

Consensus Costs and Conflict in Robot Swarms

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ABSTRACT

It is commonly observed that aggregation in nature provides significant benefits to the group members. However, to reach a consensus individual preferences are frequently lost. Conflict is generally avoided because of the negative influence it could have on the success of collective movements. However, it could be used to balance consensus costs with individual preferences. Using a biologically-based collective movement model, this work investigates the possibility of conflict in a group movement allowing for differing individual goals to be accomplished, while still maintaining group cohesion much of the time. Individuals focus on their own needs, which may include the protection of being a part of a group or the desire to move away from the group and towards its preferred destination. Results show that by allowing conflict in group decision-making, consensus costs were balanced with individual preferences in such a way that group level success still occurred, while significantly improving the success of differing goals.

Categories and Subject Descriptors

I.2.11 [Artificial Intelligence]: Distributed Artificial Intelligence—*coherence and coordination, multiagent systems*

Keywords

conflict of interest, collective movement, swarm robotics, coordination

1. INTRODUCTION

Group living provides significant benefits in nature, ranging from increased protection from predators to increased foraging success [13]. The flocking of birds [6], schooling of fish [5], and mass herds of migrating wildebeests [2] are just some of the examples of large-scale aggregation and coordination that have been observed and studied in nature. The same is true in artificial systems, such as robot swarms where robustness, flexibility, and scalability are beneficial [11]. To

maintain these benefits, collective decision-making and the associated coordination are necessary [8].

Collective behavior is usually viewed as a benefit for those involved, but what if the cost of the consensus was greater than that of the individuals' preferences? Conflict, however, is commonly treated as an inhibitor of collective behavior. One of the most common effects of conflict on collective behavior is to increase the time taken to complete the group's goal, sometimes to the point of even causing the group to fail to complete their goal. This work uses a biologically-based model to explore the positive effects of conflict on collective movements. Results show that conflict can increase individual goal completion percentage while still allowing for group cohesion, with a small average time difference to complete the first consensus goal.

2. METHODS

The simulations used for this work were performed using a modified version of a collective movement model developed through observations of collective movement attempts in a group of white-faced capuchin monkeys [4, 9]. The model was later confirmed in observations of sheep [10]. To integrate conflict and spatial movement into the model, significant modifications were required, including converting the model from the usage of continuous time to discrete time.

2.1 Collective Movement Model

The collective movement model uses three rules to govern the decision-making process involved in starting collective movements [4, 9]. The first rule assumes that all individuals within the group are identical and can initiate a collective movement attempt with a rate of $1/\tau_o$.

The second rule describes the rate at which followers join the collective movement attempt and is calculated by $1/\tau_r$. The time constant τ_r for the following rate is calculated using the following:

$$\tau_r = \alpha_f + \beta_f \frac{N - r}{r} \quad (1)$$

where α_f and β_f are constants determined through direct observation, N is the number of individuals in the group, and r is the number of individuals following the initiator. As the number of individuals following the initiator increases, the rate at which individuals join the movement also increases.

Not all initiation attempts are successful as initiators often cancel and return to the group. The third rule calculates this

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<http://dx.doi.org/10.1145/2598394.2605683>.

cancellation rate using the following:

$$C_r = \frac{\alpha_c}{1 + (r/\gamma_c)^{\varepsilon_c}} \quad (2)$$

where α_c , γ_c , and ε_c are constants determined through direct observation, and r is the number of individuals following the initiator.

2.2 Integrating Conflict

To investigate the effects of altering the rate at which individuals initiate, follow an initiator, and cancel a movement, Gautrais added an individual-specific constant, referred to as a “ k factor,” to the rate calculations of the collective movement model [4]. Initiation attempts were now calculated at the constant rate of k/τ_o , and the following and canceling rate calculations were modified as follows:

$$\tau_r = \frac{1}{k} \left(\alpha_f + \beta_f \frac{N-r}{r} \right) \quad (3)$$

$$C_r = k \left(\frac{\alpha_c}{1 + (r/\gamma_c)^{\varepsilon_c}} \right) \quad (4)$$

where the variables are the same as before. Since this k factor can either increase or decrease the three decision-making rates, it was an ideal means with which the effects of conflict could be incorporated into the model.

Like other work involving conflicts of interest [1], conflict was introduced into the group by giving individuals different preferred goal destinations. To maximize the costs associated with conflict, equal numbers of individuals were given different goals, thus ensuring that the group as a whole would encounter high levels of conflict, regardless of the current initiator’s destination. However, unlike other work on conflict, individuals were considered homogeneous, other than their different preferred destinations, and did not possess an individual “degree of assertiveness.” This decision was made for two reasons. First, it minimized the number of confounding variables in the system, thus simplifying the analysis of results. Second, it was consistent with other work in the area of robot swarms in which swarm members are assumed to be identical [11].

The conflict value c_i for individual i in following a potential leader was calculated using the angle θ between the leader’s observed direction of movement \vec{v}_l and the direction \vec{d} to the individual’s preferred destination from the leader’s current position as follows:

$$c_i = \frac{|\theta|}{\pi} \quad (5)$$

with θ having a range of $[-\pi, \pi]$ and calculated using the dot product of the vectors \vec{v}_l and \vec{d} . If a potential leader was not moving, θ was defined to be π , resulting in maximum conflict. Although neither the original model, nor the observations on which the model was based, discussed conflicts of interest for the individual animals involved, we assumed that the observed individuals encountered moderate conflict. Therefore, the integration of conflict incorporated the concept of moderate conflict ($c_i = 0.5$) which produced the same results as the original model. Also, the magnitude with which low conflict affected the model was designed to be the same as high conflict so as not to bias the model towards one conflict value over another. As a result, the conflict value c_i was then used to calculate k , as follows:

$$k = 2c_i \quad (6)$$

where the variables were the same as before. Since k had a non-inclusive lower limit of zero, the non-inclusive upper limit of two was chosen to ensure balance. In the simulations described below, conflict was limited to the range $[0.1 : 0.9]$ to ensure these limits were satisfied.

2.3 Conversion to Discrete Time

The collective movement model originally used continuous time events. However, such an approach was not practical for simulating spatial movement with discrete time requirements. As a result, significant modifications were made to the implemented algorithm to use discrete time.

First, instead of using the individual decision rates to generate decision times from an exponential distribution, the decision rates were used to calculate the probability of the decision being made at a given time step. This was straightforward since the inverse of the decision rate is the instantaneous probability.

Second, because it was possible that an individual could make a new decision at every time step, a “do nothing” decision was added to the decision-making process. This allowed the individual to continue executing a decision it had previously made (e.g., following a leader or continue initiating). However, there were situations in which a decision to “do nothing” was not valid. For example, if a leader canceled its movement or instead decided to follow another leader, a follower was required to make a new decision to either follow a new leader or initiate its own movement. With this restriction, an agent would not be forced to follow a leader in the decision to join the group.

2.4 Numerical Implementation

Numerical simulations of the collective movement model were implemented in Java¹ using the original algorithm as a starting point [4]. However, as noted above, the algorithm was converted to use discrete time events, instead of the continuous time events in the original.

The original model only used a group size of 10, but other work has shown that the success of collective movement initiations increases as the group size is increased, with most differences present in group sizes of 50 or less [3]. As such, evaluating different group sizes presents an opportunity to evaluate the effects of conflict with different group dynamics. For each evaluation environment, 2,000 simulations, each with a different random seed, were performed using group sizes from 10 to 50. Each simulation constituted a single attempt for individuals to move to their preferred destination and had a maximum of 20,000 time steps. Unlike the original model, multiple initiators were allowed at any given time step and a cancellation was not classified as an immediate failure. The model parameters used were the same as those used in the original model [4, 9].

The results that follow were from a simulation environment that was used to evaluate the effect of conflict on consensus costs when the group began a movement with moderate initial conflict. In this environment, two destinations were located at an equivalent distance from where the group began. These destinations were separated by a 74° angle. Since there was no bias in the simulations towards one destination over another, the analysis of the simulations took

¹Simulation source code and data analysis scripts are available for download from <https://github.com/snucsne/bio-inspired-leadership>.

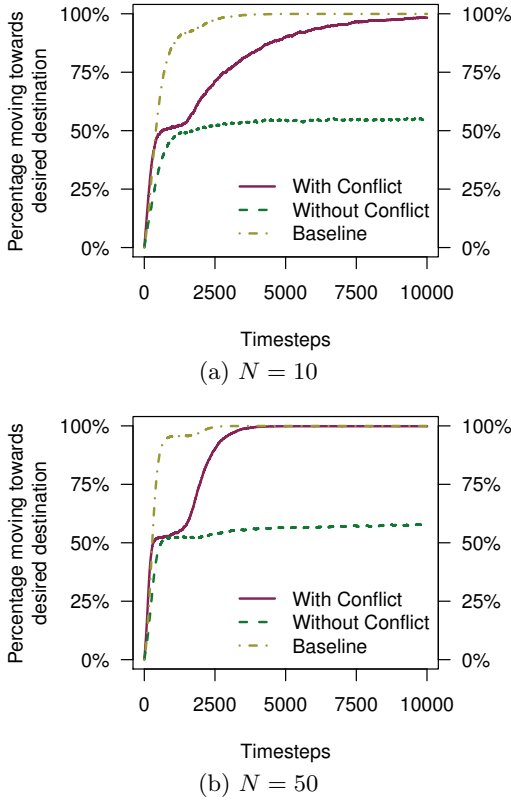


Figure 1: The percentage of the total number of agents moving towards their preferred destination are shown for groups of size $N = 10$ and $N = 50$.

Group Size	Conflict	
	With	Without
10	9.9 \pm 0.3	5.6 \pm 1.1
20	19.9 \pm 0.2	11.7 \pm 2.6
30	29.9 \pm 0.2	17.8 \pm 4.1
40	39.9 \pm 0.7	24.3 \pm 5.8
50	49.9 \pm 0.3	30.5 \pm 7.1

Table 1: The mean number of agents that arrived at their preferred destination in each simulation are shown (mean \pm std. deviation). All results for simulations with conflict are statistically significantly larger ($p < 0.0001$).

into account that the identity of the destinations was not important. Simulation results were organized into first and second destination categories, as determined by the median times in which the destinations were reached in a given simulation. Individuals evaluated in this environment initially experienced moderate conflict in deciding to follow a leader moving towards the non-preferred destination.

3. RESULTS & ANALYSIS

Three treatments were used to determine the effects of conflict on consensus decision-making: a) individuals preferred one of two destinations and conflict was used; b) two destinations were used, but not conflict; and c) a baseline

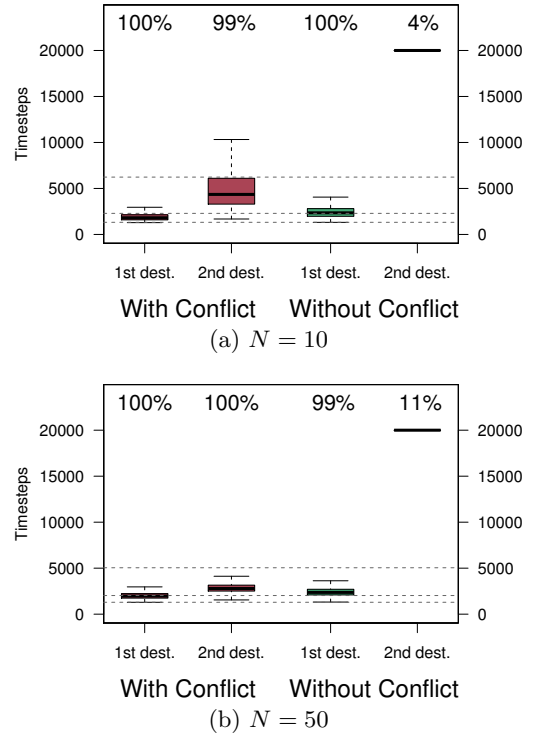


Figure 2: The median number of timesteps and the interquartile range needed for agents to reach their preferred destination are shown for groups of size $N = 10$ and $N = 50$. Percentages indicate the fraction of agents that reached a particular, preferred destination. Horizontal dashed lines represent the minimum, mean, and maximum times for baseline simulations. Times for agents not reaching their preferred destination were truncated at the maximum number of timesteps.

treatment in which all individuals preferred the same destination and conflict was not used. Two metrics were used to measure the effects of conflict on collective movements. The mean percentage of individuals that reached their preferred destination was used to determine the consensus costs incurred by individuals in the swarm. This was done by comparing the results from the treatments with conflict and without conflict to observe the difference in percentage of agents moving towards their preferred destination. The second metric that was the mean time taken for individuals to reach their preferred destination. To properly use this metric, times for agents that failed to reach their goal were truncated at the maximum number of timesteps.

Figure 1 shows the mean percentage of individuals moving towards their preferred destination during a simulation for each treatment. Simulations in the baseline treatment, as expected, had on average more individuals moving towards their goal at every time step (see Figure 2a and Figure 2b). By 10,000 time steps, simulations using conflict had comparable percentages to the baseline simulations, while simulations without conflict had approximately only 50% of the individuals moving towards their preferred destination. Increasing the group size from 10 to 50 resulted in fewer

timesteps before the simulations with conflict had comparable percentages to the baseline system. However, the larger group size only had minor effects on the simulation without conflict.

Table 1 lists the mean number of individuals that arrived at their preferred destination by the end of the simulation. When conflict was used, nearly 99% of the individuals that preferred the second goal were able to reach their goal for groups 10, and the 100% of individuals were able to reach their goal for groups of 50. Without conflict, the percentage that reached the second destination ranged from 4% for groups of 10 to 11% for groups 50 (see Figure 2).

4. DISCUSSION

In simulations without conflict, an agent that had a preferred destination that was different than that of the consensus was highly unlikely to be able to reach its goal. By integrating conflict, these agents were able to reach their goal destination with only minor increases to the time for the group to reach the first goal destination.

The median time required for agents to reach their preferred destination decreased as the size of the group was increased. Figure 2 illustrates this and shows the interquartile range of these times for groups of 10 and 50. This was consistent with baseline simulations in which increasing the group size decreased the mean time for agents to reach their preferred destinations.

These simulations made the assumption that consensus costs were too high and thus, individual goals must be fulfilled. There are times in which cohesion of a group is more important than individual preferences. For example, group cohesion is essential to the hunting success of a group of lions, regardless of individual goals. In this case, larger groups complicate this cohesion. On the other hand, larger fish shoals are a more effective defense against predation than smaller groups. Cohesion also reduces the negative effects of incorrect information on the success of the group. In an environment where consensus is not the primary objective of the swarm, conflict could provide a balance between consensus costs and individual preference.

5. CONCLUSIONS AND FUTURE WORK

This work has two significant contributions. First, these results show that the simple addition of conflict can balance consensus costs with individual preferences in a manner that still allows group level success, while significantly improving individual success. Second, these results show that the consensus costs in swarms with differing preferences can be significant if cohesion is enforced, even to the point where individuals are unable to meet their goals.

This work is part of a larger research project on collective decision-making. In the future, we plan to implement a more comprehensive concept of a “level of dissatisfaction” in place of the simplified conflict model used here. This would include situations such as too many individuals in a group, a dependence on resources, and the notion of time. Evolutionary approaches would be particularly effective in combining the various components. One particularly interesting approach would be to use grammatical evolution to evolve decision rules for determining conflict [7]. Furthermore, the current model is not very tunable. We plan on transitioning to an alternative model [12] that allows for more customiza-

tion of the decision rates, particularly for tasks other than collective movements. Evolutionary approaches would again be particularly effective in finding the appropriate parameters for each task.

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