Collective Decision Making: A Biologically Inspired Approach to Making Up All of Your Minds

Chris A. C. Parker
Dept. of Computing Science
University of Alberta
Edmonton, Alberta, Canada
Email: parkerca@ieee.org

Hong Zhang
Dept. of Computing Science
University of Alberta
Edmonton, Alberta, Canada
Email: zhang@cs.ualberta.ca

Abstract—Practical collective robotic systems will be faced with decisions that have to be made in order for them to function effectively. In this paper, we present a biologically inspired algorithm that allows system level decisions to be made. Such decisions ensure consensus amongst the robots that make up a collective system. Our algorithm is based on the collective house hunting strategy of a particular species of ant. A series of experiments were conducted in simulation in order to study our algorithm's performance. A particular variable, the quorum, was found to strongly impact decision making ability. It was found that setting the quorum as high as the robots that composed a system could reliably measure produced the best results.

I. INTRODUCTION

Robotic systems need to make decisions in order to operate in a changing, realistic environment. Collective robotic systems, robotic systems that contain multiple robots that cooperate to solve problems, are no different. The difference between traditional, solitary robots and collective robotic systems with respect to decision making is the level at which decisions must be made. A solitary robot needs only to make up its own mind and act accordingly. Decentralized\(^1\) collective robotic systems must make decisions at the system level, a level above any of the individuals that make them up. In [6], the notion of joint intention was introduced. A joint intention is an intention to act that is shared amongst team members. The team members cannot drop such an intention until they believe that the goal of the intention has been achieved, is impossible or no longer is relevant and all of the other team members share this belief.

We have taken a similar approach in our study of decision making in collective robotic systems. To say that such a system makes a decision to carry out some task means that the global behaviour of the system will change such that it is consistent with achieving the task [4]. Many good examples of system level decision making can be found in the realm of team sports. Consider a situation in a soccer game in which two players decide to pass and then shoot the ball. The two players must agree on their roles. If both were to decide to pass the ball, then the play would fail [9], as no player would have taken the role of receiver. In this example, the players individual decisions were inconsistent with the system level decision to complete a pass-shoot play. Bowling et al. also have studied team decision making. In [1], they implemented a play selection system for a RoboCup robotic soccer team. Team plays were selected from a static list, with each play including information for coordination, termination, etc. In [4], a scheme employing coordination graphs was presented to allow team level decision making in a RoboCup game. Both of these approaches to decision making in multiple robot systems stressed system level coordination.

In this paper, we present a new approach to making system level decisions in multiple robot systems based on the house hunting strategy of a particular species of ant, *Leptothorax albipennis*. In the next section, we will take a closer look at the collective decision making of this ant, as well as that of another social insect species. In Section III, we will generalize *L. albipennis*’ behaviour into a more widely applicable decision making algorithm. Section IV introduces a new collective robotic application, collective relocation, which was used as a test bed for experiments with our algorithm. Next, we will describe our experimental environment and outline the experiments that we carried out to measure our system’s performance. Section VI presents the results of our experiments and provides insight and explanation for the behaviour of our robots. We close with a set of conclusions and outline future work to be conducted.

II. COLLECTIVE DECISION MAKING BY SOCIAL INSECTS

Social insects present many solutions to collective tasks that are of interest to collective robotic researchers. Already, social insects have served as the inspiration for several collective robotic tasks, including collective transport [5] and collective construction [8]. In this section, we take a closer look at the collective decision making strategies of two social insects species: honey bees and ants.

In [2], Britton et al. studied the manner in which a particular species of honey bee finds and selects a new nest site. When the bees are ready to find a new home, scouts search for candidate sites to move to. When the scouts return, they advertise their finds to the rest of the colony. With multiple scouts returning, each potentially having found a different site, the colony must somehow choose one of the sites to move to. Britton et al. liken the behaviour of the bees to that of political

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\(^{1}\)In a decentralized system, no single robot is in charge and thus in a position to make decisions on behalf of the other robots that make up the system.
parties. The bees recruit supporters for their sites and the site with the most support “wins”. Effectively, the bees vote their support and the site with the strongest support is chosen by the colony.

The ant *Leptothorax albipennis* chooses a new home in a similar fashion. This ant is of particular interest to us as it already has served as the inspiration for the work that we presented in [8]. *L. albipennis* lives in particularly small colonies of up to about 300 ants [3]. Over the life of a colony, its nest may become damaged or get too small as the colony grows. At this point, the ants must find a new nest site to which they can move.

The algorithm employed by these ants can be divided into three phases: research, recruitment and committing. In the research phase, some of the ants that make up the colony conduct a search of the environment around the initial nest. This phase essentially gathers the choices that the colony will deliberate over in the next phase: recruitment.

In the recruitment phase, the ants that searched for sites return to the initial nest with the knowledge of the candidate sites that they found. The ants are able to assess the absolute quality of the sites that they have seen [7] and are able to remember where their found sites are so that they can return to them later on [3]. Having seen a candidate site, an ant might recruit another ant to inspect its site. When one ant recruits another, the recruiter gets the recruited ant to follow it to its candidate site. At the site, the recruit assess the site’s quality and both ants estimate the number of other ants there. This estimate serves as a poll of the site’s popularity. Ants at a site are there either because they believe it to be the best candidate site or because they were recruited by ants who thought so. If an ant estimates that there are enough other ants at the site, that the site has met or exceeded quorum [10], then that ant will enter the final phase of the algorithm, committing. If an ant, upon visiting a site, does not estimate that quorum has been met for it, it will return to the initial nest and remain in the recruitment phase and might attempt to recruit other ants to its site. The likelihood of an ant recruiting another increases with the quality of the site that the ant has most recently seen.

Once an ant enters the committing phase, it carries other ants to the site, which adopt it as their new home. An ant in the committing phase will not assess quorum at its site again. Eventually, it will stop carrying other ants to the site and simply stay there.

Because sites of higher quality have a higher likelihood of recruiting ants to them then do sites of lower quality, the higher quality sites tend to gain supporters faster than (and perhaps at the expense of) lower quality sites. The higher the quality of a candidate nest site, the faster it will gain supporters and the more likely that it will reach quorum first and be selected by the colony as its new home. We see it, the ants simply are solving a problem with an ingenious decentralized algorithm.

First, the ants research solutions to the problem, which take the form of potential new nest sites. Next, a sort of debate or campaign is conducted over which site to select. Once enough of the colony favours a particular site, the entire colony selects it as its new home. In the next section, we present a general purpose version of this algorithm that we implemented in simulation in order to study its performance.

### III. An Algorithm for Collective Decision Making in Multiple Robot Systems

The house hunting strategy of *L. albipennis* presented in Section II can be recast as a general purpose decision making algorithm. Just as the ants had to choose only one of sites presented to them, there are numerous cases in collective robotics where a system must choose a single solution to some problem confronting it. For the following discussion, let us assume that some collective robotic system has been presented with a problem, which we will refer to as \( \Gamma \). The system can decide upon a solution to \( \Gamma \) as follows:

1. Upon being presented with \( \Gamma \), the some of the system’s robots take on the role of researcher, searching for solutions to the problem. The remaining robots wait to hear from the researchers about their solutions to \( \Gamma \).
2. Once a robot finds some solution \( \gamma_0 \) to \( \Gamma \), it assesses the solution’s quality. The robot next either will search for another robot to recruit to \( \gamma_0 \) or abandon its solution and wait to hear of a solution to \( \Gamma \) from another robot.
3. The better a robot believes its solution to \( \Gamma \) is, the more likely it will be to search for another robot to recruit to its solution.
4. Upon finding another robot receptive to recruitment, the robot will inform the receptive robot of its solution. Once the receptive robot has been informed of a solution to \( \Gamma \), we say that it has been recruited to that solution.
5. Once a robot has been recruited to a solution to \( \Gamma \) or has just recruited another robot, it will assess the quality of its solution, estimate the number of other robots that also hold its particular solution to \( \Gamma \) and then act as follows:
   
   - If the robot estimates that \( n \geq q_0 \) other robots share its solution to \( \Gamma \), where \( q_0 \) is a preset quorum threshold, then the robot concludes that quorum for its solution to \( \Gamma \) has been met and then commits to its solution.
   - If the robot estimates that \( n < q_0 \) other robots share its solution to \( \Gamma \), then the robot will retain its initial belief that quorum for its solution to \( \Gamma \) has not been met. The robot will continue to recruit others to its solution as outlined in points 3, 4 and 5.
6. When a robot committed to its solution to \( \Gamma \) finds a robot receptive to recruitment, it will inform the other robot of its solution and tell the robot to start implementing the solution.
7. Periodically, uncommitted robots will re-assess the quality of their solutions and re-estimate whether quorum for them has been met.
8. Committed robots eventually will abandon searching for robots receptive to recruitment and instead will begin to implement their particular solution to \( \Gamma \).
9. Any robot can be recruited to any solution to \( \Gamma \), even if it is searching for robots to recruit to its own solution.
Upon being recruited to some solution $\gamma_a$, a robot will adopt that solution as its own and will abandon any solution $\gamma_b$ that it might previously have held.

This algorithm leads to a process where robots come up with solutions to a problem facing their system and then iteratively recruit other members of the system to their solutions. Because any robot can be recruited and because the probability of a robot attempting to recruit others to a particular solution increases with that solution’s quality, the better solutions will tend to gain supporters while lesser solutions will tend to decrease in popularity. A particular solution to the problem will be implemented when it becomes popular enough. The quorum threshold $q_0$ specifies how “popular” a solution must be before the system should commit to it. The best solution will tend to reach quorum first and thus be chosen by the system.

IV. COLLECTIVE RELOCATION: AN APPLICATION FOR COLLECTIVE DECISION MAKING

In this section, we introduce a new collective task: collective relocation. Collective relocation requires a multiple robot system to find the “most suitable” geographic location accessible to it and then relocate the entire collective system to that location. When a multiple robot system carries out this task successfully, all of the members of the system will adopt the same new location as their “home”. Collective relocation has many applications in robotics. For example, when a team of robots is observing a target, the entire team may need to relocate to a better vantage point. In another situation, a team may need to move to a “safer” location in order to avoid harm.

The ants of [3], [7] and [10] and the honey bees of [2] both carry out the collective relocation task when they need to find and move to a new nest site. It is important for the insects to reach a consensus about which candidate nest site to move to. If individuals in the colony were to move to different sites, their colonies would lose some of their strength in numbers.

The system that we describe in this paper initially calls a centrally located region it’s “nest”. Their goal is to relocate the entire system to the best site available to them. Our robots’ controllers are patterned after our general decision making algorithm outlined in Section III, with a few notable differences. In our general algorithm, robots are receptive to recruitment at any time. Also, robots will attempt to recruit others to their solution with some probability that increases with their solution’s quality. In order to simplify the finite state machine that our robots’ controllers consist of, we implemented an alternate, but equivalent approach. Our robots only are receptive to recruitment in one of two states. These states are the idle and delay states. The delay state is entered by robots returning from a potential nest site upon reaching the current nest site before they attempt to recruit other robots to their site. In the idle state, a robot remains near its home nest and simply waits to be recruited. Robots in the delay state behave just like those in the idle state, except that they will enter a recruiting state after they have been in the delay state for some period of time. The poorer a robot’s candidate site, the longer it will remain in the delay state. Thus robots favouring poorer sites will be more receptive to recruitment and less likely to recruit other robots to their site than those robots favouring better sites. Robots championing poorer sites are more likely to be recruited to better sites than vice versa. Thus best site will tend to get robots to commit to it first. Next, we will outline the experiments that we conducted with our system.

V. EXPERIMENTAL SETUP

This paper is concerned with the performance of our collective decision making algorithm. In order to measure its performance, we conducted a series of experiments in simulation. Of particular interest to us was the relationship between the quorum required for commitment to occur and the decision making ability of our system. Further, we wanted to investigate the scalability of our algorithm - how well it would perform with different system populations. We initially believed that the quorum threshold would be a key variable in determining system performance. If quorum was set too low, the system might not reach consensus. If quorum was set too high, robots might never commit to a particular solution, regardless of its popularity.

![Fig. 1. This figure shows a screen shot of a simulated experiment. The central square is our system’s initial nest. The other squares are candidate new nest sites. The goal of our system is to relocate to one of the candidate sites. The dark circles are robots. Those in the center are waiting to be recruited to inspect a site. Those at the bottom are searching for sites. One robot is inspecting the upper right site and one robot is leading another from the initial nest to that site.](image-url)
entire system to one of the two candidate nest sites presented to them. One of the candidate sites was of good quality and the other was of mediocre quality. A good nest site is of higher quality (and thus a better solution) than a mediocre nest. A mediocre nest site is one that would be chosen over an even worse site, but should be rejected in favour of a good site. This terminology and experimental setup is consistent with that of [3].

The initial experiments that we conducted varied system population size and quorum threshold. System populations of four, eight and twelve robots were studied, each employing quorums of 0%, 25%, 50% and 75% of system population. One hundred trials were conducted for each of the resulting sixteen configurations. In each configuration, four robots would search for candidate sites and the remaining robots would begin idle, waiting to be recruited to the sites found by the searchers. Each trial was allowed to run for up to 200,000 simulated time steps or until all of the robots in the simulation had chosen either the good or the mediocre nest site. The robots recorded their state transitions in logs along with the particular nest site that they were favouring. After examining the data from the initial experiments, it became apparent that the vision range of the robots might play a role in the system’s performance. To investigate this hypothesis, the above experiments were repeated with the robots’ vision ranges increased from two meters to four meters.

VI. RESULTS AND DISCUSSION

We used three metrics to gauge the performance of our decision making system. Our first metric, which we call the success rate, is the percentage of the trials that ended with a unanimous decision having been made. At the end of a trial that was successful, all of the robots will have moved to the same new nest site.

![Success Rate vs Quorum Threshold, Two Meter Vision Range](image)

Fig. 2. This graph plots success rate of our system, the ability of the system to make a unanimous decision about which site to move to, versus the quorum as a percentage of the system’s population. Because of the robots’ limited vision range, the eight and twelve robot systems had difficulty measuring the higher quorums reliably. This phenomenon accounts for the drop in the success rate for the eight and twelve robot systems at 75% quorum.

The success rate tells us nothing about which of the two potential nest sites was chosen. Our second metric, the ability to choose the better site tells us how often the system was able to choose the good site over mediocre site in the cases where a unanimous decision was made. That is, the ability to choose the better site is the fraction of the unanimous decisions in which the decision was in favour of the good site.

![Ability to Choose the Better Site vs Quorum Threshold, Two Meter Vision Range](image)

Fig. 3. The ability to choose the better site is the fraction of successful decisions that were made (see Figure 2) in favour of the good site. As quorum increases, so does the ability of the system to choose the better site.

Ultimately, what we desire is a system capable of making unanimous, good decisions. Thus a metric that is a combination of the success rate and the ability to choose the better site is what we would like. We call the rate at which the system makes good, unanimous decisions the true success rate.

![True Success Rate vs Quorum Threshold, Two Meter Vision Range](image)

Fig. 4. This graph plots the true success rate, the rate at which the good site was chosen by all of the robots, versus quorum. We consider the true success rate to be the best metric of decision making ability.

Refer to Figures 2, 3 and 4. These graphs plot the success rate, the ability to choose the better site and the true success rate versus the quorum for all three system populations for robots with a two meter vision range. In Figure 2, we can see
that the success rate is low for both small and large quorums. When the system quorum is less than 50% of the system’s population size, it is possible for both sites to reach quorum and thus have robots commit to them. Here, even though all of the robots might have moved to a new site, the system would have split between the two possible choices. Once the quorum required reaches 50% of the system population, only one site can reach quorum. In order for one of our robots to commit to a site, it must observe q0 other robots while it is at that site. In the extreme case, where quorum is set to 100% of system population, it is mathematically impossible for a robot to observe quorum, even if all of the system’s robots are recruiting to the same site. For large quorums less than 100%, commitment still might not occur. Again, a robot must observe q0 robots at its potential nest site for it to commit to that site. The robots recruiting for a particular site might be spread out: some recruiting at the initial nest, some at the potential site and still others in transit between the two. The higher quorum is, the less likely it will be that a robot will happen to observe quorum at its site.

Based on the previous statements, we would expect the ability to choose the better site to increase up to quorums of 50% of system population. This precisely is what we observe in Figure 3. Note that the curves continue to increase as quorum increases above 50%. Because higher quorums decrease the likelihood of quorum being observed during each re-assessment of a site, more visits to a particular site will be required on average in order to observe quorum there. This phenomenon serves to prolong the recruiting phase of the decision making process, allowing more time for the robots recruiting to the good site to recruit robots favouring the mediocre site thus increasing the probability that the good site would be chosen if a successful decision was made.

The true success rate is the product of our first two performance metrics. Thus we should expect that the true success rate should appear similar to the success rate. This precisely is what we observe in Figure 4, which closely resembles Figure 2.

In both Figures 2 and 4, we observe definite peaks in the systems’ performances. However, the peaks do not all occur at the same quorum. For a system containing four robots, the best performance is observed at a quorum of 75%. For the other two system populations, the peak performance occurs at a quorum of 50%. How can we account for this difference?

The actual value of q0 for each system population is different for a given quorum. When quorum is set to 50%, a robot in the four robot system must observe two other robots at its candidate site to in order to commit to it. The eight and twelve robot systems must have robots observe four and six robots, respectively, for commitment to occur. Because our robots have a limited vision range and field of view, the maximum number of other robots that a single robot can observe at the same time also is limited. Thus there is a practical upper limit on q0, regardless of the system population. Figure 5 illustrates this point. The white robot here only sees five other robots - the other two robots are just outside of the white robot’s field of view. Increasing the robots’ vision range would increase the maximum number of robots observable and thus the maximum q0 that can be used by a system. We hypothesized that an increase in the vision range of the robots would make the success rate and true success rate curves for the eight and twelve robot experiments better resemble the curves of the four robot experiments.

Figure 6 shows the success rate for the three system populations for the experiments conducted with robots that have a vision range of four meters. Indeed, the three curves are much more similar with the greater vision range than they were in the earlier experiments. The same observation is made regarding the true success rate data for this second set of experiments, shown in Figure 7. The ability to choose the better site for these experiments resembled that of our initial experiments.

When implementing a collective decision making system, we want to have a system that is capable of making good, unanimous decisions. When setting system quorum, one might...
be tempted to pay too much attention to the ability to choose the better site and set the quorum quite high. However, we have shown here that given finite sensory capability, there is a practical upper limit to the actual number of robots that a robot can observe at one time. Setting system quorum so high that \( q_0 \) approaches this limit results in a dramatic decrease in a system’s success and true success rates, the ultimate gauges of a system’s decision making ability. As we briefly mentioned earlier, increasing system quorum also increases the duration of the recruitment phase of our decision making algorithm. If run time were not a concern, one would want to maximize decision making ability and thus should set quorum as high as possible (but still below 100%) without making \( q_0 \) greater than the maximum practical number of robots observable by a single robot.

VII. CONCLUSIONS AND FUTURE WORK

As the state of the art advances, collective robotic systems will become more robust and will be applied to numerous problems. Like any intelligent system, collective robotic systems will have to make decisions about what actions to take, etc. Many of these decisions, such as choosing a location to move to, must be made at the system level and adhered to by all of the robots that compose a system. Since many of the studied applications of collective robotic systems require the effort of multiple robots to succeed, the fragmentation of such a system represents a loss of system functionality.

In this paper, we presented a new approach to making system level decisions in collective robotic systems in a decentralized fashion. Our algorithm was inspired by the house hunting strategy of a particular species of ant, *Leptothorax albipennis*. When these ants move to a new nest site, system level consensus about which site they move to is of great importance, otherwise their colonies might become fragmented. This emphasis on unanimous decisions is reflected in our algorithm. In a manner similar to the ants, our robots conduct a search of the solution space of the problem presented to them and then enter into a process where they iteratively recruit each other to the various solutions found for the problem. Since the robots recruit each other with a likelihood that increases with the perceived quality of their solution, the better solutions gain adherents at more quickly than do the poorer solutions. When a solution gains the support of a set number of robots, which we called the necessary quorum for a decision, robots begin to commit to it. It is the best solution that tends to reach quorum first and gets chosen by the system as a whole.

We conducted an experimental study of our algorithm using collective relocation as a test application. Here, robots had to relocate their system to the best site that they could find in their environment. We found that a quorum of 75% of the system population size led to the best performance, assuming that the robots had the sensory capability to measure such a quorum. Systems containing four, eight and twelve robots all performed with similar success.

From our experimental results, there seems to be one major obstacle to wide range scalability of our algorithm: the ability of a robot to measure quorum. The ants on which our algorithm was based definitely cannot simultaneously “see” dozens of other ants. Instead, they randomly wander candidate sites and use the rate at which they encounter other ants there as an estimate of quorum. This approach is attractive to us and will be investigated further in the future.

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