# Guiding a Robot Flock via Informed Robots

Hande Çelikkanat, Ali Emre Turgut and Erol Şahin

**Abstract** 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 path. In its original form, this behavior does not have a preferred direction and the flock would wander aimlessly in the environment. In this study, we extend the flocking 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 rest of the swarm by their tendency to move in the desired direction. Through experimental results obtained from physical and simulated robots we show that the self-organized flocking of a swarm of robots can be effectively guided by a minority of informed robots within the flock. In our study, we use two metrics to measure the accuracy of the flock in following the desired direction, and the ability to stay cohesive meanwhile. Using these metrics, we show that the proposed behavior is scalable with respect to the flock's size, and that the accuracy of guidance increases with 1) the "stubbornness" of the informed robots to align with the preferred direction, and 2) the ratio of the number of informed robots over the whole flock size.

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# 1 Introduction

Swarm robotics takes its inspiration from natural swarms and aims to develop self-organization in 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 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 behaviors that lead to self-organization in a robotic flock can be externally controlled.

A number of studies investigated external control on animal swarms. In two interesting works, Vaughan et al. [17] used a robotic sheepdog to guide a duck flock to a predefined goal point, while Lien et al. [7] compared various approaching and steering strategies for external shepherds, utilizing them for herding, covering, patrolling, and collecting behaviors. In [8] they extended the results to the multiple shepherds case. Halloy et al. [4] manipulated the collective shelter selection process of cockroaches with robots that are socially integrated into the swarm.

Meanwhile, the decision making mechanisms in natural flocks, and the possibility of their being guided by some of the individuals inside the flock are also investigated in various studies. Reebs [12] 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. [2] modeled the decision making of flocks in which there are few informed individuals. Numerical simulations showed that the accuracy of the informed individuals in guiding the flock increases as the size of flock increases while the ratio of informed individuals is kept fixed. If the proportion of the informed individuals is moderate, increasing the importance given to the preferred direction increases the accuracy of the motion, however it also increases the fragmentation of the flock. The increase in the accuracy is not observed when the proportion of the informed individuals is either too small or too large.

In [14], Shi et al. investigated the effect of informing some individuals in a flock with an external reference signal, from the control theory perspective, using point mass dynamics. They showed that stable motion, in which the agent velocities eventually converge to the desired velocity, can be achieved even if there is a single informed individual who could receive the signal, whereas increasing the number of informed individuals does not necessarily increase the convergence rate.

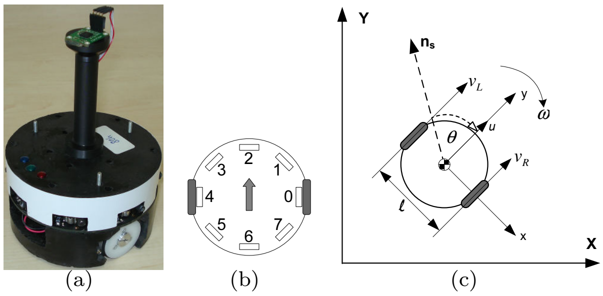
Inspired by the works of [12], [2] and [14], in this paper we try to achieve a similar guidance mechanism in a robotic flock. Flocking in artificial swarms was first studied by Reynolds, who proposed a set of simple rules for obtaining realistic looking flying bird animations [13]. In robotics, Matarić [11] was the first to achieve flocking in a collective homing behavior, composed of safe-wandering, aggregation, dispersion and homing behaviors. Kelly and Keating [9] developed a novel infrared (IR) system for the robots to sense the relative range and bearing of neighbors. The robots followed a leader which was elected by wireless communication. Hayes and Tabatabaei [5] proposed a leaderless distributed flocking algorithm, assuming that the robots could sense the range and bearing of their neighbors to compute the center of mass of the flock, which was used for cohesion and alignment. Although the algorithm was implemented successfully on the Webots simulator, in the physical experiments the sensors had to be emulated using an overhead camera. Holland et al. [6] proposed a flocking behavior for unmanned air vehicles based on avoidance, flock centering and alignment behaviors, with the range, bearing and velocity information received from a base station. Campo et al. [1] used a specifically designed colored LED system surrounding the body of s-bots through which the s-bots negotiate their a priori estimations of the nest location, in order to collectively carry a prey.

In [16], Turgut et al. presented a truly self-organized, leaderless, decentralized flocking in a robot swarm. In this study, we extend this behavior by informing some of the robots about the preferred 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 preferred 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, without an explicit leadership mechanism. Then we analyze the system's performance under various conditions.

## 2 Experimental Platforms

In this study, we use Kobot and its physics-based simulator CoSS [15]. Kobot is a light-weight (12 cm diameter), differentially driven robotic platform (Fig. 1(a)). It has two main sensory systems: the Infrared Short-Range Sensing System (IRSS) and the Virtual Heading Sensor (VHS). IRSS is composed of 8 infrared sensor modules located at 45° intervals around the base (Fig. 1(b)), and is used for short-range proximity measurements. It uses modulated infrared signals to minimize the environmental interference, and crosstalk among robots. The sensors can detect objects within a 21 cm range at seven discrete proximity levels, and can distinguish kin-robots from obstacles.

The VHS is used for virtually "sensing" the relative headings of the neighboring robots. It consists of a digital compass and a wireless communication module. The robot's heading with respect to the sensed North is measured using the compass module and is broadcasted to other robots through wire-




(a) (b) (c)

**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 (gray 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. With kind permission from Springer Science+Business Media: Swarm Intelligence, Self-organized flocking in mobile robot swarms, volume 2, number 2-3, 2008, Ali Emre Turgut, Hande Çelikkanat, Fatih Gökçe and Erol Şahin, Fig. 1.

less communication. Each robot receives the broadcasted heading values of the robots within its communication range. The robots whose heading values can be received by a robot are called its *VHS neighbors*.

We would like to point out that VHS *does not assume the sensing of absolute North*. As a matter of fact, metal objects are abundant in indoor environments, and the sensed North deviates much from the absolute North direction. The only assumption that VHS makes is that the sensed North direction remains approximately the same among the VHS neighbors of a robot.

In CoSS, the sensing and actuation of robots is modeled using data obtained from systematic experiments and is verified against Kobots [15]. The sensing characteristics of the IRSS is obtained from systematic experiments with Kobot. We model the noise on the VHS with the vectorial noise model [3]. A noise vector is added to the heading measurements performed by each robot. The direction of the noise vector is chosen from a Gaussian distribution, whose mean is the actual heading of the robot, and standard deviation is $\pi/2$. The magnitude of the noise vector, denoted by $\eta$, determines the amount of noise in the system, and is set to 1. The VHS module is modeled to receive heading information from 20 randomly chosen VHS neighbors within a range of 20 m at each control step.

## 3 Flocking Behavior

The flocking behavior proposed in [16] originally consists of heading alignment and proximal control behaviors, to which we now add a preference for a certain direction:

$$\mathbf{a} = \frac{\mathbf{h} + \beta \ \ \mathbf{p} + \gamma \ \ \mathbf{d}}{\|\mathbf{h} + \beta \ \ \mathbf{p} + \gamma \ \ \mathbf{d}\|}$$

where $\mathbf{h}$ is the heading alignment vector, $\mathbf{p}$ is the proximal control vector, $\mathbf{d}$ is the direction preference vector, and $\mathbf{a}$ is the desired heading vector. $\beta$ is the weight of the proximal control vector, and $\gamma$ is the weight of the direction preference vector.

The *informed robots* have a non-zero $\gamma$ to include the preference vector $\mathbf{d}$ for the desired direction, whereas the *naive robots* have their $\gamma$ set to zero, effectively discarding the direction preference term in their calculations.

The heading alignment vector $\mathbf{h}$ tries to align the robot with its neighbors, and is calculated as:

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

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 is responsible for flock cohesion and collision avoidance. The normalized proximal control vector $\mathbf{p}$ is calculated using the infrared readings from the IRSS. It is a vector sum of virtual forces which are assumed to act on each infrared sensor:

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

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 $f_k$ denote the virtual force acting on the sensor. The virtual forces are taken to be proportional to the square of the difference between the current detection level ($o_k$) of the sensor, and the desired detection level ($o_{des}$). The desired detection level is defined as an intermediate detection level (3) if the sensed object is another robot and 0 if it is an obstacle. This setting motivates the robot to keep at an optimal distance from its peers and escape from obstacles. $f_k$ is then calculated as follows:

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

The direction preference vector $\mathbf{d}$ is calculated as:

$$\mathbf{d} = \mathbf{d_p} - \mathbf{a}_c$$

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

The desired heading vector, $\mathbf{a}$, is used to calculate the forward ($u$) and angular ($\omega$) velocities. $u$ is calculated via diminishing the maximum speed $u_{max}$ according to the robot's momentary urge to turn. This urgency is given by the difference between the desired heading and the current heading of the robot, calculated by a dot product of the two vectors:

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

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

$$\omega = \frac{1}{2}(\angle \mathbf{a}_c - \angle \mathbf{a})$$

## 4 Metrics

We evaluate the performance of the system using two different metrics. The accuracy metric, adopted from [2], measures the angular deviation of the direction of the flock from the preferred direction. The angular deviation is analogous to the standard deviation in linear statistics for inherently directional data. For a given set of vectors, it is calculated as:

$$\bar{C} = \bar{R} \cos(\bar{x_0} - \alpha)$$

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

where $\bar{R}$ is the length of the mean vector of the given vectors, $\bar{x_0}$ is the direction of the mean vector, $\alpha$ is the preferred direction and $S$ is the angular deviation around this preferred direction [10].

Then, the accuracy is defined as:

$$Accuracy = 1 - S/2$$

The accuracy metric becomes 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 transient phase in which a common direction has not yet settled.

The cohesiveness metric uses the size of the largest flock within the environment to evaluate the degree of cohesion. We assumed that a robot is part of a flock if it is within the infrared range of another robot that already belongs to the flock. This metric is important since the infrared sensors have a limited range and that once a robot gets disconnected from the rest of the flock, it has little chance to find it again.

## 5 Experimental Results

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

The experiments are conducted with both physical and simulated robots. In the physical experiments 7 Kobots are used, whereas the experiments conducted in CoSS use 10, 20 or 100 robots. The weight of the proximal control behavior ($\beta$) is set to 4, while $o_{des}$ is set to 3 for kin-robots and 0 for obstacles, and $u_{max} = 7$ cm/s. The VHS noise magnitude $\eta$ is set to 1 in the simulations. The experiments are conducted for 60 s for physical robots, and 1000 s in the simulations. Physical experiments are repeated for 5 times, the simulations for 100 times. The direction of motion of the flock center is calculated during the last 40 s of the experiments with the physical robots, and during the last 125 s with the simulated ones. The robots are initialized with random orientations, and the informed robots are assigned randomly.

Fig. 2 plots the time evolution of the headings of 100 robots in two sample experiments. There are 10 informed robots (indicated with white traces) which are commanded to go in $90°$ direction, and their $\gamma$ is set to either 0.5 or 1. In both cases, the directions of the robots fluctuate until they consent on the preferred direction. In the $\gamma = 0.5$ case, the alignment is reached faster (Fig. 2(a)), however in the $\gamma = 1$ case, the informed robots are more "stubborn" to follow the preferred direction, so the alignment is reached only when the whole flock consents on the preferred direction (Fig. 2(b)).

**Flock Size Experiment:** In this experiment, we investigate the effect of the size of flock on the accuracy of flock direction. We vary the size of the flock ($10, 20$ and 100 in simulations and 7 in physical experiments) and measure accuracy for different ratios $\rho$ of the number of informed robots. In the experiments, $\gamma$ is set to 0.1 and the results are plotted in Fig. 3.

Fig. 3 shows that the accuracy is independent of the flock size for a fixed ratio of informed robots, that is, the proposed behavior is *scalable*. It is also observed in the figure that for a fixed system size, increasing the ratio increases the accuracy of the direction of motion asymptotically. Moreover, the accuracy is quite high for even low ratios, and the increase in the accuracy is very rapid with respect to the increase in $\rho$. The results of the Kobot experiments are slightly less accurate due to the limited test area used for the

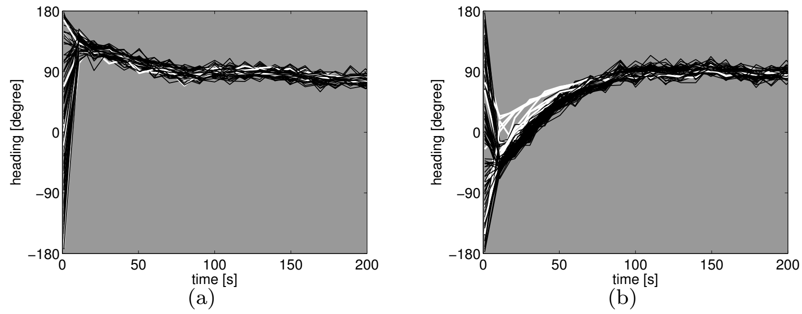



**Fig. 2** Time evolution of the headings of 100 robots in two sample experiments. 10 robots are commanded to go in 90° direction. The traces of informed robots are indicated with white bold lines. (a) $\gamma = 0.5$ (b) $\gamma = 1$

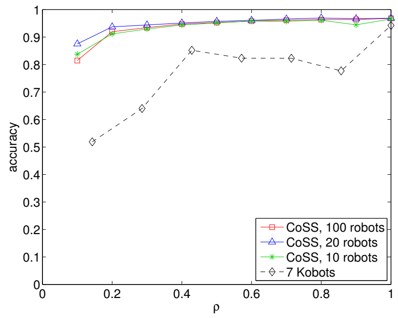
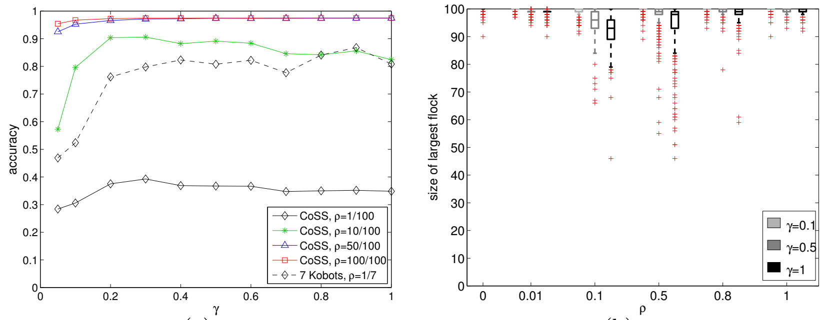



**Fig. 3** Plot of accuracy of flock direction as function of ratio of informed robots for different flock sizes. The error bars are not shown since accuracy is a function of angular deviation.

experiments, since the system may not reach to steady-state in 60 s especially for low ratios, however the trends are similar.

**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 $\gamma$ and measure accuracy for different ratios $\rho$. We also measure the size of the largest flock eventually formed for various $\gamma$ and $\rho$. 100 and 7 robots are used in simulations and Kobot experiments, respectively. The results are plotted in Fig. 4(a) and 4(b).

It is observed in Fig. 4(a) that $\gamma$ has an effect on the accuracy of motion for moderately low ratios ($\rho = 0.1$ and $\rho = 1/7$). 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, but the trends are the same.




(a) (b)

**Fig. 4** (a) Plot of the accuracy of flock direction as a function of the weight of the preferred direction ($\gamma$) for different ratios of informed robots ($\rho$). (b) Plot of the size of the largest flock as a function of $\rho$ for varying $\gamma$. 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.

In Fig. 4(b) it is seen that for the intermediate ratios, increase in $\gamma$ decreases the size of the largest flock and therefore results in increased fragmentation of the flock, which is not observed in low or high ratios ($\rho = 0.01$ and $\rho = 0.8$). The reason of this phenomenon is that the more "stubborn" are the informed robots to move in their preference, the more probable that they will be separated from the flock. Therefore, in the $\rho = 0.01$ case, the loss of a single informed robot does not have a significant effect on the largest flock size. On the other hand, when the ratio is high enough ($\rho = 0.8$, $\rho = 1.0$), the informed robots are faster in changing the direction of the whole flock, which reduces the length of the transition phase, and decreases separations.

## 6 Conclusion

In this study, we showed that the self-organized flocking motion in a robot swarm can be guided by informing a subset 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 preferred direction of motion, and furthermore, the proposed behavior is scalable with respect to the flock's size. The directional guidance of the flock becomes more accurate with 1) increasing the "stubbornness" of the informed robots, and 2) increasing the number of informed robots. We have also showed that, for moderately low ratios of informed robots, increasing the importance given to the preferred direction has the adverse effect of increasing the fragmentations in the group. Among the work that awaits to be done, there is the analysis of the transient dynamics of the system, control and reduction of fragmentation, and the analysis of sensitivity against the VHS noise, as well as the spatial locations of informed robots in terms of accuracy and cohesiveness.

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