Quorum Sensing Re-evaluation Algorithm for N-Site Selection in Autonomous Swarms

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Abstract: Flexible decision-making is a vital aspect of swarm behavior. Nature offers a level of uncertainty that could force a swarm to reconsider a site previously abandoned. While efforts are being made to allow for flexible decision-making in autonomous swarms, there is little literature in the area of re-evaluation functions as most models utilize site abandonment functions. The research in this paper produces a re-evaluation algorithm for discrete n-site selection by autonomous swarms, taking inspiration from prior work with quorum sensing models and ant colony optimization algorithms. The algorithm's success in re-evaluation trades off with decision time, but increases the accuracy of decisions made.

1 INTRODUCTION

The applications of autonomous swarms have increased tremendously in recent years with preferable uses in unsafe or inaccessible locations (Tan and Zheng, 2013). Efforts to develop more flexible decision-making models in order to successfully and efficiently select the best target or site within a search space are being made. Several decision-making models that address value-sensitive site selections have been proposed, but all these models abandon the sites with lower values (Cody and Adams, 2017; Reina et al., 2015). Therefore, there is a need for more flexible decision-making models in autonomous swarms that are capable of revisiting the sites that were previously abandoned.

The use of autonomous swarm systems in Humanitarian Assistance and Disaster Response (HADR) missions can significantly facilitate the relief operations conducted (Diamandis, 2019). As a result of natural disasters, damage caused by flooding, or toxic chemicals and radioactive materials, can cause a level of uncertainty with regard to safety in certain areas. Further, the sustainability of buildings used for temporary shelters may change rapidly as a result of damage. Additionally, overcrowding of shelters can cause significant problems. In 2017 Hurricane Maria devastated Puerto Rico, resulting in a significant power outage and lack of drinking water on the island. Medical centers were overcrowded and had limited capabilities to respond as a result of the shortages in supplies and personnel at the shelters. When it is the job of the swarm system to locate supportable shelters for those in need, the system needs to implement proper decision-making to account for the level of uncertainty in the community environment during such natural disasters.

Therefore, an algorithm in which the swarm system makes re-evaluations of past quorum decisions is needed to address the uncertainties and potential instability of a shelter location. Rather than discarding visited sites that have been deemed unsuitable, as in most swarming decision-making models that implement site abandonment, an algorithm that keeps all of the sites in its memory is needed. Thus, when a selected shelter has deteriorated, the agents of the swarm system should be able to re-evaluate the remaining sites to select the next best site.

This research paper proposes a discrete n-site selection model that allows swarms to re-evaluate past quorum decisions. The proposed model allows swarm agents to explore a defined search space, and communicate with each other about sites in the proximity. This communication then allows the agents to come to a consensus about the best site for relocation. The model takes inspiration from the decision-

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making mechanisms of ant swarms as well as the quorum-sensing decision-making model for discrete site selection model detailed by Cody and Adams (Cody and Adams, 2017). However, our model keeps visited-sites in memory rather than discarding the sites deemed dangerous or problematic a trait common to swarming algorithms that implement site abandonment such as the one developed by Cody and Adams (Cody and Adams, 2017). Our model allows for the agents to perform the re-evaluations necessary to select the best site in the search space. The aim of the model is to enable a swarm to re-evaluate its decisions to select the best site and increase decision accuracy allowing for a more flexible swarm behavior.

The paper is organized as follows. Section 2 reviews the biological inspiration and the swarm site selection research. Section 3 describes our proposed quorum sensing re-evaluation model. Section 4 describes the experimental design for simulations. Section 5 presents the results. Sections 6 and 7 discuss the results and areas of future work.

2 BACKGROUND

2.1 Natural Swarms

The *Diacamma indicum* ant species, also known as Indian queen-less ant, utilizes a process known as tandem running for nest relocation. Tandem running involves one ant leading another ant to a nesting location, one at a time and keeping close physical contact with the other ant. Additionally, the *D. Indicum* performs re-evaluations in response to changes in the target nest during nest relocation, with a negligible error (1.65%) according to a study conducted by Anoop and Sumana (Anoop and Sumana, 2015).

The *Temnothorax Albipennis* ant species, also known as rock ant, utilizes tandem running as well as a population dependent decision-making mechanism known as quorum sensing. As more and more ants visit a nesting location, a quorum of ants favoring that particular site over other sites starts to build. Once a certain known threshold is surpassed, the ants disperse to recruit other agents to the site that has been decided upon (Pratt, 2005). This recruitment mechanism has a recruitment rate three times that of tandem runs.

The decision-making model we developed draws inspiration from the recruitment methods of the *Diacamma indicum* and the *Temnothorax Albipennis* ant species.

2.2 Swarm Models

Several artificial swarm decision-making models have been developed (Tan and Zheng, 2013). The Cody and Adams value sensitive quorum sensing decision making model is one model involving discrete site selection in autonomous swarms (Cody and Adams, 2017; Reina et al., 2015).

The quorum sensing re-evaluation model described in this paper utilizes principles of the Cody and Adams model. In this model (Figure 1), agents can be in one of three states: uncommitted, favoring, or quorum, and one of two categories: latent and interactive. Agents in the uncommitted state do not have a preference towards a particular site in the search space, while favoring agents do have a preference towards a site. Agents in the quorum state have decided on a particular site and work towards recruiting other agents to that site. Latent agents explore the search space for sites and interactive agents remain in the nest and interact with other agents and recruit those agents to a particular site.

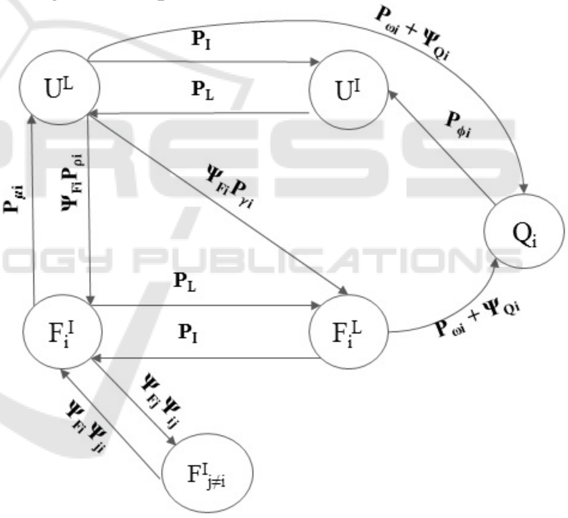

Figure 1: The Quorum Sensing Re-evaluation behavior model with its nodes and transitions. State types are represented as: U, uncommitted; F, favoring; and Q, quorum. Categories are represented as: L, latent and I, interactive. Transitions between states are depicted using symbols P and ψ, where P is a specific probability function detailed in Equations 1-8 in the text and ψ is the population of agents in the specified state (shown in subscripts). i and j denote specific sites the agent is interacting with.

3 QUORUM RE-EVALUATION ALGORITHM

The agents in the swarm start in the nest and have the goal of selecting the best site out of a total of n sites. For simplicity of this model, each site has a starting value between 0 and 1 based on its distance from the nest. Sites that are closer to the nest have a larger value. However, in real-world situations the site values will be determined by a number of other factors, including quality, size, and distance. Each agent has a known sensing and communication range. As compared to an algorithm that does not re-evaluate decisions when necessary, the re-evaluation algorithm proposed would increase decision accuracy but increase decision time.

3.1 States and Transitions

Using principles from the Cody and Adams model, the agents in the swarm system start in the nest as uncommitted latent agents. Agents can transition between uncommitted latent and uncommitted interactive with a probability P_I and P_L, where R is the inverse of the average site round trip time and i and l are the population of agents that are interactive and latent respectively as referenced in equations 1 through 3.

$$p(i,l) = \frac{i}{i+l} \tag{1}$$

$$P_I = \begin{cases} R & P_L \leq 1 \\ 0 & P_L = 0 \end{cases} \tag{2}$$

$$P_L = \begin{cases} p(i,l)R & p(i,l)R < 1 \\ 1 & p(i,l)R \geq 1 \end{cases} \tag{3}$$

Once a site has been explored long enough, the agent has the option to favor the site or leave the site and explore another site. When a site is favored, the agent can be in either the favoring interactive or the favoring latent state.

Much of the agents decision making is governed by properties of ant colony optimization (ACO), specifically through pheromone production (Ab Wahab et al., 2015). Ants produce pheromones to communicate with other ants, typically when recruiting other ants in the colony. The use of pheromones for communication is an integral part of emergent behavior seen in nature (von Thienen et al., 2014).

In ACO the probability of any one agent relocating from site i to site j is determined by equation 4.

$$P_{\rho_i} = \frac{(\tau_{ij})^{\alpha}(\eta_{ij})^{\beta}}{\sum(\tau_{ij})^{\alpha}(\eta_{ij})^{\beta}} \tag{4}$$

$$\eta_{ij} = v_j, v_j = [0,1] \tag{5}$$

$$\tau_{ij} = (1-r)\tau_{ij} + \Delta\tau_{ij} \tag{6}$$

$$\Delta\tau_{ij} = \begin{cases} \frac{R}{10} \\ 0 \end{cases} \tag{7}$$

Probability P_{ρ_i} is governed by the amount of pheromone on the path to site j (τ_{ij}) and the site desirability value, which in this case is the site quality value of site j, denoted by v_j. The amount of pheromone on a path is determined by the amount remaining after evaporation at rate r and the amount that is deposited on the path denoted by $\Delta\tau_{ij}$.

When an agent in the model transitions from uncommitted latent state to favoring interactive state, the agent utilizes the pheromone probability rule moving from the nest to the site it began to favor. When transitioning from uncommitted latent to favoring latent, the agent drops "pheromone" at the site it favors in order to help attract other agents to that site. In the case of unmanned vehicles this "pheromone" is represented as increases to the site value by a predetermined value. In this paper that predetermined value is 0.025. Additionally, the rate of evaporation is also set to 0.25 units per iteration. When an agent has determined a site better than the one it currently favors, rather than abandoning the site, as in previous models, the agents drop a different type of "pheromone", which has a lower evaporation rate, before reverting to the uncommitted latent state. In the case of unmanned vehicles, this "pheromone" is also represented as decreases to the site value by the same value; however, the evaporation rate is 0.75 units per iteration. This allows for the site value to decrease faster, indicating to other agents that this site is not suitable, but can be reconsidered if a re-evaluation is necessary.

When enough agents are favoring a site, such that the quorum threshold is surpassed, these agents transition to the quorum state. These agents then recruit other agents to the determined quorum site. In the case that the site value of the quorum site has changed, the agent can revert back to the uncommitted interactive state at probability P_{ϕ_i} and perform a re-evaluation.

$$P_{\phi_i} = \begin{cases} 1 & \frac{v_{i_2}}{v_{i_1}} < 1 \\ 0 & \frac{v_{i_2}}{v_{i_1}} \geq 1 \end{cases} \tag{8}$$

The agents compare the previous site value with the changed site value. If the new value is lower than the previous one and the value is less than the value of the other sites, the agent transitions to the uncommitted interactive state and re-evaluates the other sites to choose the next best site.

4 EXPERIMENT

It was our hypothesis that our quorum-sensing re-evaluation algorithm would increase both the decision time and decision accuracy.

To test our hypothesis, the model developed was simulated using the Processing programming language (Reas and Fry, 2014). A total of 50 agents were used to simulate site selection with two, three, four, and five sites. The search space is depicted by a 450 x 450 pixel square. The nest, in the center of the search space, is represented by a 60 x 60 pixel square and the other sites are represented by 70 x 70 pixel squares. The original site value of each site was inversely proportional to the distance from the nesting location (Figure 2). The optimal sensing range and speed for the agents were determined to be 13 pixels and 10 pixels/s, respectively. The threshold for transitioning to a quorum state was determined to be at least 5 agents per site. The simulations were run with and without changes in the quorum site value. Changing the quorum site value allows the testing of the efficiency with which the algorithm allows the agents to re-evaluate past quorum decisions. To test the ability of the swarm to re-evaluate decisions, once the agents sense a quorum at a particular site, the site value is reduced by 0.3. After this reduction, if the value of the site is less than the value of other sites, the value reduces to 0.0 to allow for a re-evaluation of the other sites. Otherwise, if the site value after reduction is still greater than the value of other sites, there is no additional change to the site value. The simulation terminates after all agents have reached a quorum decision. For each simulation group, 100 trials were run.

For each trial, the decision time and the number of agents that found a quorum at each site were noted. For trials involving two sites, the accuracy was determined by the number of agents that chose the best site. For trials involving three, four, and five sites, the accuracy was determined by the number of agents that chose the best two sites, based on the final site values. Accuracy was determined using the following: $n/50$, where n is the number of agents that selected the best sites (one or two, depending on the total number of sites) and 50 is the preset total population of agents used in the simulation.

5 RESULTS

The graphs in Figure 3 show the change in decision time over the number of sites in the search space and the change in decision accuracy over the number of sites in the search space.

Between the trials without re-evaluations and with re-evaluations, the average decision time increased by roughly 100 milliseconds. The average decision time also generally increased with the number of sites in the search space. Additionally, decision accuracy showed an increase for the trials with re-evaluations as compared to the trials without re-evaluations. Decision accuracy did, however, decrease as the number of sites in the search space increased. For 2-site selection, the accuracy increased from 99.0% without re-evaluations to 100.0% with re-evaluations. For 3-site selection, the accuracy increased from 80.7% without re-evaluations to 93.9% with re-evaluations. For 4site selection the accuracy increased from 77.6% without re-evaluations to 89.0% with re-evaluations. For 5-site selection, the accuracy increased from 80.6% to 93.84%.

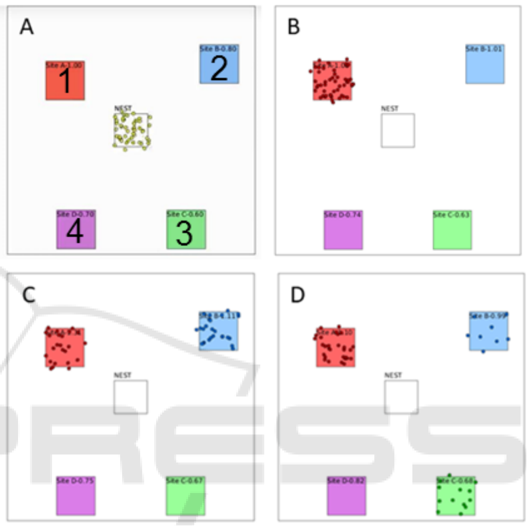

Figure 2: **A**: Screenshot of an original setup of the search space for a 4-site selection simulation. The original site value of each site is inversely proportional to the distance from the nesting location. Site 1 (red) has a highest site value of 1.0, Site 2 (blue) has a site value of 0.8, Site 3 (green) has a site value of 0.6 and Site 4 (purple) has a site value of 0.7. **B, C, and D**: Screenshots of examples of simulations after agents have sensed a quorum. Accuracy in examples B and C is 100% and accuracy in example D is 74%.

A t-test analyzing the decision time for 2, 3, 4, and 5 sites produced p-values of 0.001, $2.154 * 10^{-8}$, $1.120 * 10^{-5}$, and 0.042 respectively. Additionally, the same test analyzing decision accuracy for 2, 3, and 4 site selection produced p-values of 0.160, 0.0003, 0.0086, and 0.0004 respectively. Based on these values, we can not conclude that the re-evaluation algorithm significantly increases decision accuracy for 2-site selection. However, we have reasonable evidence to suggest that the re-evaluation algorithm increases accuracy for 3, 4, and 5-site selection.

The model was able to successfully increase the accuracy of the decisions made by the swarm with decision time as a trade-off.

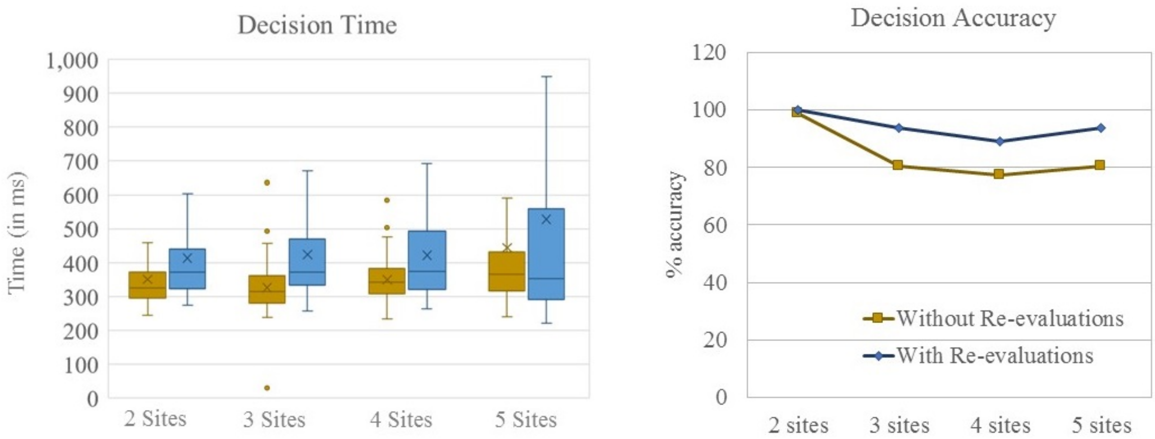

Figure 3: Box-plots showing distribution of the decision time (in milliseconds) by number of sites in the search space with average decision time, depicted with x (Left). Decision Accuracy (%) by number of sites in the search space (Right).

6 DISCUSSION

The ability to make flexible decisions is imperative for the development of swarm robotics and decision-making. Our algorithm permits the swarm agents to successfully re-evaluate sites in a defined search space. The algorithm can be adapted in HADR missions where local citizens need to be evacuated to safe shelter locations. In a disaster-struck community, agents in a swarm system can assess the shelter sites in the area using our algorithm to reach an accurate consensus regarding the safest shelter to transport the citizens to. If a potential shelter location has suddenly deteriorated, our algorithm permits the agents to re-evaluate their past quorum decisions to reach a new consensus regarding the next best shelter.

Information regarding the safest shelter location can be transmitted to first responders to safely evacuate citizens to the selected shelter. The ability to re-evaluate decisions could also help mitigate issues like overcrowding and supply shortages in shelters during such disasters, significantly contributing to the efficiency and improvement of HADR missions.

This paper demonstrates the efficiency of a quorum-sensing re-evaluation algorithm using inspiration from biological swarm systems, allowing for more accurate decisions to be made with decision time as a trade-off. In the future this model may very well prove itself useful in the location of sustainable shelters for areas devastated by disaster and be of good aid to HADR missions.

7 FUTURE WORK

Future work should focus on testing the algorithm using swarms of autonomous drones in a physical space. For simplicity, the assigned site values in our model were inversely proportional to the distance from the nest. To evaluate the suitability of our model for real-world situations, the site values will have to take into account a number of other factors, including quality, size, and distance, depending on the operation.

Additional testing can also be done with more sites in the search space. Sites of different sizes and shapes can also be tested to assess the behavior of the algorithm in more varied situations. Improvements can also be made to address the issue of agents that have traveled out of the search area and are no longer able to sense other agents or sites as well as defective agents that have developed capability issues. Addressing this issue can contribute to decreasing the decision time while increasing decision accuracy.

Future work should also focus on developing algorithms that account for multiple cycles of re-evaluation. The proposed and future quorum-sensing models will be capable of revisiting the sites that were previously abandoned and re-evaluating them under the dynamic conditions of the real-world scenarios. In addition, we would like to explore extensions of the algorithm to search large state spaces for potential solutions using multiple agents as processors.

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