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The Role of Explicit Alignment in Self-organized Flocking

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***Abstract*—Flocking is an self-organized behavior that is widely observed in nature from simple organisms such as crickets and locusts to more complex ones such as birds and quadruplets. It can be defined as the coherent and aligned motion of a group of animals at a certain direction. Coherence is the tendency of the individuals to stay together and alignment is a consequence of minimizing collisions at the individual level. In this paper, we study the alignment component of the flocking behavior in a swarm of robots. We implemented two different controllers: one with only a cohesion behavior, namely the no-alignment controller, and the other with both cohesion and alignment behaviors, namely the alignment-enabled controller. In both controllers, only a proportion of robots, called informed robots, are provided with the desired goal direction. In particular, we study the effect of three different parameters on flocking performances. The three parameters are the size of the swarm, noise in the cohesion behavior and the proportion of informed robots. Under the effect of these parameters, we perform a comparative study of the two controllers.**

We perform simulation-based experiments and evaluate the accuracy of the flock to move in a desired goal direction. The experiments are conducted in stationary and non-stationary environments: in the stationary environment, the goal direction and the informed robots do not change during the experiment, whereas in the non-stationary environment, both the goal direction and the informed robots change over time.

The results show that i) the alignment behavior results in a more aligned motion in larger swarms; ii) smaller swarms without an alignment behavior can follow the goal direction more accurately; iii) noise in the no-alignment controller helps to achieve a more aligned motion in large swarms and iv) the swarm needs enough informed robots to follow accurately the goal direction and to adapt to non-stationary environments.

***Keywords*-flocking; self-organization; swarm robotics; swarm intelligence**

I. Introduction

Coordinated motion is a widely observed phenomena in animals that are living in groups [1] such as insects like crickets [2] or locusts [3] or vertatbrates like birds [4] or human beings [5]. It can be defined as the coherent and aligned motion of the individuals towards a common direction.

Although, coordinated motion had been studied in biology, Reynolds [4] was the first to implement flocking in artificial systems. In his work, he proposed a behavior-based controller utilizing only local information based on individual perception. The behaviors he proposed are: *separation* - tendency of individuals to avoid collisions, *cohesion* - tendency of individuals to stay together, and *alignment* - tendency of individuals to head in the same direction. His flocking algorithm resulted in realistic-looking animations of bird flocks in computer.

The goal of this paper is to perform an analysis to understand under which condition an alignment behavior is needed to achieve flocking to a given goal direction. Although, it is known that some animals use visual cognition [6] and others such as fish use a special organ [7] to sense the headings of their group-mates, it is still unknown whether the same happens for insects. This rises the question on whether there exists an *explicit* alignment behavior for coordinated motion in simple organisms like insects or it is just a consequencee of their tendency to stay together and to move towards a certain direction. A recent study in robotics [6] suggested that alignment at a group level could emerge from local interaction of the robots without an *explicit* alignment behavior at the individual level when special behaviors for coherence are used. In this paper, we approach the problem in a more general way, i.e. without the use of special coherence behaviors, and try answer the question by analyzing the effect of alignment behavior on the dynamics of the coordinated motion using a swarm of robots.

Furthermore, a study regarding the systematic analysis of the alignment behavior has never been performed in literature up to now. Hence, in our study, we make a comparative study of the alignment behavior using two different controllers in order to understand its effects on the performance of flocking. Specifically, we implement two controllers; one with only proximal control behavior and the other with both proximal control and heading alignment behaviors. In both of the controllers, we inform some of the individuals about a goal direction as suggested in [8] and compare the performance of the two behaviors by varying the swarm size, noise in proximal control behavior and the proportion of informed individuals.

II. Related Work

In statistical physics, Vicsek et al. [9] were the first to study the effect of actuation noise on the emergence of the aligned motion in biological swarms. In their study, they utilized a particle-based model having only an alignment term and figured out that the particles undergo an aligned motion below a certain noise threshold. They also performed scalability experiments, and showed that the same result holds regardless of the system size. Gregoire et al. [10] studied the effect of sensing noise using an extended version of the Vicsek model. They added an attraction/repulsion (cohesion/seperation) term to the orignal model and observed that aligned and cohesive motion could still be achieved below a noise value regardless of the system size. In a recent study, Turgut et al. [11], using an extended version of a network-based model [12], modeled the flocking behavior in robot swarms and showed that robots undergo a transition from unaligned to aligned motion under varying levels of sensing noise. In [8], Couzin et al. using a simple mathematical model studied the information transfer mechanisms in animals. They performed systematic experiments and showed that a small proportion of individuals that are informed about a goal direction can guide a large swarm to this direction.

In robotics, flocking has also attracted a lot of attention after Reynolds' seminal work. The main scope of these studies is to implement flocking on robots with limited sensing capabilities.

One of the earliest studies is due to Matarić [13]. Matarić utilized a set of "basis behaviors": safe-wandering, aggregation, dispersion and homing to implement flocking in a group of robots. The robots are able to sense obstacles in the environment, localize themselves with respect to a set of stationary beacons and broadcast their position. With the proposed set of behaviors, robots are able to move cohesively towards a homing direction known a priori while avoiding their neighbors and obstacles. Kelley and Keating [14] following a behavior-based approach utilized a leader-following behavior to implement flocking in constrained environments. Robots move cohesively following a dynamically elected leader avoiding collisions between themselves and the obstacles. They used a custom-made active infra-red sensing system to sense the range and bearing of robots and radio-frequency system for dynamic leader election. Hayes et al. [15] proposed a flocking algorithm based on collision avoidance and velocity matching flock centering behaviors based on local range and bearing measurements. These measurements are emulated and broadcasted to the robots. Robots based on this information compute the local center-of-mass of their neighbors for cohesion and the change in the local center-of-mass for alignment. Holland et al. [16] proposed a flocking algorithm for unmanned ground vehicles based on separation, cohesion and alignment behaviors. All the sensory information (range, bearing and heading of robots neighbors) is emulated and broadcasted to each robot individually.

Spears et al. [17] implemented flocking using their framework of artificial physics based on attraction/repulsion and viscous forces. The robots first form a regular lattice structure using the range and bearing measurement of their neighbors and then move towards a homing direction realized by a light source in the environment. In a recent study, Moeslinger et al. [6] proposed a flocking algorithm based on attraction and repulsion forces. The algorithm is specifically designed for robots with limited sensing capabilities. It is based on setting different threshold levels for different attraction/repulsion zones situated around the robot. By adjusting these threshold levels, they achieved flocking with a small group in a constrained environment.

In [18], Tanner et al. proposed an algorithm based on attraction/repulsion and alignment behaviors to perform flocking with a leader. Robots are able to measure their position and orientation with a GPS and transmit this information to their neighbors via high speed communication link. In this way, each robot has the exact absolute position and velocity information of the other robots and the virtual leader. Campo et al. studied collective transport of a heavy object to a nest location in [19]. Each robot equipped with an LED ring and omni-directional camera estimates the nest location and signal their estimates to its neighbors by forming a specific pattern in their LED ring. Robots perceive the estimation of their neighbors via their cameras and align to the common estimation of the nest.

Turgut et al. [20] inspired by Reynolds' work proposed a behavior based on seperation/cohesion (will be called as proximal control) and heading alignment behaviors. They implemented this behavior in robots with limited sensing capabilities and made a systematic study on the effect of sensing noise in heading measurement on flocking. The robots are equipped with proximity sensors for obstacle/robot detection and a virtual heading sensor for heading measurement. Each robot measures its heading using a digital compass and broadcasts it periodically using a wireless communication unit so that the heading is sensed "virtually" by its neighbors. This strategy resulted in scalable flocking to a random direction with a small and a large group. In a follow-up study, Gökçe and Şahin [21] introduced a homing behavior and studied the effect of noise in sensing the homing direction on the long-range movement of robot swarms. Çelikkanat et al. [22] extended the flocking behavior by informing some of the robots about a goal direction. They observed that a group can be guided by a few informed individuals where informed individual proportion is dependent on the group size. Recently, following the same approach in [20], Ferrante et al. improved the performance of flocking by introducing a communication strategy for the alignment behavior based on local line-of-sight communication [23]. The simulation-based experiments showed that the new strategy outperforms the performance of the one in [20] in both stationary and non-stationary environments, and scales well with respect to the swarm size and is robust with respect to noise in alignment behavior.

III. METHODOLOGY

We used a design methodology based on artificial physics [17]. At each control step, a virtual force vector is computed as:

$$\mathbf{f} = \alpha\mathbf{p} + \beta\mathbf{h} + \gamma\mathbf{g}.$$

$\mathbf{p}$ is the proximal control vector; $\mathbf{h}$ is the alignment vector; $\mathbf{g}$ is the vector that indicates the goal direction. The vectors $\mathbf{p}$ and $\mathbf{h}$ are calculated by the proximal control and alignment behaviors. These two behaviors are explained in the next two sections. The heading direction $\mathbf{h}$ is available to the robots only when the alignment behavior is used. When the alignment behavior is not used, $\mathbf{h} = \mathbf{0}$. The goal direction $\mathbf{g}$ is available to some robots, namely the informed robots, whereas for the other robots $\mathbf{g} = \mathbf{0}$. The weights α, β and γ define the relative contribution of the different vectors. In this paper, we do not tune these parameters for obtaining optimal performance. Instead, we set them to $\alpha = 1$, $\beta = 5$ and $\gamma = 10$ to reflect our prior knowledge on the relative importance of the three components.

A. Proximal control behavior

The proximal control behavior assumes that a robot perceives the relative position (range and bearing) of the neighbors in its close proximity. This is achieved using LEDs and an omni-directional camera as in [19].

Let k denote the number of neighbors of a given robot r at a given time, d_i and ϕ_i denote the range and bearing measurements, respectively concerning the i^{th} neighbor. The proximal control vector $\mathbf{p}$ is given by:

$$\mathbf{p} = \sum_{i=i}^{k} p_i e^{j\phi_i}.$$

p_i is calculated as a function of d_i using a force function $p(d)$ as in [24]. p_i is repulsive when d_i is smaller than the desired distance (d_{des}) and it is attractive when d_i is greater than d_{des}. The function is:

$$p(d) = -\frac{2d_{des}^2}{d^3} + \frac{2}{d},$$

B. Alignment behavior

The alignment behavior assumes that a robot r measures its heading θ_r using an on-board light sensor with respect to a light source. The robot continuously sends the angle θ_r using its local communication unit. At the same time, it receives an angle θ_i from its i^{th} neighbor which represent the i^{th} neighbor heading measurement. It transforms this angle into its body-fixed reference frame[1]. In this way, we are able to simulate a robot "measuring", or "observing", the heading of its neighbors. Having received k angles from its k neighbors, it calculates the average heading vector as:

$$\mathbf{h} = \frac{\sum_{i=1}^{k} e^{j\theta_i}}{\| \sum_{i=1}^{k} e^{j\theta_i} \|},$$

where $\| \cdot \|$ denotes the norm of a vector.

C. Motion control

The computed virtual force vector $\mathbf{f}$ is mapped into rotational speed of the wheels. We first use Newton's second law of motion to compute the target velocity of the robot $\mathbf{u}_{target}$:

$$\mathbf{u}_{target} = \mathbf{u}^t + \frac{\mathbf{f}\Delta t}{m},$$

where Δt is the control-step size, m is the mass of the robot, $\mathbf{u}^t$ is the current velocity of the robot. The target velocity is then mapped into the robot's forward velocity $\mathbf{u}^{t+1}$, whose direction points forward ($\angle\mathbf{u}^{t+1} = \frac{\pi}{2}$) and its magnitude $u = \|\mathbf{u}^{t+1}\|$ is set to:

$$u = \begin{cases} \left(\frac{\mathbf{u}_{target}}{\|\mathbf{u}_{target}\|} \cdot \frac{\mathbf{u}^t}{\|\mathbf{u}^t\|}\right) u_{max}, & \text{if } \mathbf{u}_{target} \cdot \mathbf{u}^t \geq 0; \\ 0, & \text{otherwise.} \end{cases}$$

In our experiments, the maximum magnitude u_{max} of the forward velocity is set to 0.036.

The angular velocity ω of the robot is determined by a proportional controller calculating the deviation of the target angle from the current heading of the robot:

$$\omega = K_p(\angle\mathbf{u}_{target} - \angle\mathbf{u}^t),$$

where K_p is a proportionality constant whose value is set to 0.5. Finally, the rotation speeds of the left (N_L) and right (N_R) motors are set to:

$$N_L = \left(u + \frac{\omega}{2} l\right)\frac{1}{r},$$

$$N_R = \left(u - \frac{\omega}{2} l\right)\frac{1}{r},$$

where l is the distance between the wheels and r is their radius.

IV. EXPERIMENTS

In this section, we first introduce the metrics and the experimental setup used to evaluate the proposed methodology. We then present the results in both stationary and non-stationary environments.

A. Metrics

In flocking, we are interested in having a group of robots that move compactly, coherently and without any collisions. Furthermore, the group should be aligned and move towards a common direction (in our case the goal direction). In this paper, we used two metrics: order and accuracy.

[1] In our study, we define two reference frames. One is the reference frame common to all of the robots, which is available thanks to the light source. The other is the body-fixed reference frame specific to each robot. The body-fixed reference frame is fixed to the center of a robot: its $x - axis$ is coincident with the rotation axis of the wheels and its $y - axis$ points to the front of the robot.

1) Order: The order metric ψ [25] is used to measure the angular order of the robots. $\psi \approx 1$ when the group has a common heading and $\psi \ll 1$ when each robot is pointing in a different, random different direction. The order is defined as:

$$\psi = \frac{1}{N}\|\bar{\mathbf{a}}\| = \frac{1}{N}\|\sum_{i=1}^{N} e^{j\theta_i}\|,$$

where N is the total number of robots in the experiment, and $\bar{\mathbf{a}}$ is the vectorial sum of the measured headings of the N robots.

2) Accuracy: The accuracy metric δ [8] is used to measure how accurately robots are moving towards the desired goal direction. $\delta \approx 1$ when robots are perfectly aligned to the same direction (which corresponds also to an high value for the order metric $\psi \approx 1$) and at the same time this direction is the goal direction $\mathbf{g}$. Accuracy can be defined as:

$$\delta = 1 - \frac{\sqrt{2\left(1 - \psi cos(\angle\bar{\mathbf{a}} - \angle\mathbf{g}\right))}}{2},$$

where $\angle\bar{\mathbf{a}}$ is the direction of $\mathbf{a}$ and $\angle\mathbf{g}$ is the goal direction with respect to the common reference frame.

B. The task and the experimental setup

In our experiments, N mobile robots are placed with random positions and with random orientations in an empty arena and we make sure that all robots can perceive each other. Each robot is a realistic simulation of a foot-bot, in development for the Swarmanoid project[2]. We utilized the following sensors and actuators: i) A light sensor, that is able to perceive a noisy light gradient around the robot. It is used to measure θ_r, the orientation of robot r with respect to a common light source. ii) A range and bearing communication system, with which a robot can send a message to other robots that are within its line of sight [26] (2 meters in our case). iii) Two wheels actuators, that are used to control independently the left and right wheels speed of the robot. iv) 24 LEDs actuators and a camera, which are used to detect distance and bearing from other robots to perform the proximal control behavior (see Section.

In our study, we analyze the effect of three different parameters: i) the swarm size N; ii) noise in the proximal control vector $\mathbf{p}$ and iii) the proportion of informed robots ρ.

We control the noise with a scaling parameter $\sigma \in [0, 1]$. Using σ, we can compute the noisy proximal control vector $\tilde{\mathbf{p}}$: this vector has the same length as $\mathbf{p}$ but its direction is perturbed by a uniformly distributed random direction $\angle\tilde{\mathbf{p}} = \angle\mathbf{p} + \mathcal{U}\left(-\sigma 2\pi, +\sigma 2\pi\right)$.

For each experimental setting, we executed 100 repetitions. The nominal parameter values in all experiments are: $N = 100$, $\rho = 0.5$ and $\sigma = 0$.

We conducted experiments in two different environments. One is a stationary environment, where robots do not need to adapt to changes; the other is a non-stationary environment, in which we test the adaptation capabilities of flocking. Below we describe the two environments.

[2]http://www.swarmanoid.org

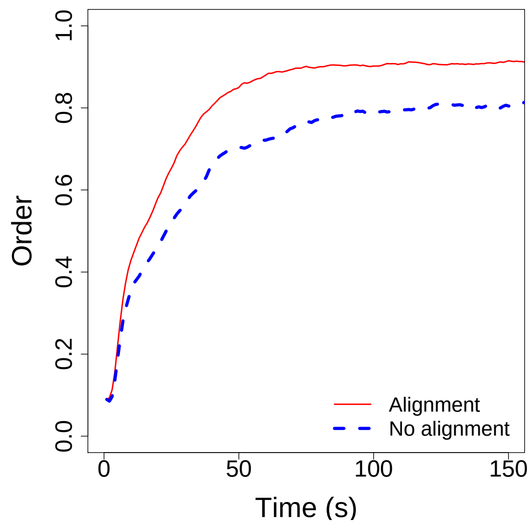

Figure 1. Alignment-enabled controller against no alignment controller in the stationary environment: order metric.

1) Stationary environment: In a stationary environment, a proportion ρ of randomly selected robots are given the information about the goal direction $\mathbf{g}$. All the other robots remains uninformed for the entire duration of the simulation. In every run, we randomize $\mathbf{g}$, as well as the selection of robots that are informed. The duration of one run is 150 simulated seconds.

2) Non-stationary environment: A non-stationary environment consists of four stationary phases. The proportion of informed robots ρ is kept fixed during the entire run. However, at the beginning of every stationary phase, the robots that are informed are reselected at random. Also, the goal direction $\mathbf{g}$ to be followed changes randomly from one stationary phase to the next one. This type of environment is used to test the adaptation capabilities of flocking. The duration of one run is 250 simulated seconds.

C. Results for the stationary environment

Effect of alignment behavior

In our first set of experiments, we compare the alignment-enabled controller with the no alignment controller under the nominal parameter setting.

Figure 1 shows the order metric for the two controllers. The alignment-enabled controller outperforms the no-alignment controller with respect to this metric. This is due to the alignment behavior, which enables robots to negotiate explicitly and achieve consensus to a common heading. In the no-alignment controller, this explicit negotiation is missing, thus order can be obtained only implicitly

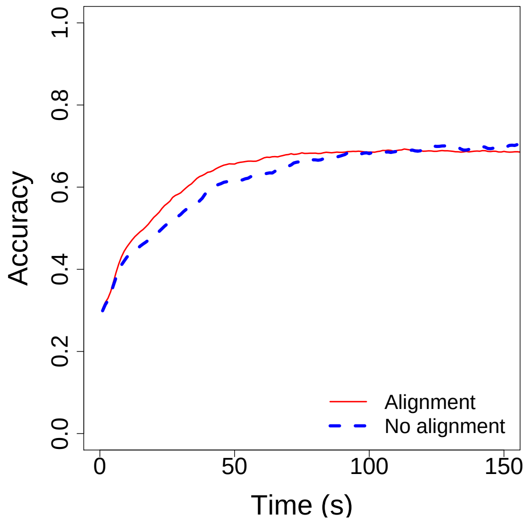

Figure 2. Alignment-enabled controller against no alignment controller in the stationary environment: accuracy metric.

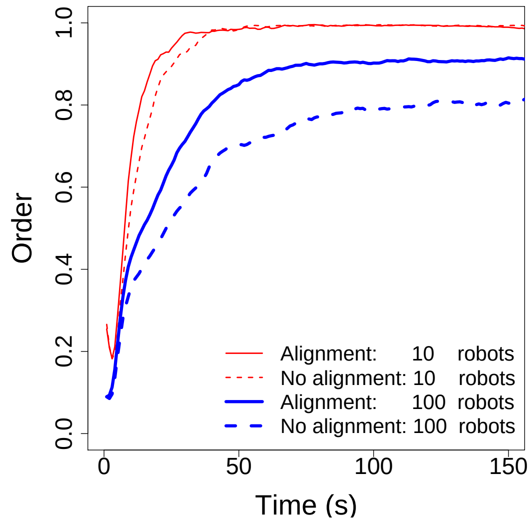

Figure 3. Alignment-enabled controller against no alignment controller in the stationary environment under the effect of different swarm sizes: order metric.

by the fact that informed robots are "pushing" towards the goal direction, whereas uninformed robots are only trying to be proximally connected to their neighbors. Specifically, uninformed robots that are close to informed robots will try to stay close to them. Since informed robots are moving, uninformed robots will move as well to stay close, thus matching the heading of their neighbors. This also produces a "cascading effect", in the sense that uninformed robots which are close to other uninformed robots will also move towards the goal direction $\mathbf{g}$.

Figure 2 shows the accuracy metric for the two controllers. The plot reveals that the two behaviors perform almost the same with respect to accuracy. This happens despite the fact that order, which is an important component of the accuracy metric, is higher for the alignment-enabled controller. This hints to the fact that there is somewhere a loss of accuracy for the alignment-enabled controller, i.e. the accuracy of the alignment-enabled controller would be lower than the accuracy of the no-alignment controller if the two controllers performed in the same way with respect to the order metric. This effect will become more clear in the next section, in which we compare the two controller under the effect of different swarm sizes.

Effect of the swarm size

Figure 3 and Figure 4 show the effect of the swarm size on the order and on the accuracy respectively.

The order metric (Figure 3), is much higher when the size of the swarm is small. With comparable level of order in the two controllers, we now clearly see how the accuracy (Figure 3) is lower for the alignment-enabled controller with respect to the no-alignment controller.

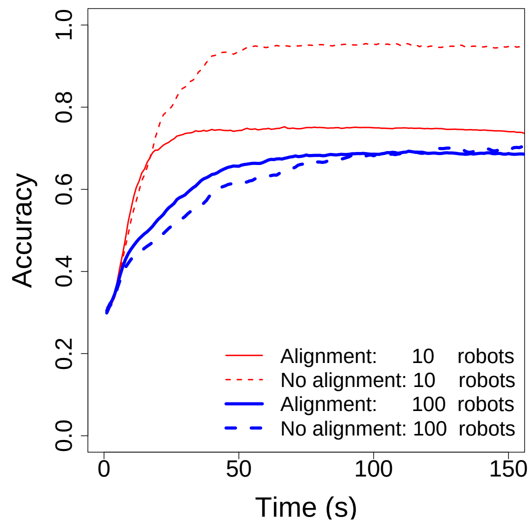

Figure 4. Alignment-enabled controller against no alignment controller in the stationary environment under the effect of different swarm sizes: accuracy metric

The explanation for this is the following. Turgut [20] observed that, when using the alignment-enabled behavior and when all of the robots are uninformed, they can achieve flocking to a common random direction. In our setting, however, a proportion of the robots is informed about the goal direction $\mathbf{g}$. This introduces a bias in the common direction negotiated by the swarm. However, this bias is not enough to compensate the bias corresponding to the random contribution of the uninformed robots. As a result, the swarm flock to a direction that is in between a totally

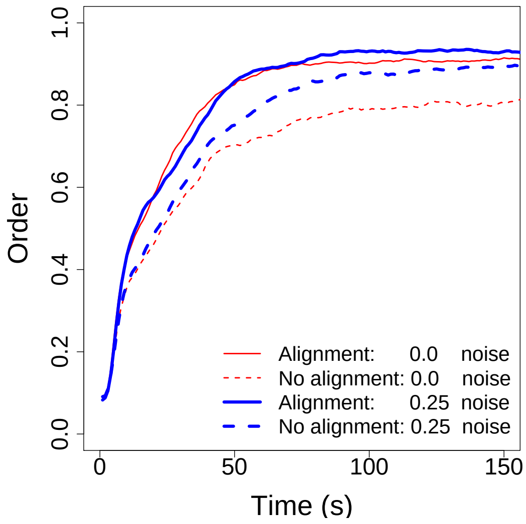

Figure 5. Alignment-enabled controller against no alignment controller in the stationary environment under the effect of noise in the proximal control vector: order metric.

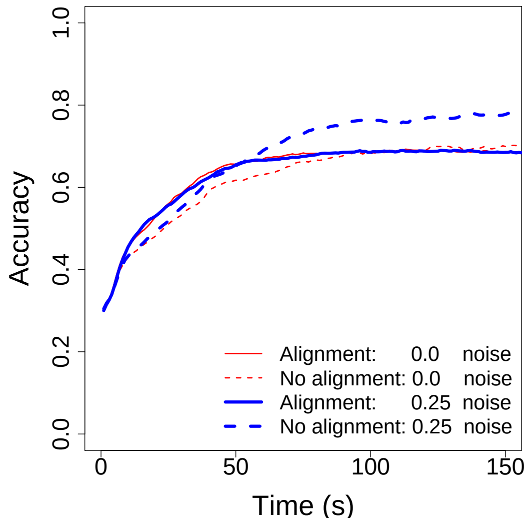

Figure 6. Alignment-enabled controller against no alignment controller in the stationary environment under the effect of noise in the proximal control vector: accuracy metric.

random direction and the correct goal direction $\mathbf{g}$.

On the other hand, when the alignment behavior is omitted, negotiation to a common direction is completely absent and hence, when no robot were informed, the swarm would not achieve flocking but would remain stationary while keeping a formation due to the proximal control behavior. When some (in this case 50%) of the individuals are informed, they introduce a bias towards the goal direction $\mathbf{g}$ which, although very small, is enough to achieve flocking in that direction, with an higher level of accuracy.

The effect explained above is particularly valid for smaller swarms. In large swarm, we observe lower accuracy levels, which however are due to lower levels of order. In the next section, while analyzing the effect of noise, we will also discuss the reason why order is negatively affected in larger swarm when using the no-alignment controller.

Effect of noise

The effect of noise on the order metric is shown in Figure 5. Results reveal that, for the alignment-enabled controller, noise has little or no effect on the order metric. This is due to the fact that the negotiation process provided by the alignment behavior compensates to the presence of noise. However, when using the no-alignment controller, results are surprising. In fact, order is positively affected by noise in the proximal control vector. This result is true particularly for large swarms.

By visual inpection of some simulation runs performed with the no-alignment controller we came out with the following explanation: When no noise is present in the proximal control behavior, we observe that uninformed robots are trying to stay close to the informed robots which are moving towards the goal direction $\mathbf{g}$. In doing so, robots align well to each other on the local scale, but with inaccuracies on large scales. On the other hand, when noise is introduced, large scale inaccuracies are compensated by noise uniformly present in the entire swarm.

Figure 6 shows the effect of noise on the accuracy metric. Due to higher levels of order, the noisy no-alignment controller outperforms all the others. Hence, noise can help to achieve higher level of order and, at the same time, a more accurate flocking behavior due to the presence of only one bias, the one of the informed robots.

Effect of the proportion of informed robots

Figure 7 shows the order metric when varying the number of informed robots ρ. When ρ is too small, the goal direction bias is not enough to move the robots when using the no-alignment controller. Hence, robots cannot be lead towards the goal direction, which in turn correspond to robots not following each other and hence not maintaining a common heading direction.

Figure 8 shows the accuracy metric when varying the number of informed robots ρ. As expected, when using the no-alignment controller, accuracy is also low because order is low. The alignment-enabled controller is also affected by a reduced proportion of informed individuals, although accuracy is higher than the one corresponding to the no-alignment controller. As a result, when few robots are informed about the goal direction, alignment helps to reach consensus to a direction which is close to the goal direction.

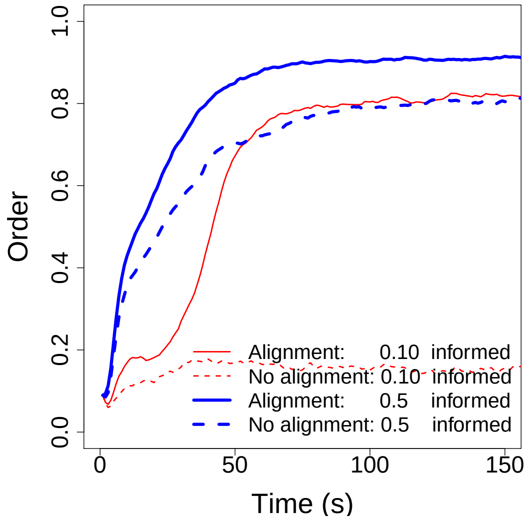

Figure 7. Alignment-enabled controller against no alignment controller under the effect of different proportions of informed individuals in the stationary environment: order metric.

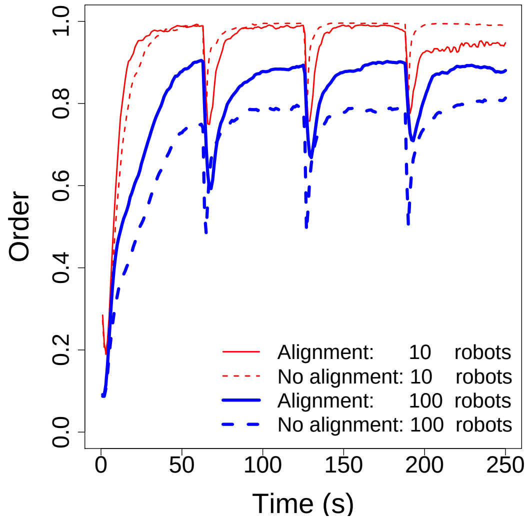

Figure 9. Alignment-enabled controller against no alignment controller in the non-stationary environment under the effect of different swarm sizes: order metric.

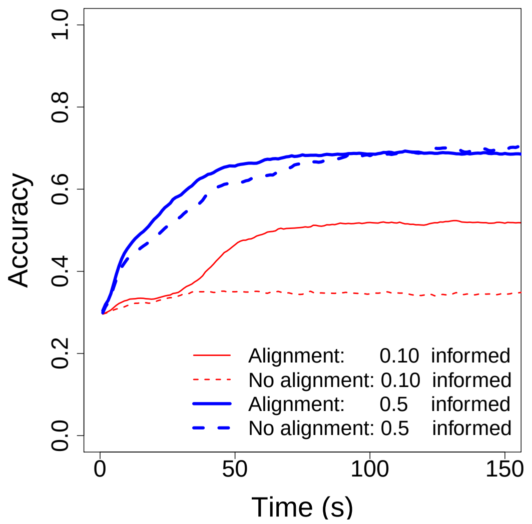

Figure 8. Alignment-enabled controller against no alignment controller under the effect of different proportions of informed individuals in the stationary environment: accuracy metric.

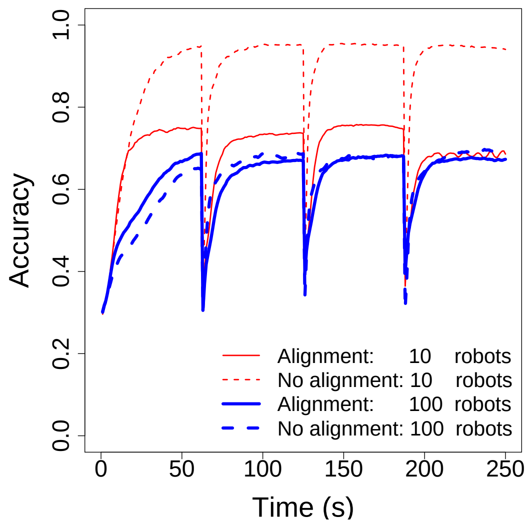

Figure 10. Alignment-enabled controller against no alignment controller in the non-stationary environment under the effect of different swarm sizes: accuracy metric.

D. Results for the non-stationary environment

Effect of the swarm size

Figure 9 and Figure 10 show the effect of the swarm size on the order and on the accuracy respectively. Results in both cases are consistent with the results in the stationary environment. With 10 robots, order is very high with both controllers, but the no-alignment controller outperforms the alignment-enabled controller for what concerns the accuracy metric. Results with a large swarm of 100 robots are also consistent with the ones in the stationary environment, with the alignment-enabled controller dominating in accuracy and both controller performing almost in the same way with respect to accuracy. With 10 robots, we observe a peculiar order (and consequently accuracy) drop in the the fourth stationary phase when using the alignment-enabled controller. This can be explained by the characteristics of our experimental setup, which has the light at finite distance from the robots. In some runs, robots might have reached the light source (especially when the swarm is moving fast),

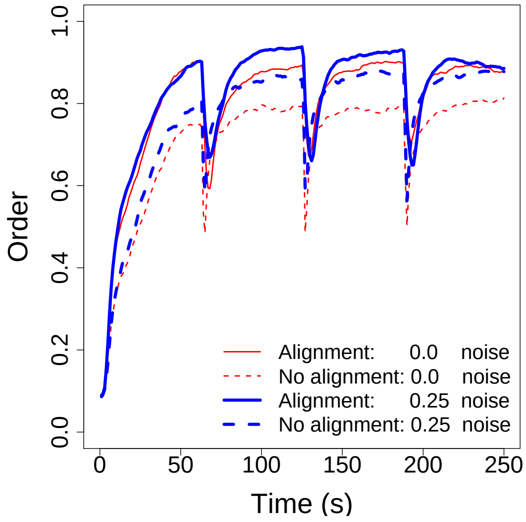

Figure 11. Alignment-enabled controller against no alignment controller in the non-stationary environment under the effect of noise in the proximal control vector: order metric.

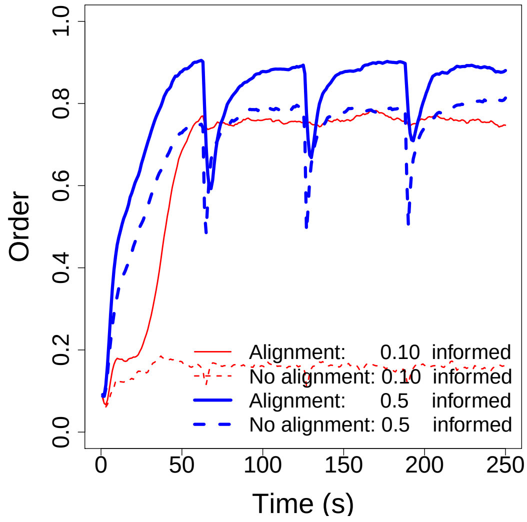

Figure 13. Alignment-enabled controller against no alignment controller in the non-stationary environment under the effect of different proportions of informed individuals in the: order metric.

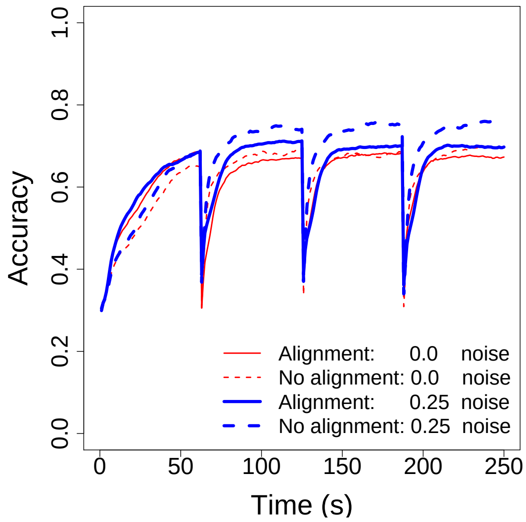

Figure 12. Alignment-enabled controller against no alignment controller in the non-stationary environment under the effect of noise in the proximal control vector: accuracy metric.

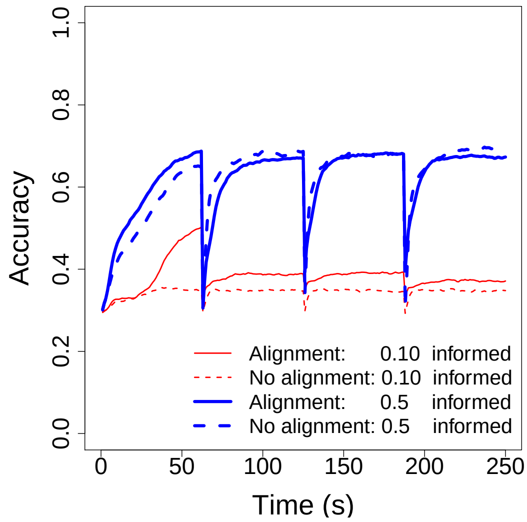

Figure 14. Alignment-enabled controller against no alignment controller in the non-stationary environment under the effect of different proportions of informed individuals in the: accuracy metric.

and at the light source robots heading measurements have no longer a semantics.

Effect of noise

Figure 11 and Figure 12 show the effect of noise in the proximal control vector on the order and on the accuracy metric respectively. Also in this case, results are consisten with the ones in the stationary environments: the order metric is high for the alignment-enabled controller and for the no-alignment controller with noise, whereas the accuracy metric is dominated by the no-alignment controller with noise.

Effect of the proportion of informed robots

Figure 13 and Figure 14 show the effect of changing the proportion of informed robots on the order and on the accuracy metrics respectively. Results here reveal that enough informed robots is needed to guarantee adaptation to non-stationary environments. In fact, with 50% informed robots, order and accuracy show that both controllers can make the swarm adapt to changes in the environment. On the other hand, with only 10% informed robots, the alignment-enabled controller reaches an intermediate level of order which remains the same regardless of changes in the environment. This is translated in a complete lack of adaptability, as shown by the accuracy metric. The no-alignment controller here performs even worse, with both order and accuracy assessing at very low levels.

V. Conclusions and Future Works

In this paper, we performed a comparative study of two flocking controllers. In both controllers, we implemented a proximal control behavior, to enable robots staying at an optimal distance between each other. One of the controllers, called alignment-enabled controller, was provided with an alignment behavior, with which robots can send their own measured heading and align to the average of the headings received from their neighbors. In the other controller, called no-alignment controller, only the proximal control behavior is present, and the alignment behavior is neglected.

We executed simulation-based experiments under different settings in order to compare the two controllers. In both controllers, a proportion of robots, called informed robots, are provided with information about the desired goal direction. Our goal was to understand under the effect of which parameter a controller outperforms the other. To measure performance, we implemented the order metric, which is used to measure at what extent robots are aligned with each other, and the accuracy metric, which measure how accurately robots are moving towards the goal direction.

We executed experiments in a stationary and non-stationary environment. In the stationary environment, the goal direction and the informed robots do not change over time. In the non-stationary environment, both the goal direction and the informed robots change over time. We study the effect of three different parameters: the size of the swarm, the noise in the proximal control behavior and the proportion of informed robots. Results showed that:

1) The alignment behavior results in a more aligned motion in larger swarms, whereas smaller swarms without an alignment behavior can follow the goal direction more accurately: In both stationary and non-stationary environments, and in a small swarm, the no-alignment controller outperforms the alignment-enabled controller, due to the fact that the goal direction alone biases the decision-making mechanism of the swarm. This correspond to better decisions made by the swarm. On the other hand, in large swarms, the negotiation mechanism provided by the alignment behavior helps to diffuse the information about the goal direction. However, a random bias in the negotiation can make this decision less accurate.

2) Noise in the no-alignment controller helps to achieve a more aligned motion in large swarms: In both stationary and non-stationary environments, the noise in the proximal control behavior has an interesting and positive effect on the order in large swarms when using the no-alignment controller. In facts, it helps to reach, more aligned collective movement, which otherwise would be affected by local errors in the alignment. This increase in order results also in better accuracy.

3) The swarm needs enough informed robots to follow accurately the goal direction and to adapt to non-stationary environments: In the stationary environment, we found that the proportion of informed robots need to be high enough in order for the no-alignment controller to work at an acceptable level. On the other end, using the alignment-enabled behavior, the information about the goal direction can spread in the swarm even when only a small proportion of robots is informed. On the other hand, in non-stationary environments, too few informed robot are not enough for achieving a sufficient level of adaptability.

The proposed study can be continued in many ways. First, a more in-depth analysis is required to understand exactly what is the effect of noise on the order in large swarm and how exactly it is helping. Second, it would interesting to understand whether the spatial distribution of informed robots matters on the collective decision-making of the swarm. Third, to have a better understanding of the dynamics of the system, an analytical model needs to be developed. Fourth and last, the proposed controllers can be ported into real robots experiments with the foot-bot platform, in order to validate our findings in a more concrete and realistic setting.

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