Control of a Mobile Robot Swarm via Informed Robots

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Summary. In this paper, we study how and to what extent a self-organized mobile robot flock can be guided to move in a desired direction by informing some of the individuals within the flock. Specifically, we extend a flocking behavior that was shown to maneuver a swarm of mobile robots as a cohesive group in free space, avoiding obstacles. In its original form, the flock does not have a preferred direction and would wander aimlessly. In this study, we extend this behavior by “informing” some of the individuals about the desired direction that we wish the swarm to move. The informed robots do not signal that they are “informed” (a.k.a. unacknowledged leadership) and instead guide the swarm by their tendency to move in the desired direction. Through experimental results with physical and simulated robots we show that the self-organized flocking of a robot swarm can be effectively guided by an informed minority. We use two metrics to measure the accuracy of the flock direction, and the ability to stay cohesive. We show that the accuracy of guidance increases with 1) the flock size, 2) the “stubbornness” of the informed individuals to align with the desired direction, and 3) the ratio of the informed individuals.

1 Introduction

Swarm robotics takes its inspiration from natural swarms and aims to develop self-organization in a large groups of robots with no centralized control while putting emphasis on flexibility, robustness and scalability. Most of the ongoing studies have focused on the application of self-organization approach. The limitations of controllability due to the use of the self-organization approach has been neglected so far, leaving the question of how useful the approach can be in real-world use, unanswered.

In this study, we are interested in how, and to what extent we can control the behavior of a swarm robotic system. Specifically, we are interested in how

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behaviors that lead to self-organization in a robotic flock can be externally controlled. There have been a number of studies that investigated the control mechanisms that exist in natural swarms or can be implemented in mixed robot-animal settings. In two interesting works, Vaughan et al. [1] used a robotic sheepdog to guide a duck flock to a predefined goal point, while Halloy et al. [2] manipulated the collective shelter selection process of cockroaches with robots that are socially integrated into the swarm. In [3], Shi et al. investigated the effect of informing some individuals in a flock with an external reference signal, using point mass dynamics. They showed that stable motion can be achieved even if there is a single informed individual, and increasing the number of informed individuals does not necessarily increase the convergence rate. However, it increases the robustness to noise. Reebs [4] has studied the decision making mechanisms in the foraging movements of fish schools, and showed that relatively few individuals with a priori knowledge can guide the whole school. Couzin et al. [5] modeled the decision making of flocks in which there are few informed individuals. The naive individuals arrange their positions and alignments according to neighbors, while the informed individuals also incorporate their preferred directions. Numerical simulations showed that the accuracy of guiding increases as the size of flock increases while the ratio of informed individuals is kept fixed. The importance of the weight of the preferred direction is less if the proportion of the informed individuals is small or large. For intermediate proportions of informed individuals, increasing this weight increases the accuracy of the motion, however it also increases the fragmentation of the flock.

Flocking in artificial swarms was first studied by Reynolds, who proposed a set of simple rules for obtaining realistic looking flying bird animations [6]. In robotics, Matarić [7], Kelly and Keating [8], Hayes and Tabatabaei [9], Holland et al. [10], and Campo et al. [11] have shed light on different aspects of the subject. In [12], Turgut et al. presented a truly self-organized, leaderless, decentralized flocking in a robot swarm. In [13], the sensitivity of the system to the behavioral parameters and communication characteristics are analyzed.

In this study, we extend the flocking behavior proposed in [12] by informing some of the individuals about the desired direction that we wish the swarm to move. The informed robots do not signal that they are “informed”, and instead guide the rest of the swarm by their tendency to move in the desired direction. We present experimental results on both physical and simulated robots, and show that the self-organized flocking of a swarm of robots can be effectively guided by a minority of informed robots within the flock. Then we analyze the system’s performance under various conditions. To the best of our knowledge, this is the first study in which the motion of a robotic flock is controlled via informing a subset of robots.
Fig. 1. (a) Photo of a Kobot. (b) Top-view of a Kobot sketch showing the body (circle), the IR sensors (small numbered rectangles), and the two wheels (grey rectangles). (c) The reference frame is fixed to the center of the robot where the x-axis coincides with the rotation axis of the wheels. The forward velocity \((u)\) is along the y-axis, \(\omega\) denotes the angular velocity of the robot. The y-axis of the body-fixed reference frame makes an angle of \(\theta\) with the sensed North direction \((n_s)\) at the instant the figure is drawn, which is the current heading of the robot.

2 Experimental Platforms

We use a custom-built mobile robot platform, called Kobot, and its physics-based simulator, that we refer to as CoSS, in our experiments [13]. Kobot is a CD-sized (with a 12 cm diameter), light-weight, differentially driven robotic platform (Fig. 1(a)). It possesses an active Infrared Short-Range Sensing System (IRSS) designed for short-range proximity measurements. This system utilizes modulated infrared signals to minimize environmental interference and crosstalk among the robots. It consists of eight sensors placed evenly at 45° intervals (see Fig. 1(b)), each of which is capable of sensing kin-robots and obstacles within a 21 cm range in seven discrete levels at 18 Hz.

Kobot is also equipped with a Virtual Heading Sensor (VHS) consisting of a digital compass and a wireless communication module to receive the relative headings of neighboring robots. The VHS module measures its own heading with respect to the sensed North at each control step and broadcasts it to other robots through wireless communication. Each robot receives the broadcasted heading values within its communication range. We define the set of robots that are “heard” by a given robot as its VHS neighbors. The angular difference between the broadcasted values and its own heading allows a robot to compute its relative heading with respect to its VHS neighbors and adjust it as needed. This operation of the VHS module assumes that the sensed North remains approximately the same among the robots within communication range.

The modeling of the proximal sensing and kin-detection characteristics of IRSS on the simulator is explained in detail in [13]. The VHS module is modeled to get information from 20 randomly chosen VHS neighbors in a...
range of 20 m at each control step [13]. The noise on the VHS is implemented using the vectorial noise model [14]. A random noise vector, characterized by a random direction and a constant magnitude, is added vectorially to each robot’s own heading measurement, since the noise in the VHS is due to the noise in the measurements of the compass, rather than a noise in the broadcasting process. The resulting noisy heading measurement is then broadcasted to the neighbors. The noisy heading measurement of the \( j \)th robot is calculated as:

\[
\theta_j' = \angle (e^{i\theta_j} + \eta e^{i\xi_0})
\]  

where \( \theta_j \) is the noiseless heading measurement of the \( j \)th robot, \( \eta \) and \( \xi_0 \) are the magnitude and the direction of the noise vector, respectively. \( \angle(\cdot) \) calculates the argument of the resulting vector. \( \xi_0 \) represents the noise chosen from a Gaussian distribution \( N(\mu, \sigma) \), where \( \mu \) and \( \sigma \) represents mean and the standard deviation, respectively. In the simulations, we set \( \eta = 1, \mu = \theta_j \) corresponding to the noiseless measurement, and \( \sigma = \pi \).

### 3 Flocking Behavior

The flocking behavior [12] consists of heading alignment and proximal control behaviors combined in the weighted vector sum, possibly with the addition of a preference for a certain direction:

\[
a = \frac{h + \beta p + \gamma d}{\| h + \beta p + \gamma d \|}
\]

where \( h \) is the heading alignment vector, \( p \) is the proximal control vector, \( d \) is the preferred direction vector, and \( a \) is the desired acceleration vector. \( \beta \) is the weight of the proximal control vector, and \( \gamma \) is the weight of the preferred direction vector.

\( \gamma \) is nonzero for only the subset of robots who are informed at the beginning of the motion to prefer a certain direction. Such individuals are called the informed individuals. For the uninformed individuals, called the naive individuals, \( \gamma \) is set to 0, effectively discarding this factor.

The heading alignment vector \( h \), which is used to align the robot with the average heading of its neighbors, is calculated as:

\[
h = \frac{\sum_{j \in \mathcal{N}} e^{i\theta_j}}{\| \sum_{j \in \mathcal{N}} e^{i\theta_j} \|}
\]

where \( \mathcal{N} \) denotes the set of VHS neighbors, \( \theta_j \) is the heading of the \( j \)th neighbor converted to the body-fixed reference frame and \( \| \cdot \| \) calculates the Euclidean norm.
The proximal control behavior uses readings obtained from the IRSS to avoid collisions and to maintain cohesion between the robots. For each IR sensor, a virtual force proportional to the square of the difference between the current detection level ($o_k$) and the desired detection level ($o_{des}$) is assumed. The desired detection level is defined as an intermediate detection level if the sensed object is another robot and 0 if it is an obstacle, so the robot keeps at a fixed distance to its peers while moving away from obstacles. The normalized proximal control vector $p$ is therefore given by:

$$p = \frac{1}{8} \sum_k f_k e^{i\phi_k}$$

where $k \in \{0, 1, \cdots, 7\}$ denotes the sensor positioned at angle $\phi_k = \frac{\pi}{4} k$ with respect to the $x$-axis (see Fig. 1(b)) and $f_k$ is calculated as:

$$f_k = \begin{cases} 
-\frac{(o_k - o_{des})^2}{C} & \text{if } o_k \geq o_{des} \\
\frac{(o_k - o_{des})^2}{C} & \text{otherwise}.
\end{cases}$$

The preferred direction vector $d$ is calculated as:

$$d = d_p - a_c$$

where $a_c$ is the current heading vector of the robot coincident with the $y$-axis of the body-fixed reference frame (see Fig. 1(c)), and $d_p$ stands for the preferred direction.

The desired heading vector, $a$, is used to calculate the forward ($u$) and angular ($\omega$) velocities. $u$ is calculated as:

$$u = \begin{cases} 
(a \cdot a_c) u_{max} & \text{if } a \cdot a_c \geq 0 \\
0 & \text{otherwise}
\end{cases}$$

The angular velocity $\omega$ is controlled by a proportional controller:

$$\omega = \frac{1}{2}(\dot{\zeta} a_c - \dot{\zeta} a)$$

4 Experimental Framework

In this section, we exploit the flocking behavior discussed above to analyze the effect of informing a subset of individuals about a desired direction of motion. We perform two different analyses: 1) the effect of the flock size for varying ratios of informed individuals in the flock, and 2) the effect of the weight of the preferred direction ($\gamma$) for varying ratios of informed individuals.
Metrics

We evaluate the performance of the system using the accuracy and cohesiveness metrics. The accuracy metric shows the degree of alignment with the selected direction, and the cohesiveness metric evaluates the degree of cohesion of the flock.

The accuracy metric, adopted from [5], depends on the angular deviation of the direction of the flock from the desired direction. The angular deviation is analogous to the standard deviation in linear statistics for inherently directional data. It is calculated as:

\[ \bar{C} = \bar{R} \cos(\bar{x}_0 - \alpha) \]

\[ S = \sqrt{2(1 - \bar{C})} \]

where \( S \) is the angular deviation, \( \bar{R} \) is the length of the mean vector, \( \bar{x}_0 \) is the direction of the mean vector, and \( \alpha \) is the desired direction [15].

Then, the accuracy is defined as:

\[ \text{Accuracy} = 1 - S/2 \]

Accuracy is 1 when the angular deviation is minimum, and 0 when the angular deviation is maximum. In this study, the angular deviation is calculated for the direction of motion of the flock center in all experiments. The direction is calculated for the final period of each experiment, discarding the transients in which a common direction has not yet settled.

Maintenance of the swarm cohesion is an important issue, due to the limited range of the infrared sensors. Once a robot gets out of the infrared range of the swarm, it cannot find the swarm again. We employ the size of largest cluster as a measure of cohesiveness. The robots are clustered in terms of metric distance. A robot is included in a cluster if it is in the infrared range of any robot that already belongs to the cluster.

Methodology

The experiments are conducted with both physical and simulated robots. 7 Kobots are used in the physical robot experiments, and 10, 20, 50 and 100 robots are employed in the simulations. The weight of the proximal control behavior (\( \beta \)) is set to 8. The experiments are repeated 10 times for physical robots, and 100 times for the simulations. The experiments are conducted for 60 s for physical robots, and 500 s in the simulations. The direction of motion of the flock center is calculated in the last 15 s of the experiments with the physical robots, and in the last 125 s with the simulated ones. In the experiments, the robots are initialized with random orientations, and the informed individuals are assigned randomly.
Results

**Size Experiment:** In this experiment, we investigate the effect of the size of flock on the accuracy of motion. We vary the size of the flock (10, 20 and 100 in simulations and 7 for physical robots) and measure accuracy for different ratios of informed individuals \( r \in \{0.1, 0.2, \cdots, 1.0\} \). In the experiments, \( \gamma \) is set to 0.1 and the results are plotted in Fig. 2.

It is observed in Fig. 2 that for a fixed ratio of informed individuals, the accuracy of motion increases as the size of the flock increases. This effect is more significant for low ratios of informed individuals. For high ratios, the accuracy converges to its maximum for all flock sizes. It is also observed in the figure that for a fixed system size, increasing the ratio of informed individuals increases the accuracy of motion of the system asymptotically which settles to approximately 0.9. The results of the Kobot experiments are slightly less accurate due to the limited test area used for the experiments, however the trends are the same.

**Weight of the Preferred Direction Experiment:** In this experiment, we investigate the effect of the weight of the preferred direction (\( \gamma \)) on the accuracy of flocking motion. We vary \( \gamma \ (\gamma \in \{0.1, 0.2, \cdots, 1.0\}) \) and measure accuracy for different ratios of informed individuals \( r \in \{0.01, 0.1, 0.14, 0.5, 1.0\} \). We also measure the size of the largest cluster for various \( \gamma \ (\gamma \in \{0.1, 0.5, 1.0\}) \) and ratios of informed individuals \( r \in \{0.1, 0.2, \cdots, 1.0\} \). The size of the flock is set to 100 and 7 for simulations and Kobot experiments, respectively. The results are plotted in Fig. 3(a) and 3(b).

It is observed in Fig. 3(a) that \( \gamma \) has an effect on the accuracy of motion for moderately low ratios of informed individuals (0.1 and 0.14). For the high ratios, the accuracy stays flat at approximately 1 irrespective to \( \gamma \). Likewise, for very low ratios, the accuracy does not increase with \( \gamma \). The results of the Kobot experiments are again slightly less accurate due to the limited test area.
Fig. 3. (a) Plot of the accuracy of the motion of the flock as a function of $\gamma$ for different ratios of informed individuals. (b) Plot of the size of largest cluster as a function of ratio of informed individuals for various $\gamma$ values. The ends of the boxes and the horizontal line in between correspond to the first and third quartiles and the median values, respectively. The top and bottom whiskers indicate the largest and smallest non-outlier data, respectively. The data in between the first and third quartiles lie within the 50% confidence interval, while the data in between the whiskers lie within the 99.3% confidence interval.

It is observed in Fig. 3(b) that for the intermediate ratios of informed individuals, increase in $\gamma$ decreases the size of the largest cluster and results in fragmentation of the flock which is not observed in low or high ratios ($r = 0.01$ and $r = 0.8$) of informed individuals.

The reason of this phenomenon is that the more “stubborn” are the informed individuals to move in their preference, the more probable that they will be separated from the flock. This effect is naturally less visible in the $r = 0.01$ case where the loss of a single individual does not alter the size of the largest cluster much. On the other hand, when the ratio of informed individuals is high enough ($r = 0.8$), they are faster in changing the direction of the whole flock, which reduces the length of the transition phase, and decreases separations. In the extreme case where all of the individuals are informed ($r = 1$), dictating a goal direction to every individual increases their tendency to move in the same direction, and thus enhances the cohesiveness of the flock and increases the size of the largest cluster to its maximum.

In Fig. 4(a), we plot a sample experiment’s time evolution of the headings of 100 robots where 10 robots (indicated with white traces) are commanded to go in $90^\circ$ direction, and their $\gamma$ is set to 0.5. It can be seen that the directions of the robots fluctuate until they consent on the desired direction. The consensus is reached faster when $\gamma = 1$, Fig. 4(b).
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![Graphs (a) and (b)](image)

**Fig. 4.** Time evolution of the headings of 100 robots in two sample experiments. 10 robots are commanded to go in $90^\circ$ direction. The traces of informed robots are indicated with white bold lines. (a) $\gamma = 0.5$ (b) $\gamma = 1$

## 5 Conclusion

In this study, we have showed that, the self-organized flocking motion in a robot swarm can be manipulated via informing a minority of the robots to prefer a certain direction of motion. The results show that, in the presence of even a small number of informed robots, the flock can consent on the desired direction of motion, which becomes more accurate with 1) increasing flock size, 2) increasing “stubbornness” of the informed individuals, and 3) an increasing number of informed individuals. We have also showed that, for moderately low ratios of informed individuals, increasing the weight of the desired direction has the adverse effect of increasing the clustering in the group. Among the work that awaits to be done, there is the control and reduction of clustering, analysis of the sensitivity against the VHS noise, and the analysis of the significance of the spatial locations of the informed individuals in the flock in terms of accuracy and cohesiveness.

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