QUORUM SENSING FOR COLLECTIVE ACTION AND DECISION-MAKING IN MOBILE AUTONOMOUS TEAMS

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Abstract: Design of controllers for teams of mobile autonomous systems presents many challenges that have been addressed in biological systems, such as behavior-based control paradigms that are decentralized, distributed, scalable, and robust. Quorum sensing is a distributed, decentralized decision-making process used by bacteria and by social insects to coordinate group behaviors and perform complex tasks. It is used by bacteria to control the colony behavior for a variety of functions, such as biofilm construction or initiating pathogenicity inside a host. It is used by social insects including the ant Temnothorax albipennis to collectively evaluate and select from amongst potentially many new nesting sites.Honeybees (Apis mellifera) use quorum sensing to collectively choose a new nesting site when the swarm grows too large and needs to split. It is shown that the quorum sensing paradigm may be used to provide robust decentralized team coordination and collective decision-making in mobile autonomous teams performing complex tasks. In this effort quorum sensing-inspired techniques are developed and applied to the design of a decentralized controller for a team of mobile autonomous agents surveying a field containing buried landmines.

1 INTRODUCTION

Today's military is increasingly reliant on the use of unmanned systems to perform a variety of missions including surveillance, precision target designation, mine detection, signals intelligence, and chemical-biological-radiological-nuclear (CBRN) reconnaissance, as described in the *Office of the Secretary of Defense FY2009–2034 Unmanned Systems Integrated Roadmap* (OSD, 2009). Many of the programs, systems and technologies described in OSD's 25-year roadmap for unmanned systems require the development of capabilities for autonomous operations for teams of these systems working together to execute missions. But developing capabilities for controlling teams of autonomous systems, and effectively utilizing these teams to achieve mission objectives, presents many technical challenges.

Fortunately, some of these challenges have been addressed in biological systems such as colonies of bacteria and social insects. In this paper we examine quorum sensing in biology and propose its use as a paradigm for implementing behavior-based control that is decentralized, distributed, scalable, and robust for teams of mobile autonomous systems. Additionally, we propose that quorum sensing may be used for ensemble decision-making tasks such as collective classification in distributed autonomous sensor platforms.

The increasing availability of autonomous and unmanned vehicle platforms to military commanders creates opportunities for the use of autonomous vehicle teams to enhance situational awareness, decrease response times, and gain tactical advantage without increased risk to human life. Teams composed of fully autonomous systems offer potential to extend operational capabilities in critical battlespace domains including the littoral zone, undersea, space, on the battleground, and in other challenging and hazardous environments. However, coordinated command and control (C2) for teams of

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autonomous systems operating in complex, dynamic, partially unknown and potentially hostile environments offers both technological hurdles as well as opportunities unique to each battlespace domain.

In this technical effort quorum sensing is applied to the development of behavior-based control for a team of autonomous ground robots (agents) tasked with searching a field for buried landmines. Each robot is equipped with one or more sensors for detecting mines, such as a metal detector, magnetometer, or ground-penetrating radar. We assume that the robots have different sensor suites mounted on them to perform landmine detection, and thereby may be considered heterogeneous from a sensing and platform perspective. The goal is to implement a decentralized control strategy such the robots must collaborate in order to identify the mines, while implicitly divvying up the labor amongst available agents to provide efficient parallel search.

2 BACKGROUND AND RELATED WORK

Quorum sensing (QS) can be classified as a decentralized decision-making process used to coordinate behavior. The key characteristics of QS are that each individual (1) senses either directly (e.g. through molecular concentration) or indirectly (e.g. by counting the number of interactions it has with others of its kind) the number or density of its own kind present, and (2) commences a predetermined response, such as adopting a specific behavior, once the quorum decision signal is triggered. QS may also be part of a collective quality assessment process, as practiced in ants and honeybees in selection of new nesting sites. In such cases the individuals make individual quality assessments and then share these assessments with the group.

2.1 QS in Bacteria

Bacteria achieve QS by detecting the density of other bacteria in the area, and then using this signal to regulate genes that in turn express behaviors (e.g. swimming, biofilm construction, pathogenicity). QS has been observed in many species of bacteria, but has been studied extensively in only a few including *Vibrio fischeri*, responsible for light production (bioluminescence) in the Hawaiian bobtail squid; in *Escherichia coli* (E. coli), which resides in the lower intestinal tract and is often credited with causing food poisoning in humans; and most extensively in *Pseudomonas aeruginosa*, where QS has been found to be employed in biofilm formation, swimming, and cell aggregation.

Bacteria use signaling molecules called autoinducers to regulate QS. These molecules are continuously secreted and detected by the bacteria, forming a kind of communication network within the colony. Once a specific density threshold of autoinducer molecules is crossed, behavior changes are induced through changes in gene expression.

Bacteria also communicate between species, using a different molecule to communicate than the one used within their own species (Ng, 2009). It is estimated that there are 10 times as many bacteria present in the human body as there are cells within the body. These bacteria, many species of which have not yet been identified, play an integral role in the proper functioning of the human body, while a few can cause serious and even fatal diseases. Identifying the chemical signaling mechanisms for various species of bacteria, both for signaling within species and between species, is an active and on-going focus of bacteriology research (Mehta, 2009).

2.2 QS in Ants

While QS has been observed in a variety of social insects, it has been studied most extensively in *Temnothorax albipennis* and *Leptothorax albipennis* ants (Pratt, 2002). Ant colonies nest in small crevices between rocks, or inside small spaces inside sticks. When the nest is broken, scout ants fan out in search of a new nesting site. When a promising nest site is found, the scout ant assesses the quality of the new site, and returns to the old nest. She waits a period of time inversely proportional to the quality of the new site before recruiting nestmates to follow her to the new nest site, a process called *tandem running*.

Ants perform tandem running visiting many candidate sites, recruiting other ants to visit the site they have chosen to nominate. While these site visits, recruiting, and tandem running are taking place, the ants are sensing the number of encounters they have with other ants. Once the number of encounters reaches a threshold a quorum decision is triggered and all of the ants return to the old nest and begin carrying the brood, queen, and fellow ants to the new nest site.

This process represents a more aggressive form of QS than that employed by bacteria in that the individuals compete to directly influence the outcome of the collective decision, selecting a new nesting site. The combination of individual site quality assessment, recruitment, and voting (by their presence) comprises an ensemble decision process that provides a means for the colony to quickly and efficiently find and relocate to a new nesting site.

2.3 QS in Bees

Honeybees (*Apis mellifera*) are social insects that, like TA ants, utilize QS to collectively evaluate and select new nest sites (Seeley, 2004). When a colony of bees becomes too large, the queen will leave the hive with a group of workers in order to start a new hive elsewhere. Once outside the nest, the workers form a swarm that may attach itself to a log, tree branch, or other convenient location where it can rest for a few days. A few of the scouts set off in search of a nest site to house the new hive.

When a potential site has been found, the scout assesses the quality in terms of whether or not it is infested with ants, how protected it is from the weather, how much sunlight it receives, etc., then returns to the swarm and performs a waggle dance to recruit other bees to the site. The number of repetitions of the dance is proportional to the quality of the site. Other scouts will fly to the potential new nesting site and perform their own quality assessments and recruiting. Once a quorum number of bees has been reached at the new site they all return to the swarm and begin a new behavior called *piping*, causing the swarm to take off and relocate to the new nest site.

Bees utilize a similar process to search for new food sources, including random search, assessment, waggle dance and recruitment. A search algorithm called the *Bees Algorithm* inspired by this process has been applied to a variety of combinatorial optimization problems including server allocation and job shop scheduling (Pham, 2005).

2.4 QS in Computational Intelligence

Quorum sensing clearly has potential for use in applications of computational intelligence, but it has surprisingly received little attention *per se* from the artificial intelligence community. This may be due in part to the fact that although QS was discovered and studied in *Vibrio fischeri* in the late 1960s, for many years it was thought to be limited to marine bacteria such as *Vibrio fischeri* and *Vibrio harveyi*. The extent to which bacteria utilize signaling to achieve decentralized coordinated action was not appreciated until recently (Ng, 2009).

A vibrant and expanding area of computational intelligence research is based on modeling the behavioral paradigms of social insects and applying them to groups or teams of autonomous man-made systems. Ant Colony Optimization (ACO) was inspired by the movement of ants in locating food sources, and the optimal paths they establish to move the food back to the colony. ACO was proposed by Dorigo (1992) as a search heuristic for finding an optimal path in a graph, and has spawned a class of heuristic algorithms for performing optimization tasks. ACO algorithms may be considered a subclass of stigmurgic methods (Bonabeau, 1998) in which agents utilize communication through the environment. Key features of ACO algorithms include the use of pheromones to create paths along which the ants (or agents) move, and the processes for strengthening and weakening such paths. ACO algorithms have been applied to a variety of challenging optimization tasks including the traveling salesman problem (Dorigo, 1996), job shop scheduling (Merkle, 2002), and distributed clustering (Bonabeau, 1998).

QS may be considered a stigmurgic method, but it is not an ACO algorithm since it doesn't use pheromones, it doesn't adapt agent paths to gradually improve its solution(s), and the focus of QS is emergent collaboration to achieve collective decisions. As such, it would be more appropriate to categorize QS as a method for distributed multiagent collaboration rather than as an optimization technique.

Sahin and Franks (2002) researched the measurement of spaces by animals, including *Leptothorax albipennis* ants, for potential use in developing behaviors for autonomous mobile robots. While the ants they studied were utilizing QS for nest assessment they focused instead on the mechanism for nest quality assessment, specifically how they measured the size of the potential new nesting sites. In their "Future Lines of Research" section they discuss collective decision-making and quorum sensing, and suggest exploring the use of social behavior in complex measurements and decision-making.

Wokoma (2003) proposed the use of a QS-based protocol to provide self-organized clustering to optimize communications routing in distributed sensor networks. They conclude that the QS-based protocol is more scalable than a centralized approach, and can adjust to changes in the environmental signal and network topology because there is no dependence on any particular node.

Peysakhov and Regli (2005) proposed a server population management scheme for wireless mobile ad hoc networks based upon QS, specifically *Leptothorax albipennis* ants. They implement a QS based protocol that automatically rebalances service availability on server hardware configured as a wireless server network. They conclude that the solution exhibits properties of emergent stability, decentralized control, and resilience to disturbances.

QS can be viewed as a simple form of voting, but it differs from voting as practiced in ensemble decision systems and human organizations in that in QS no overall tally (counting) of votes is required, the agents involved are necessarily mobile, and the quorum decision is triggered based upon a density threshold being exceeded. Related work in voting in ensemble decision systems is discussed in the next section.

2.4.1 Ensemble Decision-making

Recent advances in computational intelligence have produced techniques and algorithms for combining predictions, estimates, and decisions from multiple sources, such as expert systems or neural network models, such that the ensemble decision is at least as good (and often significantly better) than that of any one expert or model (Polikar, 2006). In human social affairs we routinely practice ensemble decision-making in numerous fora including elections, jury-trials, product reviews and rankings, medical treatment decisions (e.g., asking for a second or third opinion before surgery), talent contests, and scientific peer review. In the application of both computational intelligence and human intelligence, the use of ensemble decision-making allows the individual to benefit from the knowledge and experience of the group, and to thereby reduce the risk of making poor decisions.

Ensemble decision systems (Polikar, 2006) have been developed that use a population of decision models to perform collective decision-making. The strength of this approach is that if the model errors are uncorrelated, then the overall ensemble decision will be more accurate. Such systems often apply voting schemes in which each classifier in the ensemble is given a set of inputs and “votes” on the classification. The votes are tallied, and a combination rule is applied, such as majority or consensus.

Biological systems such as ant colonies and other social insect groups routinely demonstrate the ability to coordinate information and collaborate in large numbers to solve extremely challenging problems collectively, such as building a new nest with hundreds of complex interconnected chambers and passages, or carrying objects many times the size and weight of a single individual, despite the lack of any form of centralized or coordinated planning or control.

The study of such biological systems has recently given rise to the field of Swarm Intelligence (Garnier, 2007), which focuses specifically on the emergence of intelligence through the interactions of a large number of individuals, with each acting according to its own behavioral plan. Swarm-inspired behavior-based approaches to control of teams of autonomous systems offer several advantages over more traditional approaches (e.g., linearized optimal control (Robinett, 2010), including robustness in dynamic environments, decentralized and fully distributed controls, low computational complexity (each individual is executing a simple set of rules or behaviors), and scalability since only local interactions are considered (hence there is also no single point-of-failure for the entire system).

In related efforts for controlling teams of autonomous ground vehicles and teams of unmanned air vehicles we utilize a physics-inspired approach called physicomimetics (artificial physics) (Spears, 2004; Wiegand, 2006) where vehicles are modeled as particles, interactions between them are governed by force laws, and observation goals are represented by attractors. These techniques will allow human operators to employ teams of autonomous vehicles to perform missions and provide information to enhance situational awareness without increasing manning requirements for planning and control of the platforms.

2.4.2 Behavior-based Autonomous Team Control

In a related effort (Sofge, 2009) we are investigating planning and navigation for teams of underwater gliders to improve the accuracy of assimilative ocean prediction models for undersea warfare. The ocean environment presents numerous challenges for unmanned systems such as difficulty communicating with teammates underwater (increasing the need for autonomy), difficulty localizing the vehicle underwater and maintaining accurate positioning (e.g., inertial navigation systems are highly sensitive to drift due to currents and other ocean dynamics and the resultant accumulation of error), and difficulty controlling highly underactuated systems such as undersea gliders. The undersea environment also offers significant advantages for unmanned and autonomous systems such as the low likelihood of colliding with other objects (other than the bottom or one another); stealth provided by ocean cover; extended stay times for passive monitoring due to the low energy need (since gliders use buoyancy control to move forward, no propellers are required); emerging technologies for harvesting energy from the ocean; and long-range propagation of acoustic signatures for identification.

In other efforts we are developing an information theoretic approach to optimizing underwater distributed sensor networks (DSNs), and algorithms for merging bathymetric datasets (e.g., ocean floor profiles) that have been collected at various times by a variety of means including sonar arrays towed by survey ships, side-scan sonar collected by undersea vehicles, surveillance aircraft, and even space-based observing platforms (satellites).

Autonomous sensor networks are under development or have already been put into operation for many purposes including weather forecasting and prediction (Bell, 2010); volcanic gas emissions monitoring (Galle, 2010); tsunami early-warning systems (PTWC, 2010); monitoring bridges, tunnels, pipelines, and other critical structures (Chebrolu, 2008); and for monitoring networking and communications channels in order to detect possible activity by terrorists (Lawless, 2010). A key aspect of all of these networked systems, as well as the teams of autonomous systems described previously, is the need to coordinate information flows amongst the individual members of the team (or within the network); and to reconcile, fuse or merge, and integrate the various bits of information streaming in from disparate sources into a coherent picture for use by human operators.

3 METHODOLOGY

The goal is to demonstrate that the quorum sensing paradigm may provide robust decentralized coordination and collective decision-making for mobile autonomous teams performing complex tasks. Quorum sensing is applied to the design of a decentralized planner for a team of mobile autonomous agents surveying a field containing buried landmines. The key features of this approach are (1) each agent only interacts with its local environment, thus minimizing communication requirements and avoiding complexity (and bandwidth) scaling problems as the number of agents increases, (2) collaboration between agents is necessary to accomplish the task, both for collective decision-making and division of labor, but it is an emergent property (not explicit), (3) the approach is robust to variations in the size (and topology) of the field, number of targets (mines), number of agents, sensor performance, and quorum size.

While QS is inspired by the behavior of social insects such as ants, it relies on different mechanisms than those employed by other artificial ant algorithms such as ACO (described previously), and QS is presented as a method to achieve distributed collaboration and decision-making for a team of agents, not as an optimization technique. Therefore no direct comparison of ACO and QS methods in performing this task was performed. An ACO-based solution utilizing pheromone trails may exist, but that is beyond the scope of this study. Experiments instead focused on validating the QS approach.

3.1 Operationalizing QS

Our approach to applying QS to a target domain, such as a search or optimization problem involving multiple agents, is to first decompose the problem into two or more distinct phases. Each phase is characterized by parallel execution of agent behaviors, with no centralized control of the team.

The first phase is fundamentally a parallel search by the agents. Each agent must be capable of performing a quality assessment or recognition of whatever is being sought.

Next, each agent must have a mechanism for communicating or expressing its assessment or recognition. This could be communicated through the environment with autoinducers in bacteria, or communicated directly from one agent to another by ants and bees. Recognition functions as a voting mechanism in bacteria, while assessment is part of the recruitment process in social insects. This communication of assessment is the key to collective decision-making.

Each agent must also have the ability to trigger the quorum decision (since we require a distributed, completely decentralized approach). The quorum decision must be accepted by each agent. Once the quorum decision state is accepted, the agent may go back into another state such as random-walk, or search, depending upon the task.

3.2 Area Coverage

Using a team of autonomous vehicles to search a field at first glance appears to be a classic area coverage problem. Such problems may often be solved efficiently by dividing the space to be searched amongst the available agents, and having each agent assume responsibility for covering a specific area.

In this application, however, this approach will not work since each agent requires the assistance of other agents carrying different sensor packages to confirm the identification of buried mines. A Brownian-motion type random walk (with a single random step taken at each time step) would not make sense either, since the agents would spend an inordinate amount of time retracing their steps and revisiting the same places they had just visited.

While many strategies may be devised to address this problem, we chose to start with a modified random walk, with "walk-length" determined by the size of the field and the number of agents. The walk-length for the agents is determined by dividing the field length by the number of agents and then multiplying by three. For example, if the field is 50x50, and there are 10 agents, then the walk-length will be 15. This gives each agent good field coverage, but no attempt was made to optimize walk-length with respect to overall team performance. Each agent chooses a random direction to move from its starting position on the grid by selecting a direction toward one of its 8 neighbors (standing still is not allowed). For each time step that passes it will continue in that direction until the full walk-length has been covered (e.g., 15 steps). The agents then select another direction at random.

3.3 The Field, Agents and Mines

The field is implemented as a square cellular toroidal grid (for simplicity) such that each agent and each mine is located at a specific Cartesian grid coordinate at each point in time. Both the mines and the agents are randomly placed on the grid at the beginning of each run. The agents will move while the mines will remain in fixed locations throughout the run.

Agents appear on the grid as small blue circles. The mines initially appear as small red stars. Each time an agent "recognizes" a mine, its star grows a bit larger on the field until the quorum decision threshold is crossed, at which point it is changed into a green square (Figure 1).

3.4 Mine Detection and Quorum Decisions

The QS paradigm requires that each agent must (1) sense the number (or density) of its own kind, and (2) commence a predetermined response once a quorum decision threshold has been crossed. Since it would be extremely inefficient to have all (or many) of the agents congregate at each mine, we decided that only a minimum requisite number (a *quorum*, by definition) must visit each mine and mark it as "recognized". In addition, a mine can only be recognized by an agent once. Recognition is a stochastic process based upon the maximum sensing range (a length of 3 cells was used for the experiments), the accuracy of each agent (also a controlled parameter), and a normally distributed random number generated for each possible recognition.

When an agent successfully recognizes a mine, the mine's hit-count is incremented. If the hit-count exceeds the quorum threshold, the mine is announced as recognized and its icon is converted from a red star to a green square. The threshold is the same for all mines and agents, and the requisite action upon recognition (that is, a mine exceeding the threshold) is to announce the mine (in an actual real-world situation the presence and location of the mine would be broadcast for further investigation and/or remediation of the mine), and continue searching for other mines. Once all of the mines are located the simulation is stopped and the time taken to find all of the mines is recorded.

3.5 Team Performance and Robustness

The performance of each agent team is measured based upon the number of simulation time steps from initialization of landmine and agent positions until all landmines are recognized by a quorum of agents. Since the starting positions, random-walk process, and recognition process are stochastic, each experiment is repeated 100 times. The number of time steps required for each run is plotted versus the variable of interest, along with the median over all 100 runs.

We define robustness as the property that the QS-inspired search strategy will continue to function effectively in the presence of changes in the parameters such as field size, # Agents, Quorum Number, etc., and that team performance degrades gracefully with increases in task complexity (e.g. by increasing number of mines, or decreasing number of agents). To avoid undue influence by pathological starting conditions we calculate the 5% trimmed mean over each 100 runs, shown as the red lines in Figures 2-6.

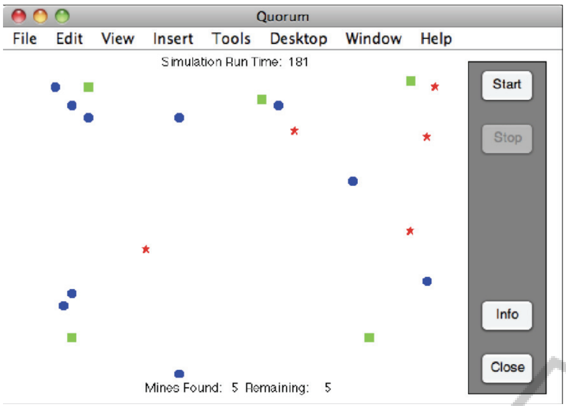

Figure 1: Screen shot from Matlab simulation of quorum sensing-based controller showing agents (blue circles) searching a 50x50 toroidal grid for landmines. There are 10 mines on the grid and 10 agents. Hidden mines are shown as red stars, and recognized mines are shown as green squares.

4 EXPERIMENTS

The focus of the experiments was validation of the QS approach as a method to achieve distributed collaboration and decision-making for a team of agents. It is not presented as an optimization technique, nor is it suggested that this is the only distributed algorithm for accomplishing this task. The efficiency of this algorithm compared with other fully decentralized approaches is beyond the scope of this paper. Instead we demonstrate the robustness of QS with respect to variations in the problem domain and resources as described.

4.1 Expectations and Hypotheses

Our expectations were that QS could be operationalized for use in decentralized, distributed mobile multiagent teams to address challenging problems in computational intelligence such as decentralized landmine detection using an autonomous multi-agent team. We hypothesize that the QS-based approach will be robust to variations in many of the variables including:

- field size
- number of mines
- number of agents
- sensor performance
- quorum size

4.2 Design of Experiments

The experiments were designed to demonstrate the application of QS to the mine detection task, and to test the hypotheses specified above. The measure of performance for the team was the number of simulation time steps until all of the mines were recognized (i.e., quorum number reached for every mine). Each experiment started by randomly initializing the positions of the mines and the positions of the agents.

Each experiment was repeated 100 times with a different set of starting positions each time. The parameters not being varied were set at the following nominal values:

Field size: 50x50# Mines: 10
\# Agents: 10 Walk-length: 3*Field size/#Agents
Quorum Number: 3 Sensor Performance: 0.6

Experiment 1: *Test robustness of team performance with respect to variations in field size.*
The field was defined as an mXm unit square toroidal cellular grid. The value of m was varied from 20 to 100 in steps of 5 units.

Experiment 2: *Test robustness of team performance with respect to variation in the number of mines.*
The number of mines was varied from 5 to 25 in steps of size 1.

Experiment 3: *Test robustness of team performance with respect to variations in the team size (number of agents).*
The number of agents was varied from 5 to 25 in steps of size 1.

Experiment 4: *Test robustness of team performance with respect to variations in sensor accuracy.*

It was assumed that different sensors have different performance characteristics in recognizing the mines. The detection of a mine is modeled as a stochastic process in which sensor accuracy, distance to the mine, and random chance determine the outcome. For all experiments the maximum range for detection was set at 3 units, with the probability of detection decreasing with distance according to a normal distribution with mean zero. The variance of that distribution was determined by sensor performance parameter psense. The nominal value of psense for all experiments except for Experiment 4 was 0.6.

To test the robustness of team performance with respect to psense, the value of psense was varied from 0.3 to 1.0 in steps of size 0.1

Experiment 5: *Test robustness of team performance*

with respect to variations in the quorum size (the number of hits required for a mine to be fully recognized by the team).
The quorum size was varied from 2 to 5 in steps of size 1.

5 RESULTS

Figures 2-6 show the results from the Experiments. Each experiment was repeated 100 times. Each dot shows time to completion for the team for a single run; the line shows the 5% trimmed mean completion times for the team versus the varied parameter (shown on the x-axis) over 100 runs.

Figure 2 shows that as the field size increases from 20X20 to 50X50, a 625% increase in area, the task completion time increases linearly at approximately the same rate as the increase in area. This shows that the QS-inspired search technique is robust to changes in field size.

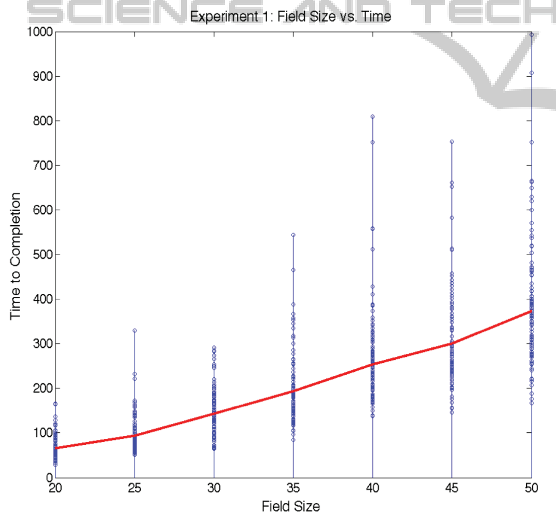

Figure 2: Experiment 1: Task Completion Time (y-axis) vs. Field Size (x-axis).

Figure 3 shows that at the number of mines increases from 5 to 25, the trimmed mean task completion time also increases at a gradual (roughly linear) rate, indicating that the technique is robust to changes in the number of targets.

Figure 4 shows that as the number of agents increases from 5 to 25, the task completion time decreases monotonically but non-linearly. This is as expected, since the number of targets is fixed at 10, adding additional agents after a certain point will not substantially reduce the search time. This also shows that the technique is robust to changes in team size.

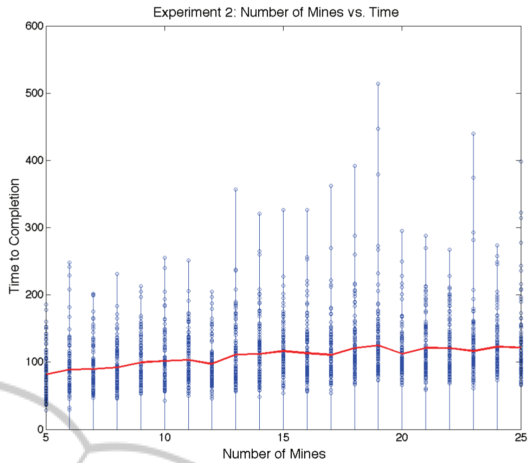

Figure 3: Experiment 2: Task Completion Time (y-axis) vs. Number of Mines (x-axis).

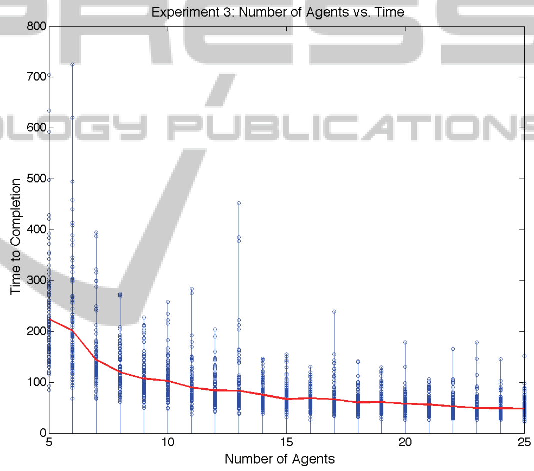

Figure 4: Experiment 3: Task Completion Time (y-axis) vs. Number of Agents (x-axis).

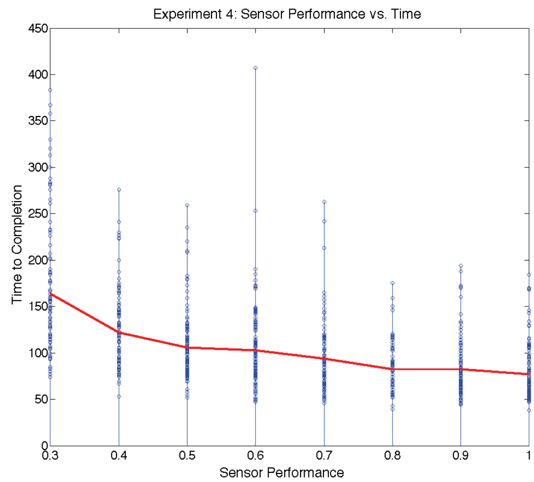

Figure 5: Experiment 4: Task Completion Time (y-axis) vs. Sensor Performance (x-axis).

Figure 5 shows that as the sensor performance increases from 0.3 to 1.0, the mean task completion time decreases monotonically, indicating that the technique is robust to changes in sensor performance.

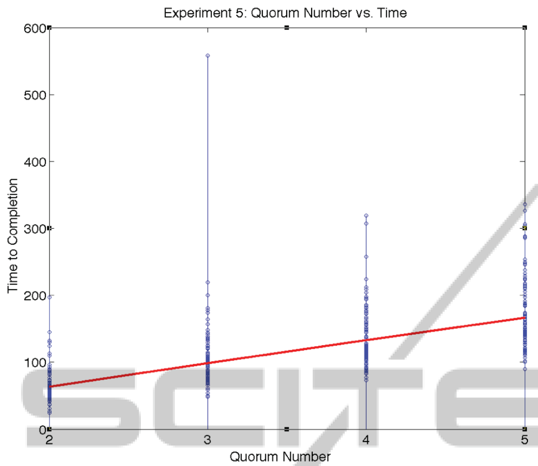

Figure 6: Experiment 5: Task Completion Time (y-axis) vs. Quorum Number (x-axis).

Figure 6 shows that as the quorum number increases from 2 to 5, the mean task completion time increases linearly and monotonically, indicating that the technique is robust to changes in quorum number, the number of collaborators needed to confirm a decision.

6 CONCLUSIONS

Quorum sensing, a decentralized decision-making process used by bacteria and by social insects to coordinate group behavior and to perform collective decision-making, provides a robust decentralized team coordination and collective decision-making paradigm for use in mobile autonomous teams performing complex tasks. In this effort a quorum sensing paradigm was used to develop a behavior-based control strategy for a team of autonomous mobile robots given the task of surveying a field containing buried landmines. The quorum sensing-based search strategy was shown to be robust to variations in field and team size, number of landmines, sensor accuracy and quorum size.

7 FUTURE WORK

Quorum sensing offers tremendous potential for design of robust decentralized control and decision-making strategies for teams of autonomous systems and distributed sensing arrays. Mobile autonomous systems capable of collaboration may provide significantly enhanced capabilities for recognizing targets, area search, reconnaissance, and other critical tasks. Future efforts will focus on refining QS-inspired approaches to collaborative tasks for multi-agent teams (such as area search and collective recognition), implementing these methods on actual autonomous system hardware, and testing autonomous teams under real-world conditions. The form of quorum sensing implemented and studied in this effort thus far is passive, much like quorum sensing employed by bacterial colonies, in that the agents do not practice recruitment to confirm their classifications. A more advanced form of QS, Aggressive Quorum Sensing (AQS), akin to that employed by ants and honeybees, incorporates recruitment and more behavior states for the agents. Once an agent makes a successful recognition of a mine (but still below the quorum threshold), it begins recruiting other agents to confirm the recognition. This technique has the potential to significantly enhance the accuracy of the team on the mine-clearing task. We will develop AQS and apply it to the landmine surveying task, comparing the performance of the AQS-based approach with that of the QS-based approach described herein.

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