A = 6, B = 6, C = 0.01; (c) A = 6, B = 100, C = 0.01. Kappa values are shown smoother using an average moving window 100 time units wide.

Figure 3. Snapshots of the graphic output of the simulation at approximately time unit 10,000 for each of the three simulation conditions under the FSR model: (a) A = 60, B = 6, C = 0.01 (left); (b) A = 6, B = 6, C = 0.01 (middle); (c) A = 6, B = 100, C = 0.01 (right). The arrows indicate the location and heading of each agent.

Figure 1.

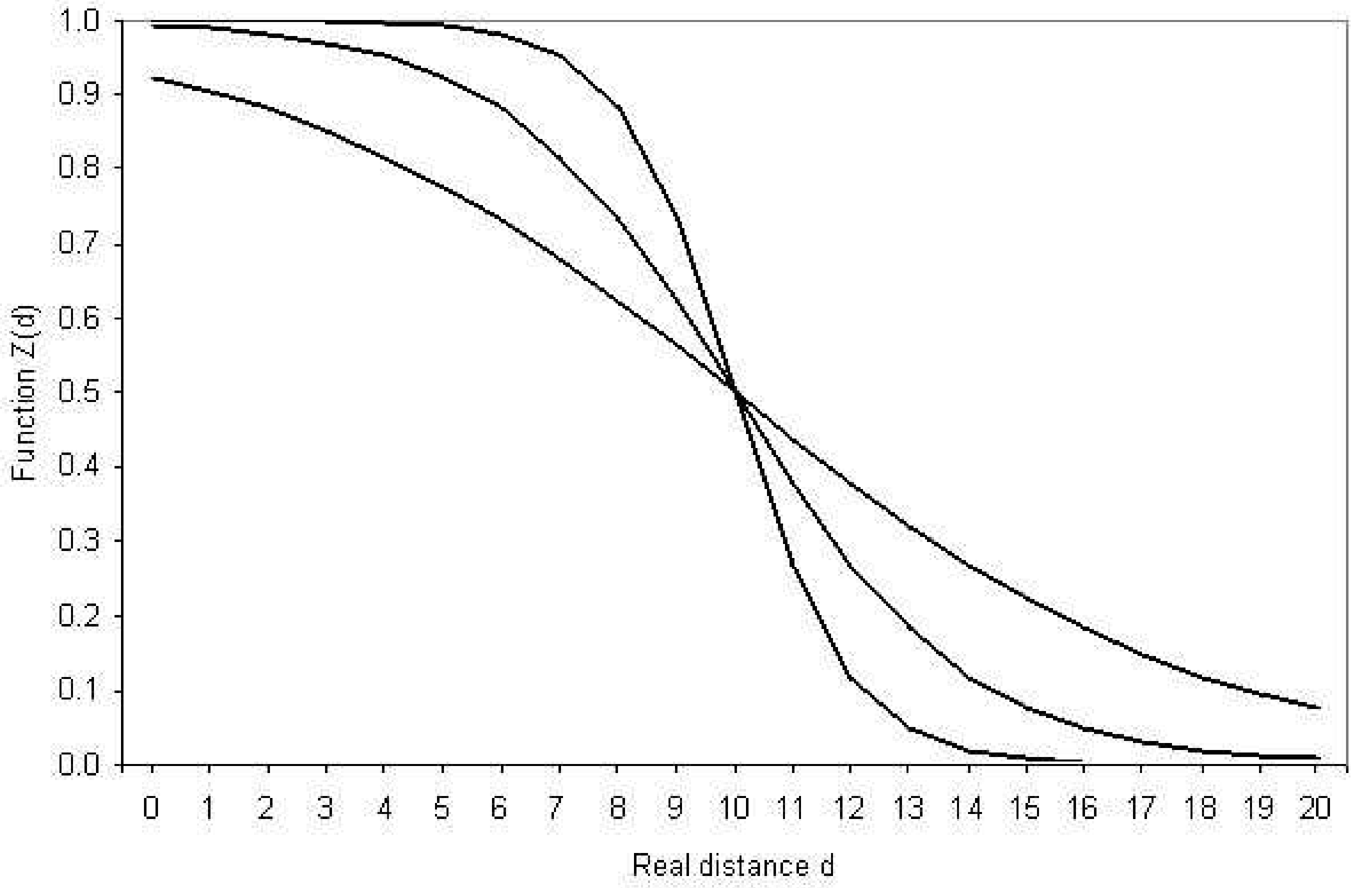
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
Function Z(d)
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
Real distance d

Figure 2

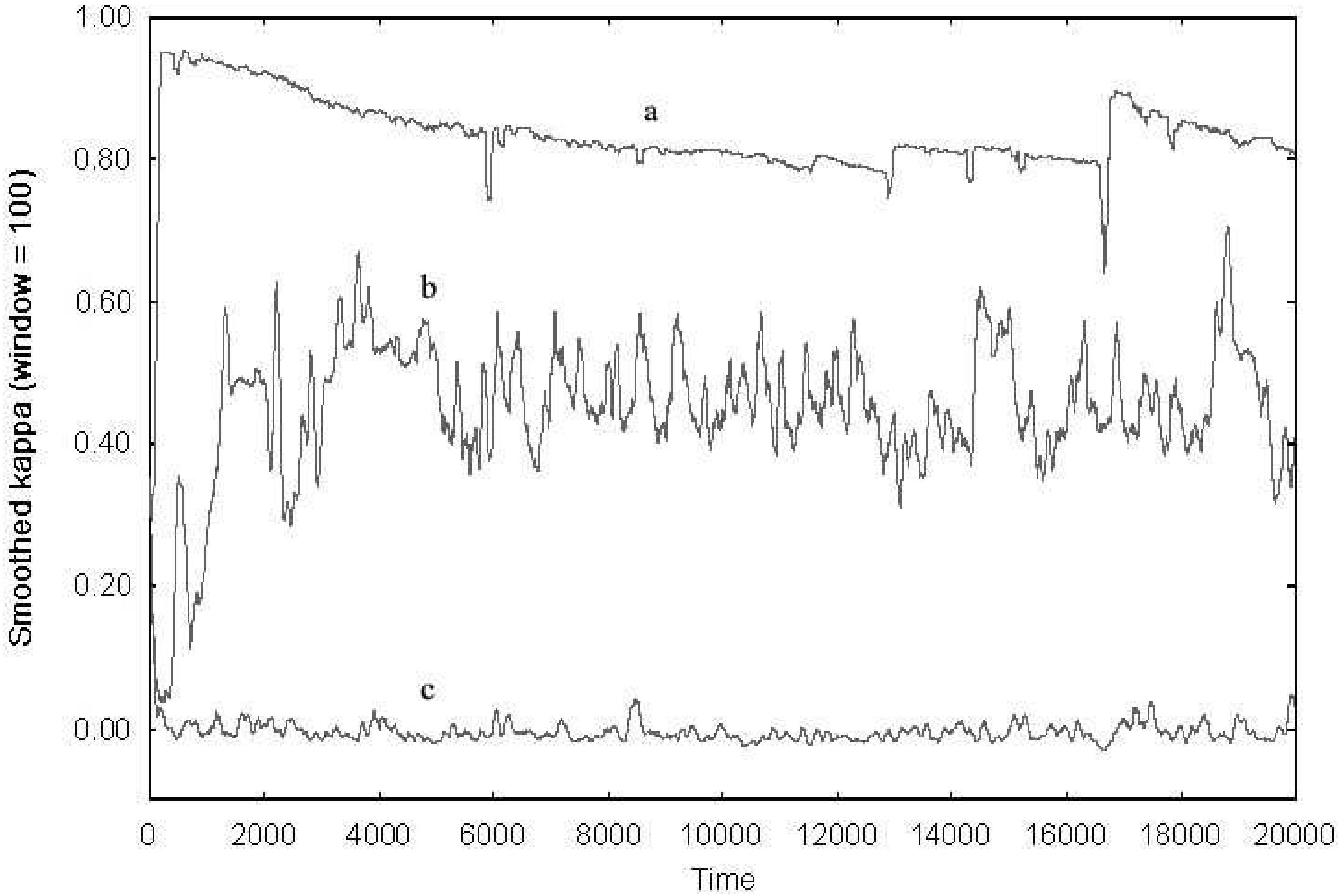
1.00
0.80
0.60
0.40
0.20
0.00
Smoothed kappa (window = 100)
0
2000
4000
6000
8000
10000
12000
14000
16000
18000
20000
Time
a
b
c

Figure 3.