Fault Tolerance in Area Coverage Algorithms for Limited Mobility Sensor Networks

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***Abstract*—In sparse deployments of mobile sensors, the mobility of sensors is required to search the coverage area in an attempt to achieve polling—complete, possibly repeated, area coverage over time. Mobile sensor platforms are vulnerable to a variety of hazards during normal operation. When sensors lose the ability to mobilize due to mechanical failure, environmental factors, or simply exhausting their energy source, coverage effectiveness can be seriously impacted. Ideally, algorithms should adjust their behavior to compensate for failure modes in order to avoid areas statically covered by disabled sensors as well as adjusting their behavior to cover the areas assigned to sensors that are no longer able to mobilize. In this work, we demonstrate the effects of disabled mobility on area coverage algorithms due to their inability to adjust behavior, and suggest mitigation strategies and the impact on improving coverage in the face of disabled mobility.**

Keywords*—*Mobile Sensors; Sensor Networks; Disabled Mobility; Algorithms

I. Introduction

There are numerous factors driving increased attention to usage of automated sensor drones that consist of a hardware platform with onboard command/control, sensors, and effectors that provide for mobility. Human safety factors have long been a primary motivator for interest in employing robots for a variety of tasks where humans would prefer not to be. Also, mobile sensor hardware platforms have seen many recently advances, such as higher computation power, relatively lower weight, and lower power requirements that allow drones to carry much more computational capacity and payload or stay deployed and functional for longer periods of time. More and more, these platforms are more readily available, as the benefits of mass production of commercially designed systems are realized.

Mobile sensors are physical devices that are subject to observable failure rates. One of the most common problems for mobile sensors is that the effectors that provide for the mobility function of the platform fail [1], or that terrain or other issues cause the mobile sensor to become stuck while all other features of the platform continue to function as normal.

It is intuitive that one requirement of an algorithm being analyzed is that for the algorithm to function, sensors must be aware to some degree of the relative position and mobility restrictions (failure modes) impacting other sensors, otherwise there is no way they can (nor any reason for them to) alter their behavior. However, mobile sensors need not support full localization. Awareness of the failure modes of other sensors allows the network to be fault-tolerant, self-healing, and to dynamically change from initially homogeneous to heterogeneous with respect to mobility as agents adopt different roles (whether by choice or as observed).

Further, we acknowledge that various subsystems of a wireless sensor exhibit different energy requirements than others. Since our primary priority is to maintain a given network quality of service, we are required to utilize the mobility feature of the sensors. What we will establish is a schedule, whereby a certain number of sensors lose their mobility but retain their other functions, and will analyze the extent to which other sensors are able to compensate for this failure mode by altering their movement strategy to preserve the required quality of service while avoiding the area covered by the disabled sensors.

Given an objective measurement for lifetime and effectiveness of a sensor network, we explore the effects of disabled mobility on these metrics. From this work, we can see that as sensors lose their mobility, they become, in essence, static rather than mobile sensors. When the deployment and/or the algorithm that governs their behavior ensures that mobile sensors are spread sufficiently to adequately cover the search area, then coverage impact can be minimal. Conversely, when the deployment is concentrated or the algorithm fails to spread sensors prior to many of them failing, coverage effectiveness is vulnerable. Additionally, when mobility fails but other functions, such as communication, continue to operate, a sensor can communicate misleading intentions to other sensors. In essence, this can have outcomes similar to an attack where blind spots are created. The disabled sensor cannot navigate to the intended location to cover it, and other mobile sensors choose not to go there because they believe it is already covered.

In this paper, we examine related work in the areas of limited mobility, reliability analysis, and fault tolerance. After a brief survey of mobile sensor platforms, their mobility limitations, and their vulnerabilities to device failure, we describe the problem of assessing the impact of disabled mobility on coverage algorithms. We define the reliability model we will use, describe the simulation platform and parameters selected for our analysis, several coverage algorithms that are used for comparison, and then present findings, conclusions, and future work.

II. Related work

Fault tolerance in mobile sensor networks, the topic of algorithms that behave in a way that tolerates failure modes while still cooperatively pursuing a goal, can be found [2], [3], [4], but the specific topic of fault tolerance with respect to limited mobility sensor networks and how failures affect coverage performance has not.

One area where limited mobility affects performance of a mobile sensor network is when sensors are deployed for blanket coverage. The lifetime of such networks, and algorithms for preserving/extending the lifetime, has been extensively studied.

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An example uses redundant sensors in a dense deployment so that as sensors fail other sensors in the same region can wake up and take over for the missing sensor [5]. There are formulae that can be used to objectively assess the expected lifetime of a network of sensors [6]. Also, many works have explored the idea of optimized message routing for sensor networks in the event that some sensors fail, so that messages can be routed through other paths [7]. However, there has been little work devoted to the area of exploring what happens when a sensor continues to function even though it is no longer able to navigate. This is a real concern given that in many real world sensor platforms, energy requirements for mobility account for a large portion relative to that required for sensing and communication. The closest analogy is the study of hybrid sensor networks, where the term hybrid refers to the fact that sensors are non-homogeneous: some are static, and others are mobile [8], [9]. However, no works were found that examine the problem of sensors failing according to a predetermined failure model, additionally that the failure is limited to the mobility feature of the device, and relates this to the impact on coverage effectiveness.

As further background, a number of works examine sensor network lifetime from a rather fatalistic point of view, expressing desire to describe and understand an inevitable upper bound on the utility of a network of sensors [10].

It was shown that effectors–devices that perform actuation (including mobility), such as the motor, appendages, treads/wheels, and related connections—was observed to account for 35% of mobile robot failure, the largest single reason for failures [1]. This makes consideration of the problem of maintaining coverage quality of service (among other goals) using cooperating sensors in the network, an important aspect of mobile sensor network research.

Various works explore fixed deployments (no mobility following the initial deployment of the sensors), where mobility is not a concern toward energy constraints on the lifetime of the network. In a dense sensor deployment scenario, more sensors are deployed than are required to cover an area, and when a sensor fails, other sensors use a protocol to decide which sensor wakes up and takes the place of sensing the missing area. In some cases, sensors have a limited ability to exercise mobility, and can move closer to the hole in coverage in order to adjust for the missing sensor.

III. Reliability in Sensor Platforms

Numerous mobile sensor platforms have been in development in recent decades, including ground-based, lift-based, buoyancy-based, and space-based. Ground-based platforms (sometimes referred to as UGV's [11]) can be tiny weighing only a few centimeters/grams, using battery-powered micro circuitry, or as large as automobiles weighing tons using internal-combustion engines. These platforms are subject to a variety of mechanical failures, are vulnerable to obstacles found on the ground in the environments in which they operate, as well as terrain variations and pitfalls. The energy source (weight and conservation) is a major factor limiting the mobility of these platforms.

Lift-based, or aerial, platforms are devices that employ the physics of lift in order to remain in a state where controlled mobility is possible. The size of these devices can range from small, hand-held devices, up to large military/commercial aircraft. Identifying aircraft with a low Reynolds number provides a way to construct devices that are useful for lab research [12]. The Reynolds number can be expressed as shown in (1), where ρ is the air density, L is airfoil length, υ is velocity, and μ is the viscosity of the substance through which the device moves. Utilizing this formula allows researchers to create small, lightweight devices that can move slowly and stay aloft for longer periods of time. However, a challenge faced by lift-based platforms is that they must expend energy to maintain continual lift. Mechanical failures are often fatal due to engineering the devices to use minimal structural material to minimize fuel requirements and allow for more payload, which in turn makes the devices more fragile than their ground-based cousins.

$$Re = \frac{\rho L \upsilon}{\mu} = \frac{\rho \upsilon^2}{\frac{\mu \upsilon}{L}} = \frac{inertia}{viscosity} \tag{1}$$

TABLE I: Approximate weight and buoyancy of various substances

Substance	Weight	Buoyancy
Air	$1.2256Kg/m^3$	—
Hydrogen (H)	$0.0857Kg/m^3$	$1.1399Kg/m^3$ (H v. Air)
Helium (He)	$0.1691Kg/m^3$	$1.0565Kg/m^3$ (He v. Air)
Water (H_2O)	$988.2Kg/m^3$ @ $20\,^{\circ}\mathrm{C}$	$0.24875Kg/m^3$ (Air v. Water)

Buoyancy-based platforms solve many of the problems faced by ground-based and lift-based platforms. Examples of this type of platform include blimps and boats. These devices can be tiny to enormous commercial tanker ships. They are characterized by the ability to maintain a stable navigational state for long periods of time (indefinitely, barring other issues, such as leaks), and the ability to support a much larger payload over time than lift-based or even ground-based platforms. Vulnerabilities include currents in the substance (typically water or air) in which the devices operate, weather, and obstacles. When we consider the relative densities of substances, we can approximate the weight and buoyancy for devices utilizing these substances as shown in Table I. Thus, the desired payload can be defined and the device characteristics tailored to fit.

Space-based platforms have been in use for nearly six decades. These devices must use some combination of lift, buoyancy, and thrust in order to place the device in "space" where it is capable of remaining aloft in a state where its navigational attributes are governed by inertia and orbital mechanics, and where the viscosity becomes negligible. Such platforms are vulnerable to impacts with other objects traveling at very high velocities, orbital decay causing atmospheric reentry, cosmic rays and radiation, extreme heat and cold, in addition to standard mechanical failures with rare opportunities for service/repair.

Reliability analysis studies the probability of devices performing the function for which they were designed over a period of time within specified parameters. In [13], we see analysis of failure rate models for devices. We describe time-to-failure as a probability density function (PDF) or cumulative density function (CDF). The probability of failure over time $F(t)$ may be expressed mathematically as shown in (2). Alternatively, the probability of reliability over time $R(t) = 1 - F(t)$. The function $f(x)$ represents a distribution of failures over time, and the interval between t_0 and t_1 is the period of time during which the devices are observed.

$$F(t) = Pr\{T : t_0 \leq x < t_1\} = \int_{t_0}^{t_1} f(x)dx \qquad (2)$$

Failure rates for these various platforms are becoming more widely available as technologists spend more time settling on one design and tracking its reliability [14], [4], [1], [15], [11], [16]. As these platforms become more common, we will be able to develop more applicable and accurate failure rate models for each type of platform.

IV. Problem Details

We define the coverage field as a region that is observed as a plane to sensors. A set of mobile sensors is deployed using a deployment function. In this paper, we focus on two deployment schemes. First, a purely stochastic means of evenly distributing sensors throughout the field. Second, a stochastic method that produces a Gaussian approximation of a Poisson distribution around a point, as if the sensors might have been dropped from an aircraft and dispersed organically at various distances and orientations relative to the drop point.

We focus on sparse deployments in which the number of sensors n is defined in (3), A is the area of the coverage field and r is the sensing range. This relationship ensures that the number of sensors being lower than required to make blanket coverage possible. This allows us to focus on finding solutions to the problem of polling–minimizing detection time for any events in the coverage field, while maximizing the number of times we can poll all points in the coverage field over a given period of time.

At this point we define *polling frequency* as the number of times the entire coverage field is sensed in a given time period.

$$n < \frac{4A}{3\sqrt{3}r^2} \qquad (3)$$

In balanced deployments, the problems shift from finding solutions that minimize the time to achieve (and maintain) blanket coverage, whereas in dense deployments the problems shift from the challenge of providing polling to one of maintaining blanket coverage or redundant blanket coverage. When a sensor becomes mobility-disabled in balanced to dense deployments, the network's ability to maintain blanket coverage for a length of time can be shortened as sensors ultimately fail completely and the inability of other sensors to take their place causes coverage holes.

The mobility of the sensors is considered to be limited, in that there is a probability that at a certain time interval from the drop time that a given sensor might suddenly lose the ability to move. This simulates the lifetime of the mobility feature of the sensor. However, the sensor continues to be able to take measurements of its environment from this location. The number of sensors that have failed over time is controlled such that it follows a probability density function. As an example, the number of sensors that have failed over time might look like one of the models shown in Figure 1.

The "bathtub curve" model for failure rates has been described [13]. In this model, numerous initial failures are observed, followed by a stable period where few failures occur, and finally a period of time where devices succumb to the useful lifetime of any of a number of their components causes a relatively higher failure rate to account for a majority of the remaining devices. While this model describes the failure rate of an entire population of devices over time, this model may not be as useful for studying the effects of failures of a specific set of devices in use in the field. This is due to the fact that initial testing and quality control measures will identify defective products prior to deployment, and devices may be replaced in the field long before they actually fail during use. For this reason, we focus on the cumulative distribution function (CDF) model for our simulations that assumes no failures initially, but a growing number of failures as the simulation progresses, followed by a few sensors that fail later.

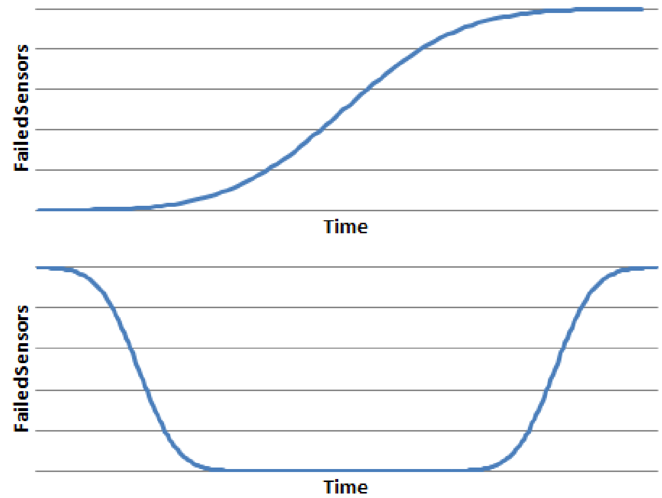

Figure 1: Cumulative distribution function (top) illustrating how we will distribute the disabling of mobility of sensors over time, plus Bathtub Curve (bottom) showing another well known failure rate model

V. Algorithms

In our simulations, we chose several algorithms to analyze and compare with varying sensor count (sparsity), two deployment schemes (random and Gaussian around a point), with and without applying the schedule of disabled mobility, and in some cases with and without modifications to the algorithm to mitigate the effects of disabled mobility.

The Random Walk and Random Direction Walk [17] are used. The Random Walk algorithm has sensors simply choose at each opportunity in time a random direction to move, whereas the Random Direction Walk algorithm chooses a random direction up front and continues that direction for the life of the simulation. Although these algorithms include no cooperative features, nor do they attempt to avoid gaps or redundant coverage in any way, they provide a good baseline for comparison to other algorithms.

The Proxy [18] and WGB [19] algorithms were also used. The distributed Proxy-based algorithm involves both static and mobile sensors which bid for new locations in order to heal holes in coverage. The WGB algorithm, also a distributed heuristic-based approach, uses an internal tile-coloring model to merge data about what areas nearby are not covered (white), have sensors nearby that could cover (gray), and areas that are already occupied (black), in order to identify the location of highest need. We focus on WGB in order to eliminate the variable of static sensors from disabled mobility sensors. Other algorithms, such as Virtual Force (VF) [20], [21] were also examined.

VI. Effects of Disabled Mobility

We anticipate a few challenges that will affect coverage efficiency in the face of disabled mobility. First is the fact that a disabled sensor is sitting in one place sensing the area around it and other sensors that pass through this area will duplicate coverage resulting in a loss of efficiency. Second, the disabled sensor could have been expected to have covered a portion of the field itself had it not become disabled, thus, other sensors may need to adjust their movement plan in order to cover the area excluded by the loss of the disabled sensor. Another factor of interest is the probability of detection and the detection time delay behavior in the presence of the disabled mobility schedule.

With some algorithms, disabled sensors may in fact mislead other sensors about their intended mobility plan and affect coverage in ways that would not be seen if the sensor were to completely fail.

Let us consider a scenario where we assume a random distribution of sensors across the search area, where sensors have unlimited mobility (range). The sensing distance is configured so that this is a sparse to balanced deployment (i.e., the ratio of sensor range to number of sensors relative to search area precludes blanket coverage). The goal is to maximize area coverage over time (or synonymously to minimize detection delay). We examine two reference algorithms. First, the Random Walk algorithm, where each mobile sensor starts exploring the area in random moves. Second, we examine the Random Direction Walk algorithm, where each sensor begins by picking an initial direction and continually moves straight in that direction indefinitely.

Analyzing the results of a schedule of sensor mobility disability surfaced a challenge with this scenario. Examining the initial deployment, we observe a random distribution of mobile sensors throughout the search area. Also, at any time in the future, a snapshot of the region also shows a distribution with no less random features than the initial deployment. Despite the fact that the point at which a given sensor becomes disabled is according to a pre-determined schedule, the location at which it resides when it becomes disabled is again no less randomly distributed than the initial deployment. Thus, observing simulation of this scenario over time as seen in Figure 2 shows that although the performance isn't great at any point in time throughout the runs, disabling the mobility of the sensors doesn't hurt the algorithm in an interesting or unexpected way.

Using the Random Direction Walk algorithm produces analogous results, and both algorithms are consistent even when the number of sensors is varied. Figure 3 shows a consistent drop-off in polling frequency with random direction walk across a variety of sensor counts. Polling frequency eventually flattens due to the sparse deployment density and the fact that disabled sensors fail to iteratively cover the area over time. This produces an equivalent increase in average detection delay as more and more of the area must be polled by a decreasing population of sensors with mobility.

When we examine the effects of disabled mobility on the WGB algorithm, we see a consistent drop in coverage performance, and falling to as much as 20% loss of coverage as sensors begin to lose mobility. Figure 4 illustrates how many

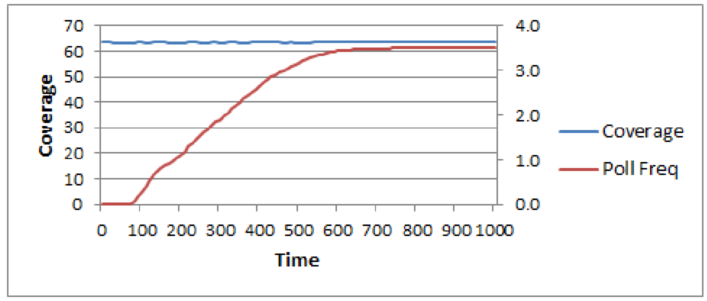

Figure 2: Random walk coverage and polling frequency over time

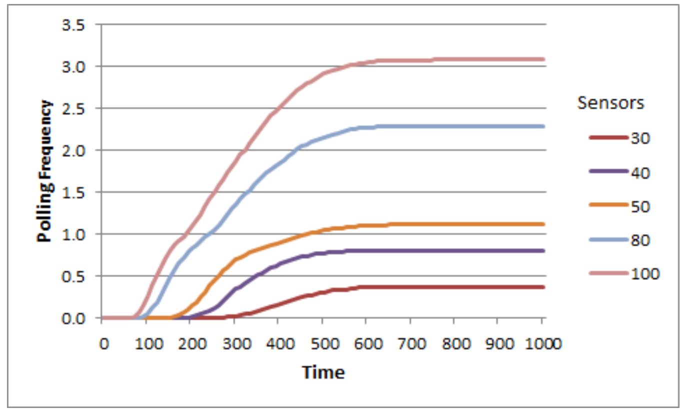

Figure 3: Random direction walk polling frequency over time

percentage points coverage drops with the WGB algorithm in particular, simply by adding the schedule of disabled mobility over time. This is actually quite good considering that the algorithm pushes sensors from their initial deployment to a balanced coverage of the area rather quickly.

We can also see from Figure 5 a representation of the performance of the WGB algorithm in terms of the coverage percentage over time for a varying number of sensors. In order to properly interpret the sparsity of the deployment given the specified sensor counts, we refer once again to (3) with a configuration of coverage area and sensor range that results

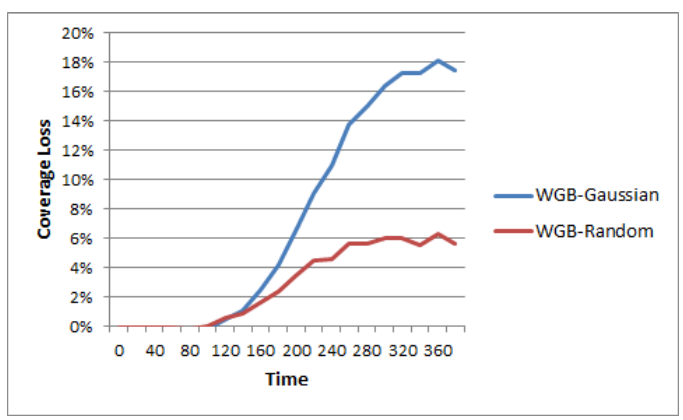

Figure 4: The number of percentage points lost by adding disabled mobility to WGB algorithm

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TABLE II: Max coverage % for various sensor counts

Sensors	Max %
25	39.26
30	47.12
35	54.97
40	62.83
50	78.53
80	125.66
100	157.07

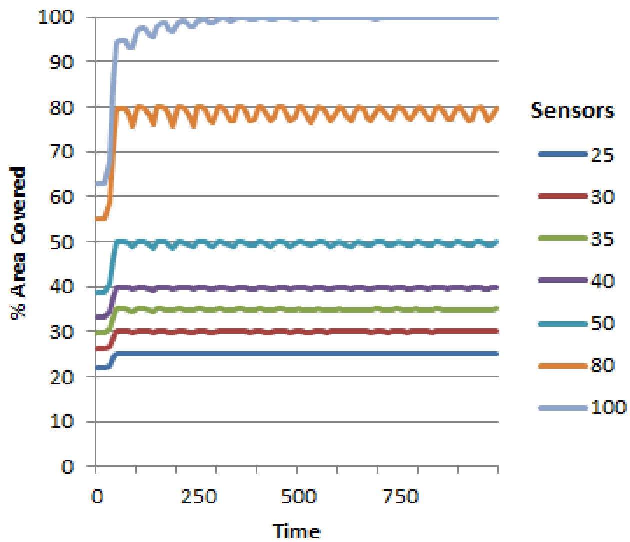

Figure 5: WGB algorithm, coverage area over time varying sensor count

in a balanced deployment would require a value of $n \approx 76.98$. Given the size of the coverage field in these simulations relative to sensor range and number of sensors, we can see the computed maximum coverage achievable for various sensor counts. These are upper bounds, and rely on none of the sensors overlapping areas covered by other sensors. In practice, for our distributed algorithms to consistently achieve polling, the number of sensors remains at 80 or below.

Regarding the problem of disabled mobility causing potentially misleading information being broadcast to other sensors, we see that there is a clear impact to coverage efficiency. By making a small adjustment to the WGB algorithm to detect this failure mode, plus a behavior change when the failure mode occurs such that sensors refrain from broadcasting an intention to move that will not occur, we see an improvement in both Gaussian and Random deployment modes of a full percentage point. Figure 7 shows the improvement for one configuration. As shown, the improvement begins as sensors start to fail. When a growing number of sensors are unable to move, the ability for the WGB algorithm to continue to cooperatively explore the coverage field without gaps or significant redundant coverage becomes apparent as compared to Random Walk, Random Direction Walk, and other algorithms.

VII. Conclusions

One thing we can observe from these results is that coverage algorithms that do a good job of quickly reaching a desirable location from their initial deployment, cooperate to avoid gaps and redundant coverage, and continue to leverage what mobility is available throughout the sensor network, produce better results as sensors lose their mobility than algorithms that rely on statically touring or other more methodical means of exploring and covering their environment. The WGB algorithm, for example, saw only minimal degradation of coverage quality of service, and performed well in sparse to balanced deployments in the face of a schedule for disabled mobility.

With extremely sparse deployments, sensors that are mobile come into contact with disabled sensors less often. In these scenarios, we observe through simulations that algorithms, such as random direction walk have less of an impact than algorithms that tour an established territory, because in the latter case, once a sensor becomes disabled, there is no sensor to cover that sensor's territory. As the deployment becomes less sparse, algorithms that try to avoid one another are more

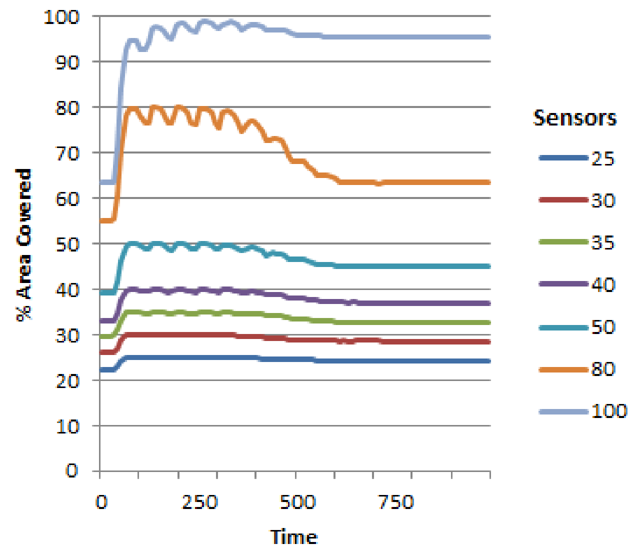

Figure 6: WGB algorithm with disabled mobility, coverage area over time varying sensor count

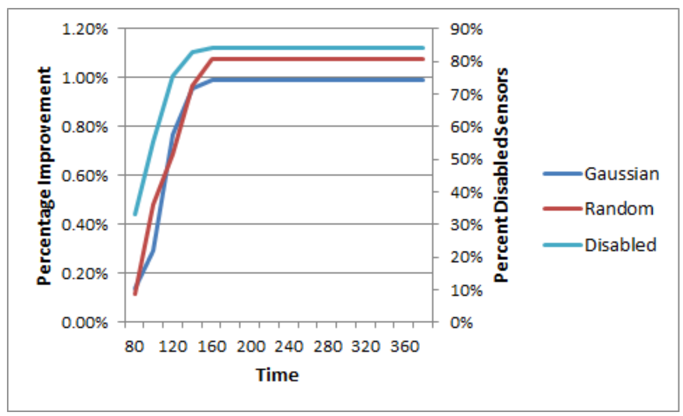

Figure 7: Percentage improvement in coverage efficiency by detecting failure mode

vulnerable to being misled by disabled sensors that continue to broadcast their intentions to move, but never do.

The disabled mobility problem has particular significance because, as defined, the outcome can be demonstrated clearly as an extension of prior proven simulation techniques. The proposed approach introduces a factor whereby sensors become immobile at various rates over time. When the coverage algorithm is to pick a random direction, then sensors will disregard the location and coverage provided by disabled sensors and will proceed to duplicate coverage. When algorithms avoid those areas, coverage effectiveness can be shown to increase. As more sensors become disabled, coverage becomes degraded, as we have shown.

VIII. Future Work

Communication protocols have been extensively studied from a number of perspectives. However, there is potential for augmenting these protocols to transmit failure modes along with existing packets in order to allow distributed algorithms to reactively modify their behavior to make the sensor network self-healing fault tolerant. For example, consider a mobile sensor that is able to transmit a set of p failure modes $F = \{f_0, f_1, ..., f_p\}$, where $f_i \in \{0, 1\}$. Each failure mode represents a test result from an onboard sensor that tests an aspects of the sensor's normal operational state and report about what portions of the sensor are working (1) or not (0). If we assume a homogeneous set of mobile sensors, then each sensor would understand what aspect of its counterpart was malfunctioning by reading this stream contained within a packet sent according to the communication protocol used by the mobile sensors. Thus, we could develop algorithms that adjust their navigation choices after filtering data from other sensors. Such algorithms would not be as susceptible to being misled by the communicated intended actions of other sensors.

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