Application of Swarm Robotics Systems to Marine Environmental Monitoring

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***Abstract*—Automated environmental monitoring in marine environments is currently carried out either by small-scale robotic systems, composed of one or few robots, or static sensor networks. In this paper, we propose the use of swarm robotics systems to carry out marine environmental monitoring missions. In swarm robotics systems, each individual unit is relatively simple and inexpensive. The robots rely on decentralized control and local communication, allowing the swarm to scale to hundreds of units and to cover large areas. We study the application of a swarm of aquatic robots to environmental monitoring tasks. In the first part of the study, we synthesize swarm control for a temperature monitoring mission and validate our results with a real swarm robotics system. Then, we conduct a simulation-based evaluation of the robots' performance over large areas and with large swarm sizes, and demonstrate the swarm's robustness to faults. Our results show that swarm robotics systems are suited for environmental monitoring tasks by efficiently covering a target area, allowing for redundancy in the data collection process, and tolerating individual robot faults.**

I. Introduction

With the increasing exploration of the marine environment there is a high demand for collecting large amounts of spatially and temporally dispersed data [1]. Sensor networks have played a major role in marine environmental monitoring, replacing expensive manned vessels and allowing data collection across multiple sites in parallel [2]. Sensor networks, however, have inherent limitations. Specifically, they have fixed sampling locations, and therefore lack the ability to self-reconfigure in response to unexpected events, or to increase the spatial coverage of an area of interest. One promising solution is the use of robotic platforms, which can add mobility to the sensor nodes and bring to light the full potential of automated environmental monitoring. Groups of robots can collect data from multiple places simultaneously, allowing a spatial and temporal resolution that would be impossible with a single robot or static sensing nodes [1].

Most multirobot solutions are, however, based on centralized path-planning solutions, and therefore require regular communication between a base station and the robots. These constraints can prevent such robotic systems from being deployed in remote locations, limit the scale of deployment, and limit the robots' ability to address dynamic tasks where autonomous decision-making is required. Furthermore, since there is a central point of failure, malfunctions in the base station or in the communication system may cause the mission to fail. As stated in a recent survey of automated environmental monitoring approaches [1] "*methods are required for resource allocation to solve various observation objectives, as well as decentralized cooperative control of large groups of mobile sensing systems, particularly with low-communication bandwidth and significant asynchronicities and latencies in data transmission and information processing...*".

We propose the use of swarms of aquatic surface robots to address these limitations. Swarms of robots [3] can adapt to unknown or dynamic environments by relying on autonomous decentralized control, local communication, and onboard sensing. Such a system can potentially be used for various environmental tasks that require high temporal and spatial resolution or to track dynamic elements like sea-life or plumes. In this paper, we study the application of swarm robotics systems to marine environmental monitoring. We first synthesize control for an area coverage task, where the robots must cooperatively cover the area delimited by a user-defined geo-fence and gather water temperature data. Performance is validated using a swarm of eight real aquatic surface robots. We then conduct a simulation-based study to assess how such systems scale to large application scenarios. We show that the swarm behavior can scale to large number of robots, large areas, is robust to individual faults (that is, unit failure does not compromise the overall mission success), and can provide redundancy in the data collection process.

II. Related Work

A. Sensor Networks

A key aspect in marine environmental monitoring is the measurement of relevant environmental variables [1]. According to Ballesteros-Gómez and Rubio [4] in their survey of recent advances in environmental analysis, environmental sensor networks (ESNs), that is, wireless networks of sensors distributed throughout the environment, have recently emerged as a promising technology for marine environmental monitoring. ESNs allow for real-time measurement and/or monitoring in locations that are potentially challenging to access. Sensor networks can thus play a major role in marine environmental monitoring, replacing expensive manned vessels and time-consuming and weather-constrained manual data collection [1], [4]. ESNs additionally enable data collection across multiple sites in parallel [2] and higher-fidelity data [1].

ESNs were the first major shift in distributed, real-time monitoring and observation in marine environmental monitoring [1]. Corke *et al.* [5] reviewed the recent developments in sensor networks for agricultural and environmental applications. In the marine domain, ESNs have typically been used in applications such as water quality monitoring and temperature profile measurements. Despite their potential, ESNs currently face a number of technical challenges and have inherent limitations. A major limitation of ESNs is that they typically have fixed sampling locations [1], and therefore lack the ability to self-reconfigure in response to unexpected events, or to increase the spatial coverage of an area of interest. Although remedies such as cable winches can be used to improve spatial coverage of ESN measurements [6], such solutions are still significantly limited in terms of their movement capabilities.

B. Autonomous Robots for Environmental Monitoring

One promising solution to overcome the limitations of ESNs is the use of robotic platforms, which can add mobility to the sensor nodes and realize the full potential of ESNs. Groups of robots can collect data from multiple places simultaneously, allowing a spatial and temporal resolution that would be impossible to achieve with a single robot or static sensing nodes [1].

Environmental robotics has been the subject of significant progress in recent years. Relevant scientific and engineering achievements include, for example, the development of energy-efficient platforms [1], [7], which enabled an increase of the operation time of robots. As a result of progress in the field, different types of robots have been applied to multirobot environmental monitoring scenarios. In Leonard *et al.*'s study [8], a group of six relatively complex and expensive gliders carried out an ocean sampling task during a period of 24 days. Similarly, Smith *et al.* [9] used two gliders to track and monitor algae blooms. Valada *et al.*'s [10], on the other hand, developed a low-cost multirobot platform that could sample water quality in an area specified by the human operator. These studies, however, are based on centralized path-planning solutions and additionally require regular communication between a base station and the robots. For example, in Valada *et al.*'s [10] study, robots provide online situational awareness to the operator, but the paths need to be centrally planned and re-planned according to the measurements obtained. These constraints can prevent such robotic systems from being deployed in remote locations, limit the scale of deployment, and limit the robots' ability to address dynamic tasks where autonomous decision-making is required [1]. Furthermore, since there is a central point of failure, malfunctions in the base station or in the communication system may cause the mission to fail.

Overall, autonomous robots have the potential to overcome the inherent limitations of ESNs. However, new methods are required for resource allocation to solve various observation objectives, and to enable efficient control of large groups of cooperative, mobile sensing systems [1]. To address the limitations of current approaches, we propose the use of large-scale swarm robotics systems [11] composed of simple, inexpensive, and autonomous robots with decentralized control.

C. Swarm Robotics Systems

In a swarm robotics system, the robots rely on decentralized control. Each robotic unit is autonomous and makes decisions based on sensory readings and information received from other robots in its immediate vicinity. In this way, individual robots can dynamically respond to events in the environment and cooperate with neighbors on the basis of local cues. The robots can incorporate the sensory readings into the decision-making process, in order to follow environmental gradients, track sea life, and so on. Decentralization of control leads to a number of key properties [3], [11], [12], [13] that make swarm robotics systems particularly well-suited for marine environments, namely:

Robustness to individual faults*:* Given the decentralized nature of the robot control, there is no central point of failure in a swarm robotics system. In this way, the swarm is robust against the failure of individual robots and, since there is redundancy within the swarm, faults do not compromise the completion of the mission. Such robustness is especially relevant for long-term missions in marine environments, as waves, wind, and debris can cause unexpected failures in the robots.

Scalability*:* Swarms can scale dynamically to tens or hundreds of robots [14], as the robots only interact with other robots in their immediate vicinity. Such scalability is essential for monitoring large bodies of water, as it enables data sampling at several places simultaneously.

Flexibility*:* Robots in a swarm robotics system can display different behaviors in response to changes in the environment and sensory inputs, instead of relying on pre-specified mission scripts.

The application of swarm robotics systems to marine environments is advantageous in tasks where large and dynamic environments have to be monitored. Having multiple dynamic measuring points enables a high spatial and temporal resolution of the gathered data, which is particularly relevant in environments where the features being measured change throughout time and space.

III. Experimental Setup

A. Robotic Platform

We developed a swarm robotics system composed of ten autonomous, small (65 cm) and inexpensive (300 EUR) aquatic surface robots (see Fig. 1) in order to validate the concept of swarm robotics systems applied to marine environmental monitoring. Each robot is controlled by a Raspberry Pi 2 single-board computer and is equipped with a GPS receiver, a digital compass, a water temperature sensor, and Wi-Fi communication. Propulsion is provided by a differential-drive system which drives twin propellers. Each robot weighs 3 Kg, has a maximum speed of 1.7 m/s, a maximum turning radius of 90°/s, and an autonomy of 90 minutes when moving at full speed.

The robots communicate with nearby robots every second by broadcasting UDP packets containing their location and heading. Neighboring robots that receive the packets record the information, which can then be used to calculate relative distances and angles. The robots make autonomous decisions based on different pieces of information: (i) the relative distance and angle of nearby robots, (ii) the boundaries of a user-defined geo-fence, and (iii) the relative distance and angle to a user-defined waypoint. Furthermore, the robots are equipped with a water temperature sensor. Additional details about the hardware and software platforms can be found in [15].

Fig. 1. Six units of our swarm robotics platform (out of a total of ten developed) on land, prior to deployment.

B. Control Synthesis

We resort to evolutionary robotics (ER) techniques [16] to automatically synthesize self-organized swarm control. In ER, evolutionary algorithms generate candidate solutions, evaluate them and select the highest-performing ones, and apply variation operators to obtain the next generation of candidate solutions. The process continues for a number of predefined generations, or until a fitness threshold is reached. The evolutionary process is conducted offline, in simulation. For the control synthesis process, we use JBotEvolver [17], an open-source neuroevolution framework and simulation platform. Each robot is controlled by an artificial neural network (ANN), which receives normalized sensory data as input, and outputs the desired heading and speed. The heading and speed are then converted to the corresponding left and right motor speeds. The configuration of the ANN is optimized by the NEAT neuroevolutionary algorithm [18]. NEAT differs from standard evolutionary algorithms by optimizing both the networks' topology by through the addition of neurons and connections, in addition to tuning the connection weights.

For the environmental monitoring task, we define a geo-fence which delimits the area where the robots should collect temperature data. The robots start from a base station and are deployed to random positions within the area. After they reach the target locations, the monitoring behavior is activated for a certain period of time. After the data collection task is over, the robots autonomously return to the base station. During the task, the robots are aware of the geo-fence boundaries, the position of the neighboring robots (up to 40 m), and record the temperature sensor's readings.

The monitoring area was divided into a grid in order to assess the performance of the controllers. Each robot visited cells within the coverage radius V, setting its value to 1. The value of previously visited cells decayed linearly over a time frame of 100 s to 0, and controllers were scored based on how much of the grid was covered over time. See [13] for details regarding the evolutionary process and the definition of the fitness function.

IV. Real-robot Temperature Monitoring Experiments

The controllers synthesized in simulation were then transferred and tested to a real swarm of aquatic robots, composed of eight units. We evaluated the performance of the swarm in a task were the robots had to collect water temperature data in a given area, within a limited amount of time. We ran three separate experiments, each with a different area: square, rectangle and L-shape. In all setups, the total size of the area was 10,000 m^2 (1 ha). The robots started randomly distributed inside the area, and were given 5 minutes to cover the area.

Figure 2 shows the coverage of the different areas through time, and how that coverage affected the temperature map of the regions. The temperature maps were built using all the observations from all the robots, up to different points in time, and using Kriging interpolation. The coverage results show that the regions are explored uniformly through time. The evolved controllers transferred well to the real robots, the behavior patterns displayed by the swarm were visually identical to those observed in simulation, and the swarm was able to successfully perform the mission. By the end of each mission (after 5 minutes), the respective area was almost completely covered. The temperature maps show how the increasing coverage can progressively increase the resolution of the map over time, capturing more local variations. Overall, our results show that the swarm behavior is well suited to such monitoring missions, as the swarm rapidly provides a rough overview of the gradients across the whole area, which gets progressively refined as the mission progresses.

V. Simulated Large-scale Experiments

We setup a series of tests in simulation to assess how our swarm robotics system can scale to larger application scenarios in terms of: (i) effectiveness in covering large areas, (ii) scalability with respect to the number of robots, and (iii) tolerance to faults in individual robots.

A. Area Coverage

We first studied the capability of the swarm to cover large areas of different shapes, and how the size of the swarm (i.e., the number of robots) affects the coverage of the area. We considered three different areas for this study, with similar shapes to the areas used in the real-robot experiments, but 625× larger in terms of total area:

- **Square:** A square area with 2.5 km × 2.5 km (625 ha).
- **Rectangle:** A rectangular area with 4.2 km × 1.5 km (630 ha).
- **L-Shape:** A square area with 2.9 km × 2.9 km with a cutout of 1.45 km × 1.45 km, making the final area L-shaped with 630 ha.

The swarm size was varied from 5 to 50 robots. The robots started in random positions inside the given area, and were allocated 240 minutes (4 hours) for the task. Each experimental configuration was repeated in 10 independent simulation trials. The capabilities of each individual robot are similar to the robotic platform used in the real-robot experiments (see Section III-A). The only difference is that in the simulation-based experiments, the communication and sensor range of the robots were increased to 250 m (opposed to the 40 m in the real-robot experiments).

In Figure 3, we show the capability of the swarm to cover regions with different shapes, but with the same total area. To measure the coverage of the space, the areas were divided into a regular grid with 100 m × 100 m cells. The final coverage is the proportion of cells that were visited by at least one robot. The results show that the performance of the swarm is independent of the shape of the area. For each swarm size, the coverage achieved is similar for all three regions, confirming the capability of the controllers to adapt to arbitrary areas.

The results in Figure 4 show how the time required for the swarm to cover the area depends on the swarm size. The time needed to cover the area decreases predictably as the swarm size increases. Given the mission time of 240 minutes, a swarm of 20 robots is actually sufficient to cover all the cells of the area. Figure 5 illustrates how the different areas are covered over time with a swarm of 20 robots.

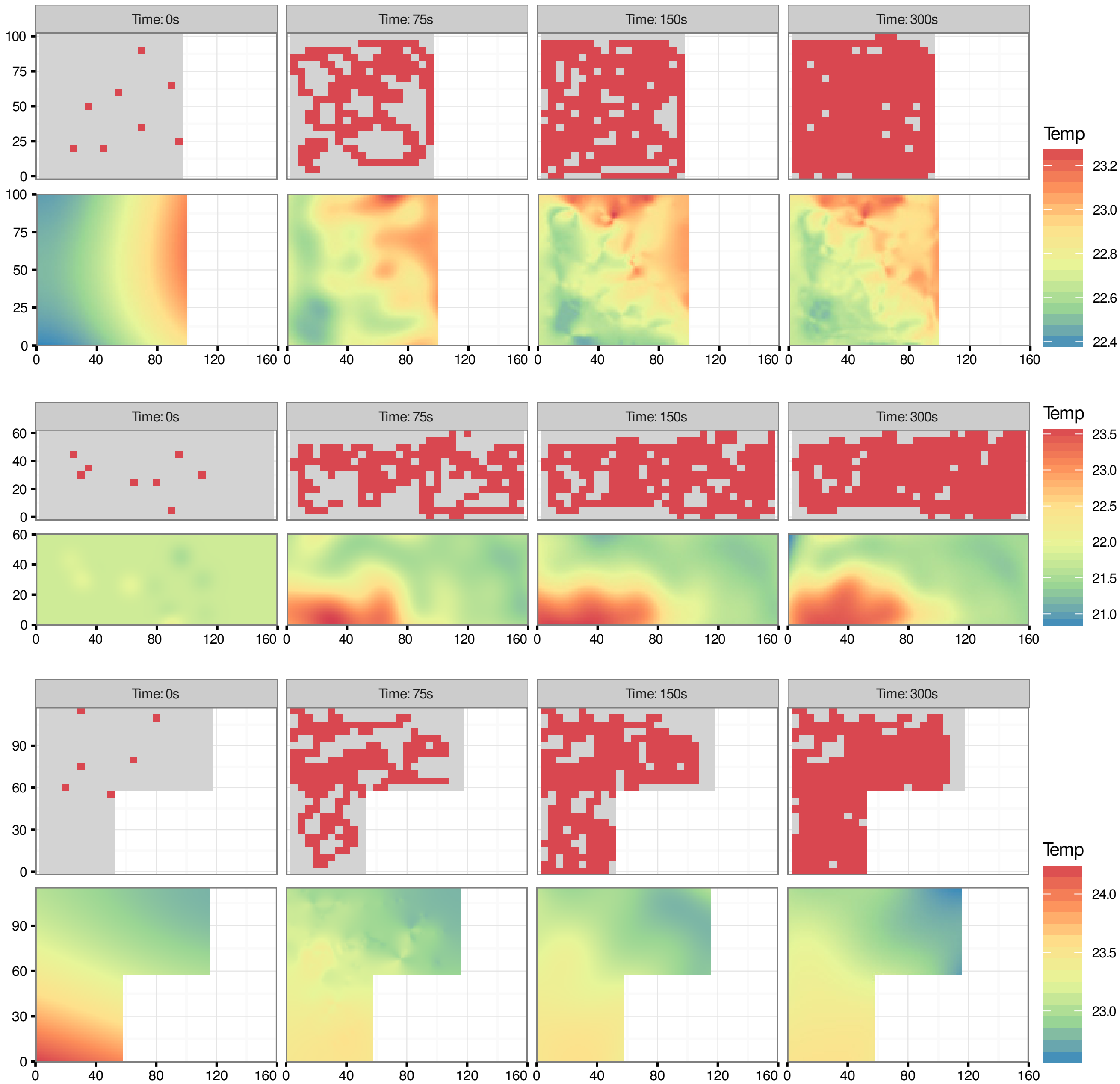

Fig. 2. Experiments with a swarm of eight robots, in three different areas (real robots). For each area, we show the coverage of the area through time (top), and the water temperatures measured by the robots, interpolated using Kriging (bottom).

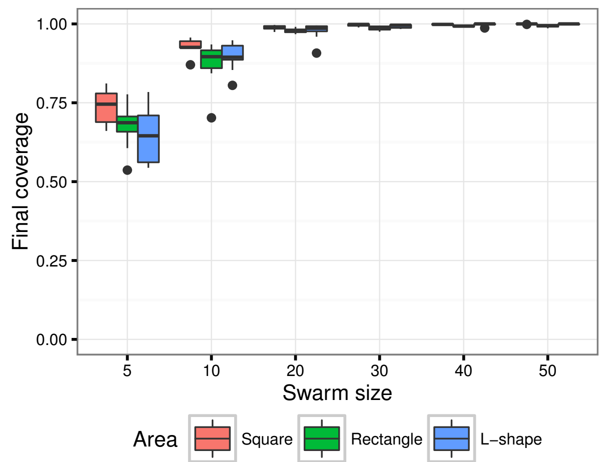

Fig. 3. Proportion of the environment covered by the end of the simulation missions, for each swarm size and and environment type.

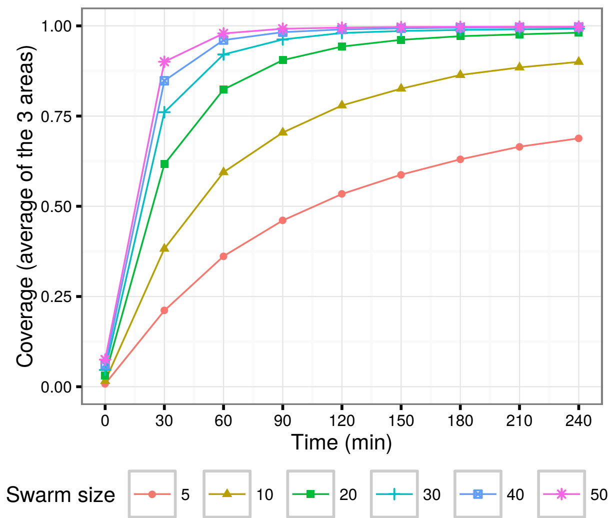

Fig. 4. Proportion of the area covered over time, averaged over the three different areas, and ten simulation samples for each area.

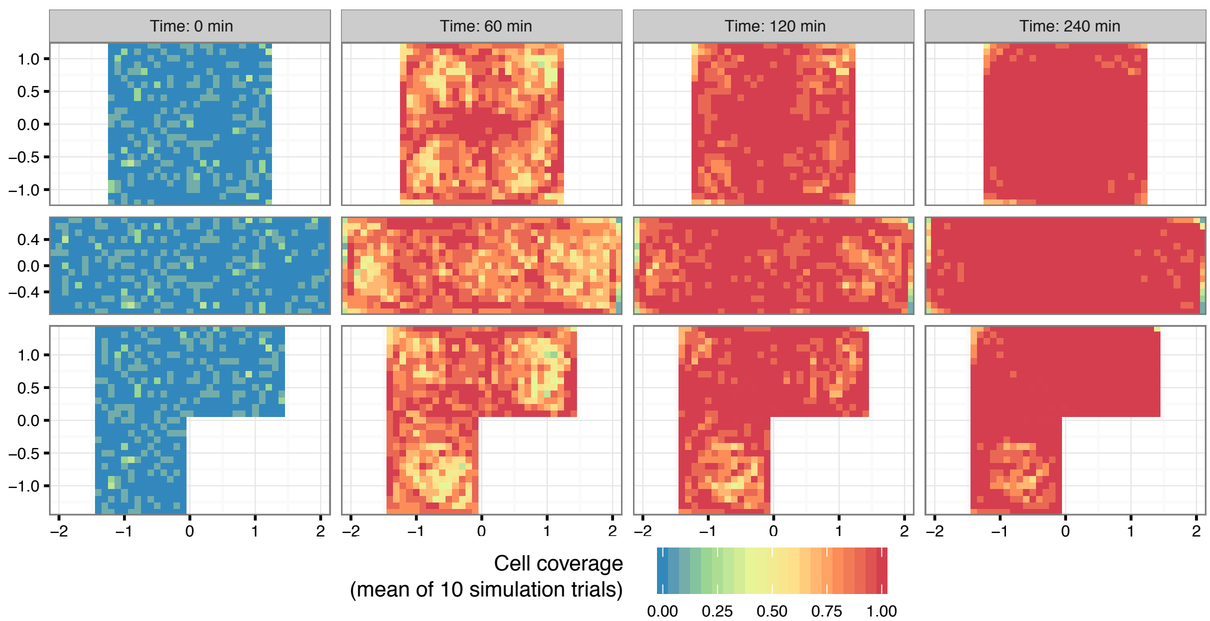

Fig. 5. Coverage of the area over time with a swarm of 20 robots (simulation). The color of each map cell varies according to the proportion of simulation missions in which that particular cell was covered by at least one robot.

B. Robustness to Faults

One potential advantage of swarm robotics systems is their inherent capacity to tolerate faults in individual units. We assessed the robustness of the swarm to such faults by injecting faults in the individual robots, with different intervals of occurrence. At every simulation step, each robot had a fixed probability of failing (stopping), which could correspond to the robot's motors breaking down or getting clogged in a real system. The robots also had a probability of recovering from the fault. The probability of individual failure was set so that, on average, each robot would fail every T minutes. We defined three variants, with T assuming the values 60, 30, and 15 minutes. The probability of recovery was the same in all variants – every minute, a robot had a 3.3% probability of recovering, meaning that each failure lasted on average 30 minutes.

For the experiments described in this section, only the square area (2.5 km $\times$ 2.5 km) was used, with 10 simulation trials for each experimental condition. Each simulation trial lasted for 240 minutes of simulated time.

The plot in Figure 6 shows how swarms of different sizes are affected by faults occurring with different frequencies. The results show that larger swarms ($>$ 30 robots) are generally unaffected by individual faults. As it has been shown in the previous section, a swarm of 20 robots is sufficient to cover this area. The failure of some robots in the larger swarms therefore has little impact on the coverage achieved. The group behavior of the swarm is maintained regardless of the type and frequency of individual robot faults. The coverage achieved with smaller swarms (5 and 10 robots) progressively degrades with the frequency of the faults, as there are not enough robots to offer sufficient redundancy.

C. Redundancy in Data Collection

Another type of fault that is especially relevant for environmental monitoring tasks are faults in the onboard sensors that cause erroneous readings to be collected. This type of fault can significantly impact the measurements in scenarios where each sensor node or robot is assigned to a unique sub-region of the area to be monitored. In swarm robotic systems, however, there is no central division of labor: the behavior of the swarm is organic and self-organized. This means that a single robot can traverse many different sub-regions in the monitoring area, and each sub-region is traversed by many different robots, thus allowing for redundancy of measurements.

We assessed this redundancy by analyzing the average number of unique robots that pass through each cell (100 m $\times$ 100 m) of the monitoring area (2.5 km $\times$ 2.5 km), see Figure 7. Without faults, 30% of the robots of the swarm, on average, pass through any given cell. With swarms with 10 or more robots, each cell is on average visited by at least three different robots, which would allow the detection and elimination of outliers in the readings of the environmental sensors. The number of different robots visiting each cell decreases with the frequency of the faults, since less robots are available.

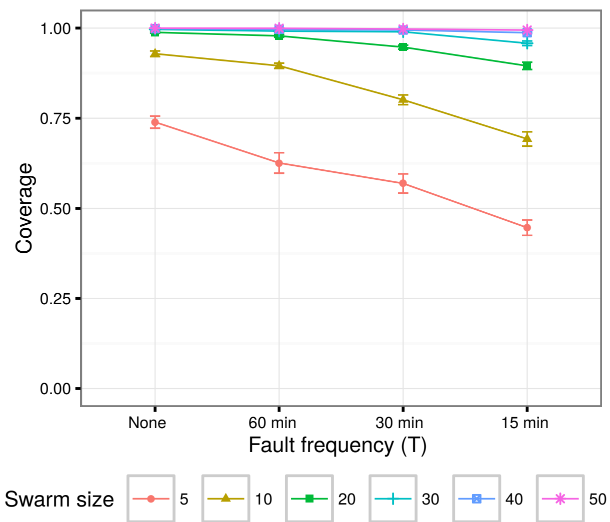

Fig. 6. Coverage of the area for a mission time of 240 minutes with temporary faults (simulation).

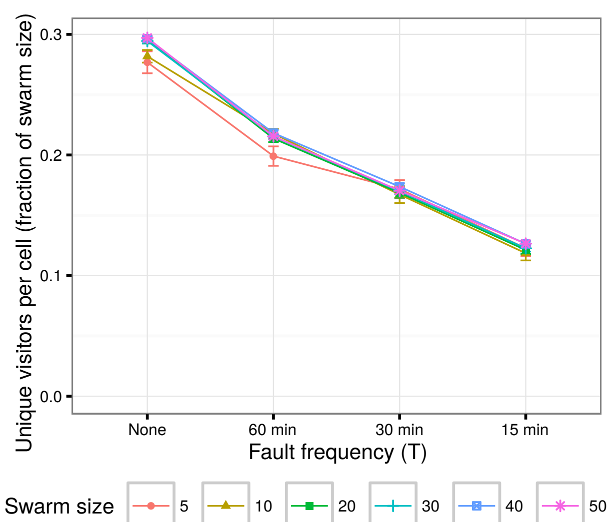

Fig. 7. The average number of unique visitors per cell, relative to the swarm size, for setups where the robots are affected by different types of faults (simulation).

VI. Conclusion

In this paper, we studied the potential of swarm robotics systems in the marine environmental monitoring task domain. In swarm robotics systems, control is decentralized – each robot is autonomous and makes decisions on how to perform the task based on sensory readings and on the interaction with neighboring robots. In the swarm robotics system studied in this paper, the robots were relatively small and simple aquatic surface robots. The robots were controlled by artificial neural networks, which were automatically synthesized in simulation using evolutionary robotics techniques.

We first demonstrated a swarm robotics system with a real swarm of up to eight robots, operating in a real environment of up to $10.000\,\mathrm{m}^2$ (1 ha). We assessed the swarm's performance in three temperature monitoring tasks, where the swarm had to cover areas of different shapes. The results showed that the swarm was effective in covering these areas, and could quickly uncover the temperature gradients in the area, increasing the resolution over time as more data was collected. We then studied the swarm's performance in a large-scale simulated environment, with monitoring areas up to $2.5\,\mathrm{km}^2$ (625 ha) and swarms of up to 50 robots. We demonstrated that the swarm behavior is scalable with respect to the number of robots, and that the swarm behavior is robust to individual robot faults.

Swarm robotics systems display a number of properties that makes them especially suited for large-scale applications, such as scalability, robustness to faults, and decentralized autonomous control. Marine environmental monitoring tasks can strongly benefit from these advantages, as the monitoring areas are typically large, and communication with a central control unit might not always be available. Swarm robotics systems allow for the collection of data with high temporal and spatial resolution, meaning that it becomes possible to obtain robust data from many different places simultaneously. Swarm robotics systems present a unique set of benefits that can be applied not only to temperature monitoring, as shown in this paper, but other marine environmental monitoring tasks, such as water sample collection, pollution monitoring, sea-life monitoring, and so on.

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