# Chapter 74
# Self-organized Flocking with Conflicting Goal Directions

**E. Ferrante, W. Sun, A.E. Turgut, M. Dorigo, M. Birattari, and T. Wenseleers**

In flocking, a large number of individuals move cohesively in a common direction. Many examples can be found in nature: from simple organisms such as crickets and locusts to more complex ones such as birds, fish and quadrupeds.

Reynolds was the first to propose a computational model of flocking [1]. The behavior of each individual is made of three parts: separation, cohesion, alignment. Separation means that the individual moves away from its neighbors. Cohesion means that the individual stays close to its neighbors. Alignment means that the individual matches the velocity of its neighbors.

This paper studies flocking in the robotics setting. One of the earliest attempt to realize flocking in robotics was done by Matariç [2]. She created a set of "basic behaviors": safe-wandering, aggregation, dispersion and homing. Turgut et al. [3] implemented flocking on real robots using two behaviors: proximal control and alignment control. Proximal control combines the separation and cohesion components and was realized using the framework of artificial physics as done by Spears et al. [4]. Alignment control is realized through a novel sensing system which they called virtual heading sensor.

More recent research in biology showed that only a small group of informed individuals who have information about a desired goal direction is sufficient lead the whole group in that direction [5]. These leaders are implicit, in the sense that the rest of the swarm is not aware of their presence. Inspired by [5], Çelikkanat [6] extended [3] by providing the goal direction to only a proportion of the robots, which they referred to as informed robots. They found that, similarly to [5], only a minority of informed robots is enough to guide the whole group.

In this paper, we study flocking of a swarm of robots when information about two distinct goal directions is present in the swarm. This case can be instantiated

E. Ferrante (✉) · W. Sun · A.E. Turgut · M. Dorigo · M. Birattari
Université Libre de Bruxelles, Brussels, Belgium

E. Ferrante · A.E. Turgut · T. Wenseleers
Katholieke Universiteit Leuven, Leuven, Belgium

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in many practical examples: a swarm that has to go in one direction while avoiding an obstacle; a swarm that has to avoid a dangerous locations while going to a target location; or a swarm that has to execute, in parallel, two tasks in two different locations. In general, we can identify three different macroscopic objectives that we might want to attain: (a) a swarm that moves to the average direction among the two (for example to avoid the obstacle) without splitting; (b) a swarm that selects the most important of the two directions (for example the direction to avoid danger) and follows it without splitting; (c) a swarm that splits in a controlled fashion in the two directions (for example, in the parallel task execution case).

This paper proposes a solution for the first objective: a method for moving the swarm in the average between the two conflicting goal directions. We show that this objective can be attained using a similar methodology as the one proposed in [3] and [6]. We execute systematic experiments using a realistic robotics simulator. In the experiments, a small proportion of robots is informed about one goal direction, another small proportion about the other goal direction, and the rest of the swarm is non-informed. We study the effect of what we believe are the critical parameters: the overall proportion of informed robots, the difference between the size of the two groups of informed robots and the difference between the two goal direction.

## 74.1 Method

We use a similar method as the one used in [3]. At each time step, a flocking control vector is calculated as $\mathbf{f} = \alpha\mathbf{p} + \beta\mathbf{h} + \gamma\mathbf{g_i}$, where $\mathbf{p}$ denotes the proximal control vector, $\mathbf{h}$ denotes the alignment control vector, $\mathbf{g_i}$ with $i = \{1, 2\}$ denotes the vector that indicates the two goal directions denoted with $\theta_1$ and $\theta_2$. For informed robots $\gamma = 1$, whereas $\gamma = 0$ for uninformed robots. The values of the other parameters are fixed to $\alpha = 1$, $\beta = 4$ for all the robots.

Using proximal control, each robot keeps a desired distance ($d_{des}$) with its neighbors to avoid collisions and to achieve cohesion. To do this, the robot only needs to know the relative distance $d_i$ and bearing $\phi_i$ of each neighbor $i$. The formula $p_i(d_i) = 12\epsilon[\frac{{d_{des}}^{12}}{d_i^{13}} - \frac{{d_{des}}^{6}}{d_i^{7}}]$, based on the Lennard-Jones potential [7], encodes attraction and repulsion rules. If the actual distance $d_i$ is smaller than $d_{des} = 0.6$ m, $p_i(d_i)$ is negative and the rule is repulsive, otherwise it is attractive. The parameter $\epsilon = 0.5$ controls the strength of the attraction/repulsion rule. After computing $p_i(d_i)$ for each neighbor, the proximal control vector is computed as $\mathbf{p} = \sum_{i=1}^{k} p_i(d_i)e^{j\phi_i}$, where $k$ is the number of neighbors.

Using alignment control, each robot aligns to the average orientation of its neighbors. Each robot detects its own orientation $\theta_0$ and sends it to its neighbors. The robot receives an angle $\theta_i$ from its $i$th neighbor that represent the neighbor's orientation. In this way, it is as if the robot can sense the orientation of its neighbors. The robot then calculates the alignment control vector as: $\mathbf{h} = \frac{\sum_{i=0}^{k} e^{j\theta_i}}{\| \sum_{i=0}^{k} e^{j\theta_i} \|}$, where $\| \cdot \|$ denotes the norm of a vector and $k$ denotes the number of neighbors. Given the flocking control vector **f**, the robot's forward and angular speed are computed as the projection of **f** on $x$-axis and $y$-axis of the robot as in [8]. The forward speed $u$ is directly proportional to $x$ component of force, and the angular speed $\omega$ is directly proportional to $y$ component of force: $u = K_1 f_x, \omega = K_2 f_y$. $K_1 = 2$ and $K_2 = 2$ are the forward and angular gains, respectively. We also limit forward speed and angular speed to $u \in [0, U_{\max}]$ and $w \in [-\Omega_{\max}, \Omega_{\max}]$, with $U = 20$ cm/s and $\Omega_{\max} = \frac{\pi}{2}$ rad/s.

We use the simulated version of the foot-bot robot developed in [9]. We use the following sensors and actuators: (i) A light sensor able to detect the bearing of a distant light source, that is used by the robot to measure its orientation; (ii) A range and bearing sensing and communication device (RAB), that is used by the robot to obtain range and bearing of the neighbors in proximal control and to communicate its orientation in alignment control; (iii) Two wheels actuators that is used by the robot to move. For motion, we use the differential drive model as in [3] to convert the forward speed $u$ and the angular speed $\omega$ into the linear speed of left and right wheels: $N_L = u + \frac{\omega}{2}l, N_R = u - \frac{\omega}{2}l$, where $l = 5$ cm is the distance of two wheels.

## 74.2 Experiments

We use the ARGoS simulator developed in [10]. It is a modular, multi-engine, open-source simulator for heterogeneous swarm robotics.

### *74.2.1 Experimental Setup*

A swarm of $N = 100$ foot-bots is placed, with random orientations, in an arena of $12 \times 12$ m. A remote light source is positioned far from the robots to provide common reference frame. A proportion of $\rho_1$, $\rho_2$ robots are informed about the goal direction $\theta_1, \theta_2$, respectively. Thus, $N_A = N\rho_1$ is the number of robots informed of goal direction $\theta_1$ and $N_B = N\rho_2$ is the number of robots informed of goal direction $\theta_2$.

We study the capability of the swarm to follow the theoretical average direction in different parameter conditions. In particular, we are interested in determining (i) the impact of the total proportion of informed robots, (ii) the impact of the difference between $N_A$ and $N_B$ and (iii) the impact of the difference between two goal directions $\theta_2 - \theta_1$. For the second case, we classify the experiments in three sets: no difference between $N_A$ and $N_B$ ($N_A = N_B$), small difference ($N_A - N_B = 2$) and high difference ($N_A - N_B > 2$). To study the impact of $\theta_2 - \theta_1$ and to reduce the parameter space, we fix the $\theta_1 = 0$, and we only vary $\theta_2 \in \{10, 20, \ldots, 170, 179, 180\}$. We consider the following values of $\rho_1$ and $\rho_2$ (proportion of informed robots): $\{(0.01, 0.01), (0.01, 0.05), (0.02, 0.04), (0.1, 0.1), (0.09, 0.11), (0.01, 0.19)\}$. Each experiment is repeated $R = 100$ times and lasts $T = 500$ simulated seconds.

### 74.2.2 Metrics

In this paper we are interested in having a swarm that is cohesive and moves along the theoretical average direction between the two given goal directions. We use two metrics to evaluate the degree of attainment of these two objective: split probability and average group direction.

**Split Probability** To measure split probability, we first compute the number of groups $g$ at the end of each experiment as suggested in [5]. $g_i$ denotes the number of groups at the end of the $i$th run. After executing $R$ independent runs, the split probability is calculated as: $p = \frac{\sum_{i=1}^{R}(\min\{2,g_i\}-1)}{R}$.

**Average Direction** The average group direction is simply the vectorial average of all robots orientations: $\bar{\theta} = \angle \sum_{i=1}^{N} e^{j\theta_i}$. We plot the average group direction against the theoretical average direction, that takes into account the number of robots informed about each goal direction: $\hat{\theta} = \angle(N_A e^{j\theta_1} + N_B e^{j\theta_2})$.

## 74.3 Results

According to the results (not shown), no matter the value of $N_A$, $N_B$ and $|\theta_2 - \theta_1|$, the swarm does not split.

We now report and discuss the average group direction in the three cases: $N_A = N_B$ (no difference), $N_B - N_A = 2$ (small difference) and $N_B - N_A > 2$ (large difference).

**No Difference ($N_A = N_B$)** Figure 74.1(left column) shows that, in most of the cases, the average direction strictly follows the theoretical average direction $\hat{\theta}$. The most noticeable exception is the $\rho_1 = \rho_2 = 0.01$ case (Fig. 74.1(a)). In this case, the robots are not able to follow the theoretical average direction when $\theta_2 - \theta_1$ is too high, and the distribution of the average group direction has high standard deviation. This can be explained by the fact that the total proportion of informed robots is not high enough to drive the swarm in the desired direction, as argued in [6]. In fact, Fig. 74.1(d) shows that, with higher total proportion of informed robots, the swarm follows the theoretical average direction more precisely for most configurations of $\theta_2 - \theta_1$.

**Small Difference ($N_B - N_A = 2$)** Figure 74.1(central column) shows that, no matter $\theta_2 - \theta_1$, the group follows the theoretical average direction. When $\theta_2 - \theta_1$ is high, larger total proportion of informed robots (Fig. 74.1(e)) correspond to lower spread in the distribution. $\theta_2 - \theta_1 = 180$ degrees is a special case as it presents many outliers. Otherwise, the swarm is able to follow the theoretical average even for $\theta_2 - \theta_1 = 179$ degrees.

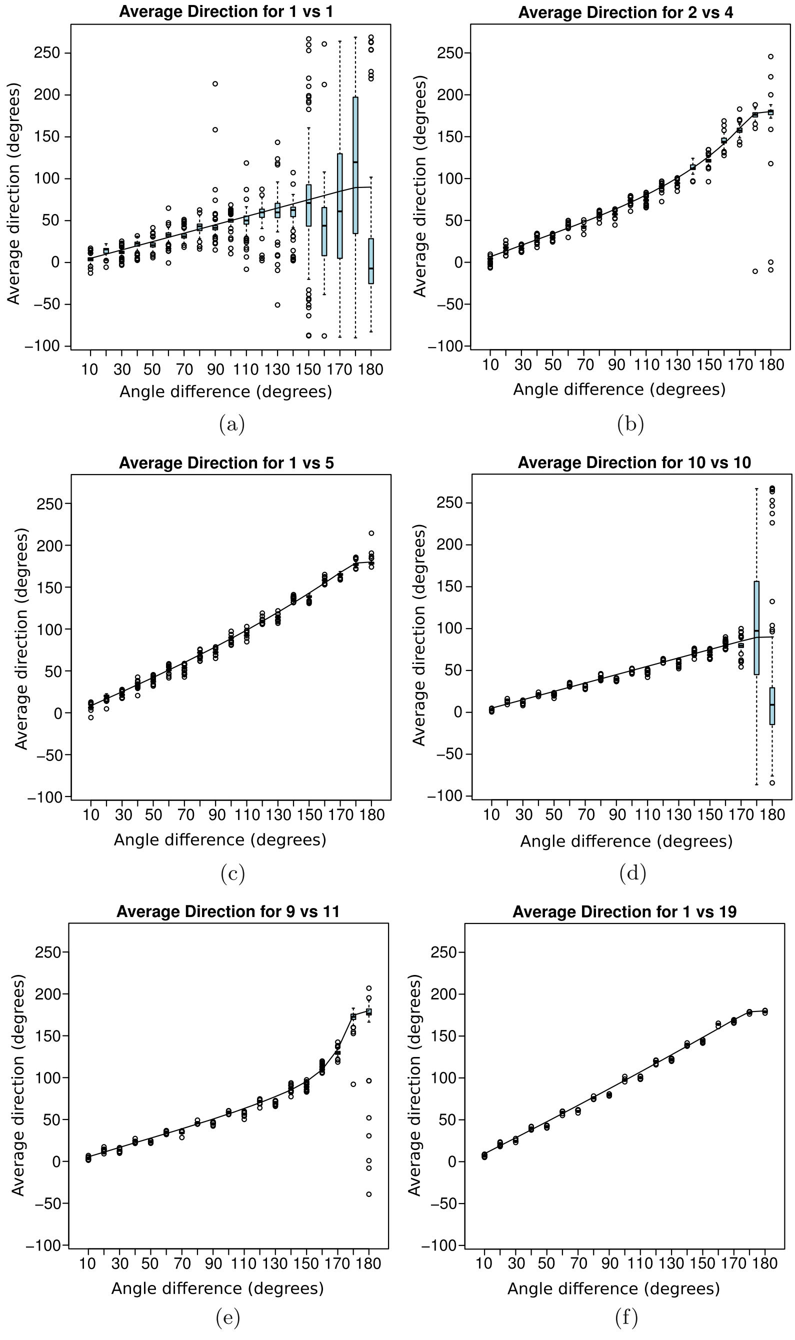


**Fig. 74.1** Distribution of average for $N_A = N_B$ (*left column*), $N_B - N_A = 2$ (*central column*) and $N_B - N_A > 2$ (*right column*). *Solid black line* represents the theoretical average direction in total informed robots. The above and nether edges of the box indicate first and third quartiles. *The black center line* indicates the median for each dataset

**Large Difference ($N_B - N_A > 2$)** Figure 74.1(right column) shows that the theoretical average direction represents the goal direction that is known by the majority. Here, a precise following of the theoretical average direction always takes place, even when $\theta_2 - \theta_1 = 180$. Additionally, when the total proportion is small, there are a few outliers (Fig. 74.1(c)). These outliers are otherwise not present for higher total proportion of informed (Fig. 74.1(f)).

## 74.4 Conclusion and Future Work

We studied flocking of swarm of mobile robots where information about two conflicting goal directions is present in the swarm. In this setting, we believe three possible macroscopic objectives can be identified: (a) making the swarm follow the average direction between the two without splitting; (b) making the swarm follow one (the most important) direction between the two without splitting; (c) making the swarm split in a controlled fashion and allocate to the two goal directions. In this paper, we propose a method based on [3, 6] and we show that it is capable to attain the first objective. This result presents some difference with the results in [5], where they also studied the conflicting goal direction case but showed that the resulting average direction strongly depends on the difference between the two goal directions. This lack of agreement might be due either to the different methodology or to the different level of detail in the simulations.

This work open many doors for possible future extension. In fact, in a parallel on-going work [11], we are studying how to attain the second objective. This objective was attained by using a special communication strategy called self-adaptive communication strategy (SCS). However, in that work we assumed that the priority of the goal directions are known by the informed robots.

We believe that information transfer and communication are the key to attain the desired macroscopic objectives in self-organized flocking, even in presence of conflicting goal direction. Future work will deal with how to design direct or indirect communication strategies to make the swarm split in a controlled fashion or to deal with the second objective under the case where the priority of the goal directions are not known in the swarm.

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