Examining the Information Requirements for Flocking Motion

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Abstract. Flocking is an archetype emergent behavior that is displayed by a wide variety of groups and has been extensively studied in both biological and robotic communities. Still today, the exact requirements on the detail and type of information required for the production of flocking motion is unclear; moreover, these requirements have large potential impacts on biological plausibility and robotic implementations. This work implements a previously published flocking algorithm (Local Crowed Horizon) on a robotic platform and in computer simulations to explore the effects that the type and detail of information have on the produced motions. Specifically, we investigate the level of detail needed for the observation of flock members and study the differences between the use of pose and bearing information. Surprisingly, the results show that there is no significant difference in the motions produce by any observation detail or type of information. From the results, we introduce and define information-abstracted flocking algorithms, which are structured in such a way that the rule is agnostic to the observation detail and/or type of information given as input. Moreover, we believe our implementation of the Local Crowded Horizon flocking algorithm produces motions that require the least and most simplistic type of information (bearing only) which has been validated on robotic hardware to date.

1 Introduction

Flocking is a collective spatial behavior displayed by a wide variety of groups and has been studied in several research communities including biology, physics, and robotics. As an archetype emergent behavior, gaining an understanding of what the individual flock members observe and compute presents several challenges; one critical challenge is identifying how much detail is required when observing other flock members. It remains unclear how detailed the observations of other flock members need to be in order to produce flocking motion. For example, do individuals form a cohesive flock even if sub-groups or local densities (group-centric information) are observed rather than clearly discernible/identifiable individuals (member-centric information)? The results in this work prove that it is possible to produce flocking motion through the use of group-centric information.

The use of group-centric information shows that flock members do not need to detect individual flock members, which is difficult and error prone; instead, flock members need only detect groups of flock members. One conceivable implementation of a group-centric flocking algorithm is to design an agent which only detects *objects* that have a particular image-size. This would suggest that groups further away could still influence the flock members motions similar to the way a nearby flock member would. By reducing the complexity of the required sensing, a flocking algorithm can be implemented on a more simplistic agent (*e.g.,* doing some of the processing via an attentional mechanism) , which makes the algorithm more biologically plausible and easier to successfully implement on a robotic system.

Another challenge in studying flocking, is understanding what type of information (*e.g.*, pose, bearing, velocity) must be gathered/sensed from the observations, and what implications the chosen information may have on biological plausibility and/or robotic implementations. The vast majority of the literature uses pose information (at least) to produce flocking motion [3, 8, 10, 1], with relatively few works using only bearing information [9, 6]*. The bearing only algorithm studied here is not the first example of flocking motion produced by only using bearing information, but it is the first example of an algorithm that produces flocking motion which is equivalent when using either bearing or pose information. For the first time, we are able to compare the effects that different types of information have on the produced flocking motions through the implementation of a single algorithm.

To investigate the effects of the level of observation detail and the type of information sensed, we implemented the Local Crowded Horizon (LCH) rule [10] on a mobile robotic platform. The LCH was chosen for two reasons; (1) the rule has a unique structure that affords the ability to study the two aforementioned questions (level of observation detail and type of information) without modifying the algorithm and (2) Viscido *et al.* [10] shows the LCH produces flocking motions that are observed in biological flocks. In addition to the robotic implementation proof of concept, we implemented a computer simulation in order to better study the information requirements for flocking motion.

From the results of the robotic implementation and the computer simulations, we identify the notion of **information-abstracted flocking**, which refers to flocking algorithms that are structured in such a way that the resulting motion is agnostic to the detail of the observation and/or to the type of information sensed. In other words, if the motions produced by a flocking algorithm are equivalent under different types of information (*e.g.,* pose, bearing), then the algorithm is considered to be information-abstracted on type. The concept of information-abstracted flocking algorithms is rooted from the work of generic programming [7], where a single implementation of an algorithm can be *instantiated* with different data representations, an idea analogous to abstraction in abstract algebra. Information-abstraction is actually stronger, as it actually pro-

* The model presented in [9] requires velocity; however, the velocity parameter is constant for the simulations; it cancels out leaving only the use of bearing information.

duces comparable emergent behavior despite being instantiated with different data representations.

Additionally, the results in this work support the following claims:

- Some flocking algorithms may be structured so that the resulting behaviors are independent to the detail of the observation or the type of information given to the algorithm.
- Comparison of one flocking algorithm with another purely on the basis of the motion they produce is inadequate. This is especially the case when one is trying to make a claim about biological behavior on the basis of similar behavior generated through some computational means. The existence of information-abstracted flocking rules imply that, despite the output motion appearing equivalent, major pieces of the puzzle could remain underspecified.
- The vast majority of the literature assumes pose information is required to produce flocking behaviors, we further support the suggestion that biological flocking motion is possible using bearing information only.

Furthermore, we believe that our implementation of the LCH using only bearing information is the simplest biologically plausible, flocking algorithm to date.

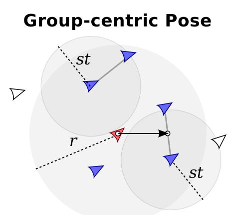
2 Local Crowded Horizon

The LCH was presented by Viscido *et al.* [10] as a biologically plausible explanation for flocking motion exhibited in the presence of a predator. In the original work there is a discrepancy between the theoretical design and the simulated version of the LCH. The authors describe the LCH by stating "[Flock members] use the density of the entire [flock] to determine their [next pose]"; however, their implementation has flock members "move toward the average [pose] of [all of the detected flock members.]" This discrepancy leaves the LCH with at least four different variations in regards to the information requirements; (1) group-centric pose, (2) group-centric bearing, (3) member-centric pose, and (4) member-centric bearing. The two **group-centric** variations use a subset of the detected flock members where the two **member-centric** variations use all of the detected flock members to compute the next pose. Figure 1 is a pictorial and prose description of the four different variations.

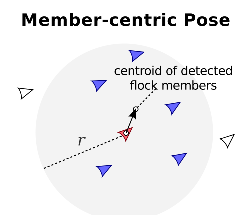
Both member-centric variations follow the same structure for the production of flocking motion. The member-centric variations take a set of all the detected flock members ($\mathbf{I}$) and moves one unit (d) towards the average of the feature vectors in $\mathbf{I}$. A **feature vector** contains all of the sensed information required for the computation of the next pose (*e.g.*, pose, bearing, velocity) for each flock member in $\mathbf{I}$. The only difference between the two member-centric variations is in how the averaging of the feature vectors are handled.

In the member-centric variation using pose (see algorithm named Variation 2) the function AveragePose($\mathbf{I}$) calculates the average pose of the set $\mathbf{I}$. To correctly average the flock member bearings (algorithm in full omitted, due to space), AverageBearing($\mathbf{I}$) replaces AveragePose($\mathbf{I}$) in variation 2 and calculates the bearing from the average unit vector from the flock member and all members in the set **I**, *i.e.* 2-dimensional pose information is not required, only 1-dimensional bearing information.

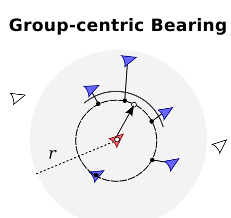
The group-centric variations are identical to the member-centric variations, except that the motion command that is computed depends on only a subset ($\mathbf{I}'$) of the set **I**. This models the idea that the motions follow some strict prioritization where attention need only be paid to some salient (or dense, or tightly-clustered) individuals. In both group-centric variations, the flock member computes the set $\mathbf{I}'$ based on density ($\mathbf{I}'$ contains all flock members that exist in the highest density cluster) and moves one unit towards the average of the feature vectors in the set $\mathbf{I}'$. Analogous to the case described above, different density selection functions are needed to handle the differences in the feature vectors. In our implementation of the group-centric variations, member-centric information is used to calculate the group-centric information to utilize the same detection process for all parameterizations. Of course, group-centric pose computations are only permitted to use group-centric information.



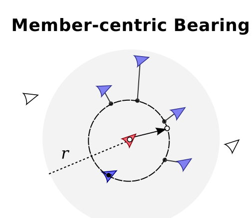
(a) The sensing flock member chooses the largest subset of the detected flock members and moves towards that group's average pose.



(b) The sensing flock member moves towards the average pose of all the detected flock members.



(c) The sensing flock member chooses the largest subset of the detected flock members and sets its new heading to the average bearing to the selected flock members.



(d) The sensing flock member's new heading is the average of bearings to each of the detected flock members.

Legend:

Sensing flock member Detected flock member Non-detected flock member

Fig. 1: The four variations of the LCH flocking algorithm used in this study. Variations 1a and 1b require pose information where 1c and 1d use bearing information. Variations 1b and 1d utilize all of the detected flock members where 1a and 1c only use a subset of the detected flock members.

LCH Variation 1: Member-centric LCH Pose (Corresp. to Fig. 1(b))

Input: Set of detected flock members ($\mathbf{I}$) in egocentric coordinate frame.
Parameters:
$d \doteq$ *distance to travel*
$\mathbf{r}_i \doteq$ *current pose*
Output: Desired pose in a member-centric coordinate frame.

```
if |I| = 0 then
    return [0, 0]
else
    v ← AveragePose(I)
    return
        [r_{i^x} + ((v/||v||) * d), r_{i^y} + ((v/||v||) * d)]
```

$$\left[\mathbf{r}_{i^x} + \left(\frac{\mathbf{v}}{||\mathbf{v}||} * d\right),\ \mathbf{r}_{i^y} + \left(\frac{\mathbf{v}}{||\mathbf{v}||} * d\right)\right]$$

LCH Variation 2: Group-centric LCH Bearing (Corresp. to Fig. 1(c))

Input: Set of detected flock members ($\mathbf{I}$) in egocentric coordinate frame.
Parameters:
$st \doteq$ *splitting threshold (angle)*
$d \doteq$ *distance to travel*
$\mathbf{r}_i \doteq$ *current pose*
Output: Desired pose in a member-centric coordinate frame.

```
if |I| = 0 then
    return [0, 0]
else
    CC ← ConnComponents(I, st),
    where CC ≥ 1
    I' ← MaxConnComponent(CC)
    θ ← AverageBearing(I')
    return
        [r_{i^x} + (cos(θ) * d), r_{i^y} + (sin(θ) * d)]
```

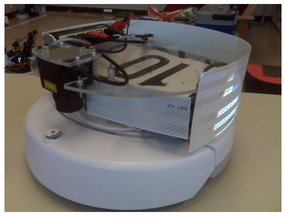
$$[\mathbf{r}_{i^x} + (\cos(\theta) * d),\ \mathbf{r}_{i^y} + (\sin(\theta) * d)]$$

In both group-centric variations, the flock member groups the detected members based on a threshold (st) in the set $\mathbf{CC}$ (st could either be a distance or angular based threshold). The algorithm then selects the largest group from the set $\mathbf{CC}$ to compute the next pose. The function MaxConnComponent($\mathbf{CC}$) takes $\mathbf{CC}$ and returns the largest group of flock members. The details of the group-centric variation using bearing information can be seen in Variation 2 (the group-centric variation using pose is not shown here due to space).

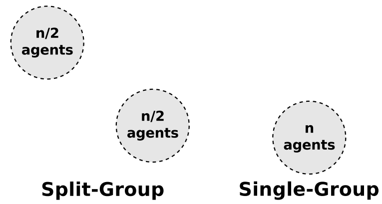
3 Robotic Implementation

Each robot (flock member) is an iRobot Create [5] equipped with a ASUS Eee PC and a Hokuyo URG-04LX-UG01 [4] laser range-finder; see Figure 2a. The robots are wrapped in a highly reflective material and each robot has a modified Gearbox 9.07 driver [2] that allows for the detection of other robots. The trials conducted for this study consider four robots in the single-group starting formation (Figure 2b) in a obstacle free space that can be considered infinite for the presented trials.

We conducted several trials for each of the four LCH variations mentioned earlier; Figure 3 shows time series from a few of these trials. There is no significant difference observed in the motions produced by the four different variations of the LCH. We do observe that the motions produced by our robotic implementation do not collapse into a single group, as observed in the simulations of Viscido *et al.* [10]. However, the robots do indeed collapse into a single group, but because of the robot's limited field of view (FOV), the flock exhibits directional motion. This directional motion occurs when one or more robots do not observe other robots in the flock, therefore they continue moving in their current



(a)



(b)

Fig. 2: Figure 2a shows a single iRobot Create with a Hokuyo laser and a ASUS Eee PC wrapped in high reflectance material for robot detection. Figure 2b shows the two starting formations used in this study. The exact poses of the flock members, within the formation, were chosen at random for each run.

direction; see Figure 4a. We show, through computer simulations, that the FOV limitations of the robots is the primary cause of the motion differences.

We should note that Figure 3 does not show any results from trials using the group-centric variation because the size of our system is not large enough to show the desired motions. When the there is only one robot in the selected group, the robots will exhibit motions that can best be described as a *follow the leader* behavior. Figure 4b is a pictorial representation showing how the *follow the leader* motions are generated.

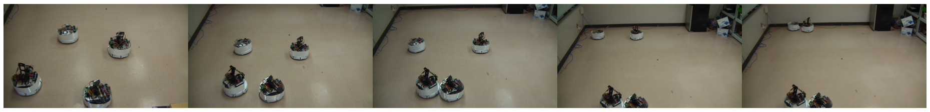
3.1 The effect of a limited field of view

Using MatLab (version R2011b) we implemented all four variations of the LCH similar to the implementation in [10]. Each flock member has access to the global information for every other flock member but each member is only able to *detect* flock members within the sensing radius (r). Each flock member will calculate their next pose ($\mathbf{r}_i$) according to the given LCH variation. Additionally, we included the flock members FOV into our implementation in order to account for the limited FOV of our robots.

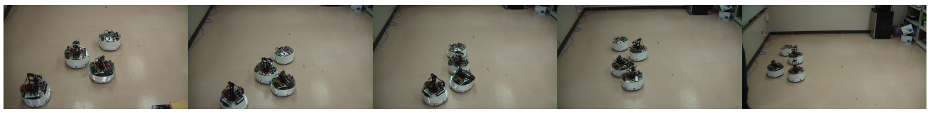
Figure 5a shows the simulated motions of 50 flock members for the member-centric variation using pose with no limitations on their FOV. These motions reveal that our implementation of the LCH is similar to the LCH implementation in [10]. Furthermore, the motions in Figure 5b show the simulated motions for the 50 flock members with a limited FOV similar to the FOV of the robots. Comparing the motions in Figure 5b and Figure 3 we notice our simulation, with a limited FOV, can produce equivalent motion to the robotic implementation. Since our implementation can produce the motions of the original motivating work and the motions produced by a robotic implementation we feel the simulation is adequate for further investigation of information (type and detail) on flocking.

4 Information-abstracted Flocking

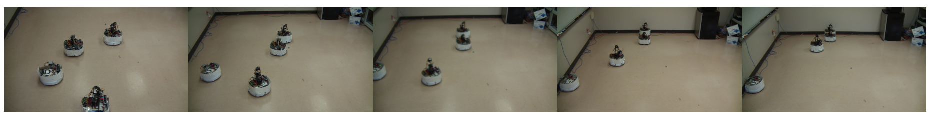
To investigate the existence of information-abstracted flocking algorithms, we conducted computer simulations for each of the 16 different parameterizations



(a) Single robot trial with four robots running the member-centric pose variation.



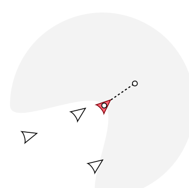
(b) Single robot trial with four robots running the member-centric pose variation.



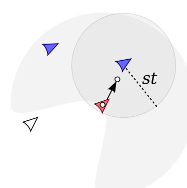
(c) Single robot trial with four robots running the member-centric theta variation.

(d) Single robot trial with four robots running the member-centric theta variation.

Fig. 3: Each time series shows the motions of our robotic system running one of the four LCH variations.



(a)

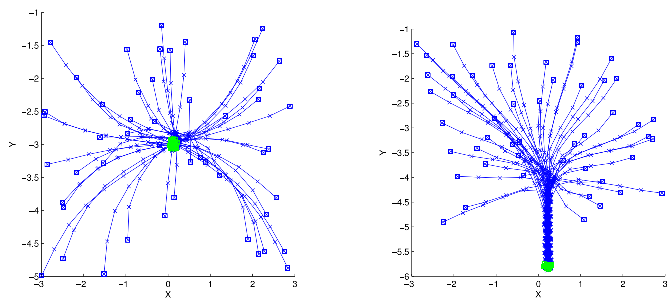


(b)

Fig. 4: Figure 4a shows that a flock member will continue in the same direction when no other flock members are observed. This behavior causes the resulting motion of the flock to be more directional than the computer simulations in [10]. Figure 4b shows how the *follow the leader* behavior is generated when there are only a few detected neighbors.

of sensing range (3000** and 3 units), starting formation (single-group and split-group), type of information (pose and bearing), and observation detail (member-

** For these results 3000 units can be considered infinite



(a) No limitations on FOV (b) Limitations on FOV

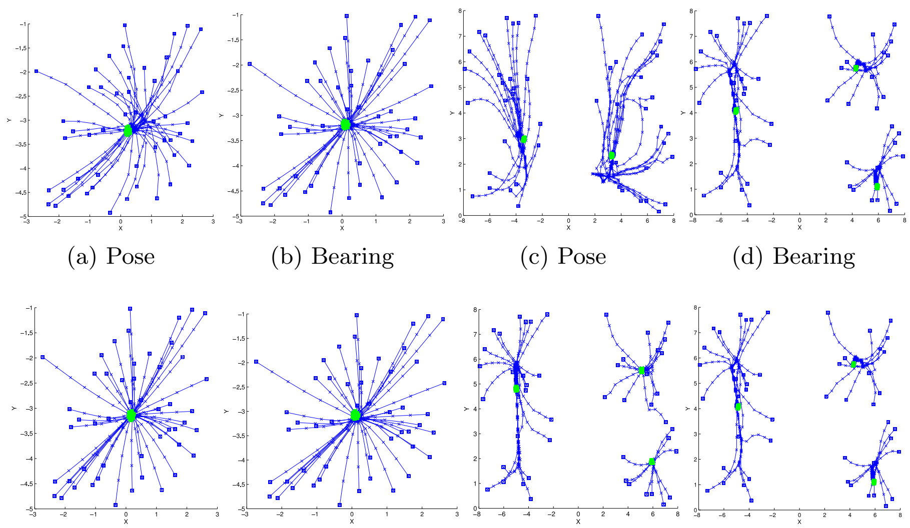
Fig. 5: These two motion plots were generated from 50 simulated flock members using the member-centric pose variation of the LCH. The blue squares represents the starting formation, which was randomly generated within a squared region, and the green squares represent the ending formation of the flock members.

centric and group-centric). For each parameterization we conducted ten trials, each with random starting positions for the flock members, resulting in a total of 160 simulations of 75 iterations for 50 flock members. To aid in the study of the underlying motions produced by the chosen variations, we do not limit the flock members' FOV.

Using motion equivalence to compare the results in Figure 6, we see very little difference in the simulated motions. Even when we look at the worst case, Figures 6c and 6g, there are no real differences in the resultant motion. Even though the motions are not identical, they still resemble the motions of the motivating biological flocks as presented in [10].

In addition to motion equivalence, Viscido *et al.* [10] proposed the use of mean median distance (MMD) from the center of the flock as a metric to describe the motions of a flock that compresses during a predator attack. To supplement the observations of motion equivalence made form the motion plots in Figure 6, we calculated the MMD for all of the parameterizations over all trials. The computed MMDs for the trials that used a sensing range of 3 units are not significantly different from the trials that used a sensing range of 3000 units, therefore we only report the MMDs from the trials that used a sensing range of 3 units; see Table 1.

When the flock starts in a single-group, Table 1 shows that there is no difference in the flock's MMD for any of the 16 parameterization. When the flock starts in two separate groups, there is a slight difference in the computed MMDs. As we would expect from the motions reported in Figure 6, there is a slight difference between the MMDs of the group-centric pose and member-centric pose trials when the flock started in two groups. These results not only show that flocking motions are possible using group-centric information, but since the group-centric variation produces a smaller MMD, this suggests that group-centric information may be preferred in certain situations.



(a) Pose (b) Bearing (c) Pose (d) Bearing

(e) Pose (f) Bearing (g) Pose (h) Bearing

Fig. 6: These motion plots are typical results of simulations conducted for this study. Each trial simulates 50 flock members over 75 iterations (only plotting every third pose per flock member), where st_{distance} is set to 0.5 units and st_{angular} is set to 10 degrees. The top row of motion plots (plots 6a,6b, 6c, and 6d) where generated using group-centric information and the bottom row of plots (plots 6e, 6f, 6g, and 6h) where generated using member-centric information. The blue squares represent the starting positions of the flock members, and the green squares represent the end positions of the flock members. Motion plots 6e, 6f, 6a, and 6b were simulated with the single-group starting formation and a sensing range of 3000 units, where plots 6g, 6h, 6c, and 6d were simulated using the split-group starting formation and a sensing range of 3 units.

Single-group

	Pose	**Bearing**
Group-centric	0.05	0.05
Member-centric	0.05	0.05

Split-group

	Pose	**Bearing**
Group-centric	3.23	4.94
Member-centric	4.95	4.94

Table 1: The MMD (in units) from all of the simulations that had a sensing range of 3 units. For each simulation, the median distance from the center of all 50 flock members is calculated from the ending formation. The medians from all ten trials were averaged to yield the MMD for the given parameterization.

5 Conclusion

The preceding results show that the information available to a flock member, while very important from an implementation and biological modeling point of view, are not necessarily distinguishable in terms of the flocking motion they produce. Additional thought is required if one is to understand what individual flock members are sensing or computing. At least two distinct aspects are worthy of consideration: the detail involved in the observation and the type of information extracted from that observation. Moreover, metrics that are intended to evaluate the flock's motion (*e.g.*, MMD) are also insufficient in and of themselves. Therefore, future work may need to focus less on metrics designed to study the resulting group motion, and instead on the impact that the requisite information has on the biological plausibility, or the ability to implement the given algorithm on a robotic system, or both.

The ability to produce biologically motivated flocking motions using either group-centric or member-centric information suggests that flocking motions may be possible using a combination of the two. In other words, the flock member may observe individual flock members when they are nearby, but may still observe groups that are further away. Furthermore, if we consider the case when flock members only make observations based on image-size, it is plausible that the flock member may not be aware of the differences between the two types of information. If this holds true, this may offer an explanation to how multiple flocks merge an split over time as occurs in large flocks of birds.

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