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Area Coverage with Unmanned Vehicles: A Belief-Based Approach

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***Abstract*—In this paper, we propose a belief-based movement approach for a network of unmanned vehicles, which is deployed to cover a given area. The spatial and temporal coverage performance of the belief-based approach is compared with legacy movement models such as random walk, random direction as well as a random sweeping model for several scenarios. Our results highlight the trade-off between how fast and how well an area can be covered and show that the proposed approach can outperform the other methods that are tested.**

I. Introduction

In this work, we consider a set of networked unmanned vehicles equipped with sensors, such as ground robots or unmanned aerial vehicles (UAVs) with cameras or other types of sensors [1]. The aim of this network of mobile nodes is to explore a certain area. To be more specific, the individual nodes should move in a way that they cover the entire area within a given mission duration. The question then arises as to which movement paths the vehicles should take, based on the area-to-cover, the number of vehicles, and other parameters.

A well-known approach is to plan the movement paths offline and with full knowledge of the area. These paths can be planned centrally or in a distributed manner and typically involve some non-trivial optimizations [2]. Our goal is to study an alternative approach that is very simple and decides the paths online during the mission: Each node moves in a certain direction until it meets other nodes. Whenever two or more nodes meet, each node makes a new decision on its direction. This *belief-based* decision utilizes some information obtained from the nodes that it meets. Such a path planning approach is interesting from a research perspective, as it represents a self-organizing system: it solves a complex overall task on the system level (area coverage) based on simple local rules and interactions of the individual entities. If successful, the approach is also interesting from an engineering perspective, as it is very adaptive to changes in the environment (it may even work in unknown environments) and changes in the network (failure of vehicles, addition of new vehicles), thus minimizing the configuration overhead.

The goal of this paper is to briefly analyze whether such an approach has any potential. Using computer-based simulations, we compare its performance in terms of area coverage to that of even simpler mobility patterns, such as random walk, random direction, and parallel-path. Section II gives background information about mobility models, coverage problems in sensor networks, and coverage problems in robotics. Section III introduces the proposed belief-based movement approach. Section IV gives a definition of area coverage, where we distinguish between its spatial and temporal component. Section V presents the results. It is shown that, in the investigated scenarios, belief-based movement leads to significant performance gains compared to the other approaches. The section also reveals a deeper insight as to how the area coverage performance depends on system parameters, such as the number of nodes. Finally, Section VI concludes the paper.

II. Background

A. Mobility Models

The system under investigation is a wireless sensor network that consists of only mobile nodes with the same transmission range. There are several mobility models that consider independent or dependent movement among mobile nodes [3]. In this paper, (i) random walk (where speed and direction are chosen uniformly-randomly); (ii) random direction (direction is randomly changed at the boundaries); and (iii) parallel-path (where each node sweeps the area from border to border in parallel to one of the boundary lines) mobility models are considered.

These models are memoryless, i.e., the current directions are independent of the past directions and the mobile nodes decide their movements independently from each other. There are several other mobility models that take into account the dependence on the mobility pattern of other nodes in the network [3], social relationships of the mobile nodes [4], or topographical information [5], etc.

B. Coverage in Wireless Sensor Networks

In static wireless sensor networks, in general, coverage problem is treated as a node-activation and scheduling problem [6]. More specifically, algorithms are proposed to determine which sensor nodes should be active such that an optimization criterion is satisfied. The criterion can for instance be achieving a certain event detection probability, or covering each point in the area by at least k sensors, etc. In addition, there are also studies that take into account not only the event (or network) coverage, but the connectivity of the wireless sensor network as well [6]. While deciding which sensor nodes should be active at a given point in time, coverage and connectivity requirements are met.

Recently, mobile sensor networks have been under investigation and it has been shown that mobility, while complicates the design of higher layer algorithms, also can improve the network, for instance, in terms of capacity, coverage, etc. [7]-[8] Optimum mobility patterns for certain applications are proposed, such as mobile target tracking, chemical detection, etc. using both ground and aerial vehicles. Mobile robots with swarming capability operate cooperatively and aim to achieve a global goal have also been considered [9]-[10].

C. Coverage in Robotics

Coverage problem is one of the main applications in robotics which is generally solved using combinations of cellular decomposition and sweeping. Whether it be snow removal, lawn mowing, car-body painting, or floor cleaning, the objective is to cover the area with certain constraints such as achieving coverage over shortest path (minimum time-to-complete), with minimum energy(e.g., with minimum number of turns), etc [11]. To this end, several mobility models have been developed. In many of these models the robots which are too close repel each other to avoid collisions but to maintain communication they attract each other when they are separated more than certain distance. Gas expansion model [12], for example, mimics the way gas particles are spread to vacuum when they are allowed to expand. This model, again, uses the attraction and repulsion forces between the robots to maximize the dispersion while maintaining the communication. Similar models have also been proposed by using an artificial force or potential fields for the robots to cooperatively move [13], [14]. However, the focus in these studies is maximizing the spread not the coverage, and they are based on the assumption that the robots have high computing capacities.

III. A Belief-Based Movement Approach

The belief-based movement approach makes use of local physical topology information without global knowledge of the network. The objective is to achieve sensing coverage of a geographical area with a given mobile sensor network. We assume that there is no prior knowledge of the nodes' locations. Since the ultimate objective is to achieve full spatial coverage, it is desirable to reduce the overlap between the sensing areas covered by different nodes and use the limited number of nodes efficiently (specifically, if the mobile sensor network will be used for a time-critical application.). To this end, we propose to utilize belief propagation models [15]. More specifically, each node computes the *belief* (i.e., probability) that it should be assigned to a certain task (i.e., move to a location) based on the *node's own perception of the system (observations)* and on the *advice* from its neighbors. Based on this computation, the node then moves to the location that has *the least chance of being covered* or, similarly, that has *minimum overlap* with the other nodes' coverage areas.

The quality of the observations as well as the resulting outcome depend on the amount of information exchanged between the nodes. For instance, the nodes can use explicit or implicit information from the neighbors to determine where to go next to minimize overlaps in the covered area. Explicit information exchanged can be "I covered such and such region" meaning each node keeps a history of the locations they covered and transmit this information to their neighbors. Implicit information is more in the form of "I'm here", and the node receiving this information would need to hazard a guess (i.e., belief) about which areas its neighbor might have already covered. The amount of information exchange is a system design parameter that could be determined by factors such as the task privacy, communication channel quality, memory capabilities, or the dynamics of the environment.

As a first step, in this paper, we assume minimal information exchange: the nodes only exchange *location* information (provided by GPS, for example). The movement direction of a node is updated at fixed intervals. More specifically, each node takes into account its own current direction and the location information received from its neighbors. Based on this information, it "draws" a geometric interpretation of its environment and assigns to each possible direction a certain probability. The probability of going toward a given direction is higher if the "perceived" or "expected" overlap between the coverage of the neighboring nodes is smaller. An example path for two mobile nodes is shown in Figure 1. Observe that each node changes its direction when it meets the other node or when it hits the boundary of the system area. At each meeting, the nodes update their direction. This procedure is illustrated in Figure 2 for node 1. Based on its current direction and the location of node 2, node 1 determines the uncovered areas from its own view. Then, the angles α_1 and α_2, that represent the uncovered regions, are computed. These angles are then used to compute the probability of choosing potential directions, shown in dashed, bold lines. The higher the angle is, the higher the probability to choose the corresponding direction. Then, the next direction is decided using the set of potential directions (bisectors) and the computed probability distribution. All nodes that meet each other run the same algorithm from their own point of view and determine their next direction.

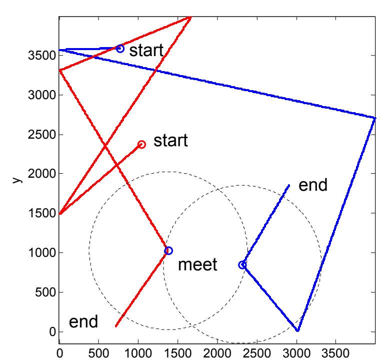


Fig. 1. Snapshot of belief-based movement for two mobile nodes. The circles represent the sensing ranges of the nodes.

IV. Spatial and Temporal Coverage

The capability of a coverage algorithm to cover each point of the system area or to find an event at an unknown location

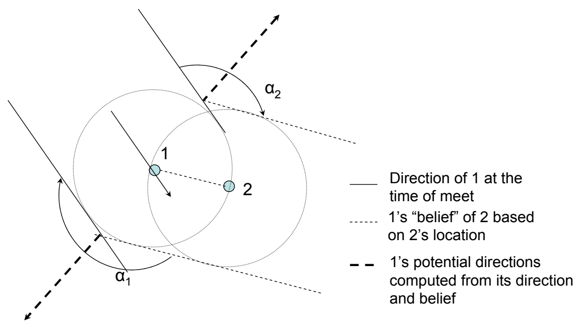


Fig. 2. Illustration of the belief-based movement algorithm.

are important performance metrics. They basically address the *spatial* component of the coverage problem. But there is also a *temporal* component of coverage, i.e., how long a certain point in the system area has been observed. This time period is important, as the coverage duration influences at what quality the sensors are able to capture a given point or subarea. In this way, a coverage map can be given in which each point in the two-dimensional system area has a height that expresses the time period this point was covered so far. Figure 3 shows an example temporal coverage map of a belief-based movement path. The lighter an area gets, the longer it has been covered by the mobile sensor network.

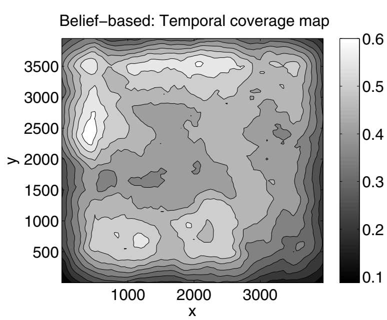


Fig. 3. Example of a temporal coverage map of a belief-based movement path, for $n = 10$ nodes with 5m/s after a certain mission duration of $\tau = 1300$ s.

There is a tradeoff between spatial and temporal coverage. For example, in some time-critical applications, it might be beneficial to first achieve fast spatial coverage at the price of low temporal coverage. In practice, for a given technology (e.g., time resolution and quality of sensors) and given environmental conditions (e.g., visibility, wind), the minimum temporal coverage might be a given parameter, where one is interested in minimizing the time to achieve full spatial coverage.

Assuming that the area of interest can be represented by a grid, i.e., a finite set of points (i, j), we make two definitions:

- Spatial coverage C_S is the fraction of points that is successfully captured by the sensors during a mission period τ. We have $0 \le C_S \le 1$.
- Temporal coverage $C_T(i, j)$ is the ratio between the total time duration that a given point (i, j) is sensed t_{ij} and the mission period τ. Note that $C_T(i, j) = t_{ij}/\tau$ can be greater than 1, if more than one node is operational. It is thus a measure of redundancy.

Let us define these metrics in more detail. A node senses the environment at fixed intervals for a duration T. A given point (i, j) is sensed $s_{ij} = t_{ij}/T$ times during the entire mission period τ. The temporal coverage at time τ is then

$$C_T(i, j) = \frac{s_{ij}\, T}{\tau} \ . \tag{1}$$

Assuming that the probability that a sensor produces valuable information during the sensing period is p, the probability that at least one of the s_{ij} senses of a given point (i, j) was successful, thus the point is "actually captured" is

$$P_c(i, j) = 1 - (1 - p)^{s_{ij}} \ . \tag{2}$$

Denoting the total number of points by N, the spatial coverage at time τ is

$$C_S = \frac{\sum_{i,j} P_c(i, j)}{N} . \tag{3}$$

While the $C_T(i, j)$-values provide a probabilistic coverage map of a given area, the value of C_S shows how much of a given area can be covered in a given time. It is important to note that when the sensing quality is good ($p \to 1$) and/or when mission period τ is short, small C_T-values are desired for a faster spatial coverage of a given area. Therefore, in this case, a mobility path with low-to-no redundancy is expected to be most efficient. In contrast, if the sensing quality is bad ($p \to 0$), the nodes would need to pass multiple times over a given area to capture it. Hence, redundancy or overlap between mobility paths is required for effective coverage.

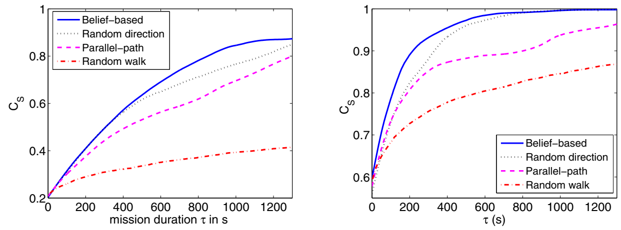
V. Performance Analysis

Let us now analyze by simulation the performance of the belief-based movement approach in terms of spatial and temporal coverage and compare it with the performance of other random movements (random direction, random walk, and parallel path).

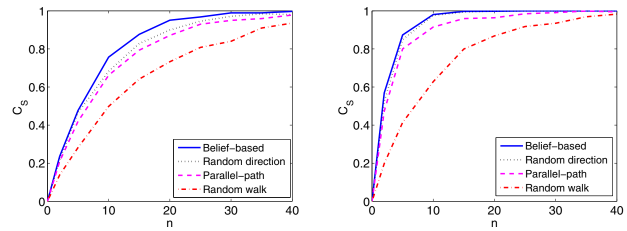
The following assumptions are made. There are n nodes. The range of each node is $r = 500$ m. The system area is square-shaped with a length of 4 km. All nodes are initially uniformly randomly distributed in the area. All nodes are mobile. Their speed is fixed at 5 m/s. The direction of each node is updated every 50 m for random walk and belief-based models. The step size for sensing is also assumed to be 50 m, i.e., the sensing period is $T = 10$ s. When a node hits the boundary of the area, a random direction toward the system area is assigned for random and belief-based mobility models. If not stated otherwise, each sense operation leads to useful information ($p = 1$). The overall mission time is τ. The simulation results are averaged over 1000 different missions.

A. Spatial Coverage

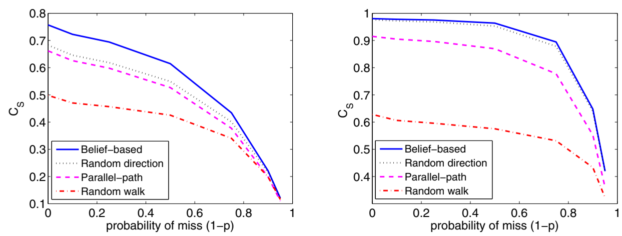
Figure 4 (a) shows the evolution of the spatial coverage C_S over time τ for $n = 5$ and 20 mobile nodes. The belief-based movement approach performs better in this scenario



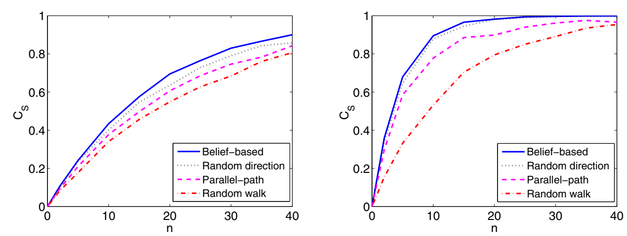
(a) Spatial coverage over time τ for 5 nodes (left) and 20 nodes (right)



(b) Spatial coverage as a function of the number of nodes at $\tau = 300\,\text{s}$ (left) and $\tau = 1300\,\text{s}$ (right)



(c) Spatial coverage as a function of the probability of miss $(1-p)$ at $\tau = 300\,\text{s}$ (left) and $\tau = 1300\,\text{s}$ (right), $n = 10$



(d) Spatial coverage as a function of the number of nodes for $1-p = 75\,\%$ at $\tau = 300\,\text{s}$ (left) and $\tau = 1300\,\text{s}$ (right)

Fig. 4. Spatial coverage performance comparison

than all other approaches. It inherently reduces the overlapped coverage areas between different mobile nodes using local information. When the node density is higher, as expected, a better coverage performance is achieved. In this case, the performance difference between belief-based and random direction mobility disappears as time progresses.

Figure 4 (b) shows the impact of the number of nodes n on the spatial coverage after a mission period of $\tau = 300\,\text{s}$ (left) and $1300\,\text{s}$ (right), respectively. If many nodes are used, all models except random walk achieve full coverage. The basic dependency between n and τ can be observed from the results in Figures 4 (a) and (b). If the timing constraints are stringent (relaxed), many (few) nodes are needed to achieve full coverage.

Next, we study the coverage with imperfect sensing capabilities. For $n = 10$ nodes, Figure 4 (c) shows the spatial coverage as a function of the probability of miss $(1-p)$ after a mission period of $\tau = 300\,\text{s}$ (left) and $1300\,\text{s}$ (right). As expected, when the probability of miss is very high, even long mission durations are not sufficient for full coverage. If τ is long (right), i.e., the timing constraints are not stringent, the probability of miss does not have a significant impact on the coverage performance and the achievable spatial coverage stays relatively constant for all movement models. If τ is short (left), as in time critical applications, the impact of misses is more severe.

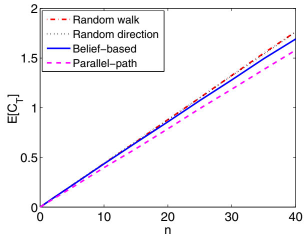
Finally, Figure 4 (d) shows the impact of the number of nodes if the probability of miss is $1-p = 75\,\%$. As with perfect sensing, given enough time, a large number of nodes can compensate for the sensing incapabilities. Comparing (d) with (b), the required number of nodes for full coverage is now significantly higher: For a long mission duration (1300 s, right), full coverage is achieved with 15 belief-based nodes with perfect sensing capabilitites. Due to the reduced sensing capability, more than 30 are now needed for full coverage. The impact is even more severe if the observation duration is short. In this case, full coverage cannot be achieved with the given number of nodes by any of the movement models under study.

In summary, timing constraints imposed by the application of interest and the sensing capabilities of the mobile sensor network determine the achievable spatial coverage. While belief-based mobility outperforms the other models under study, there is still room for improvement which can be achieved by, e.g., use of longer history or more information exchange, which is a part of our future direction.

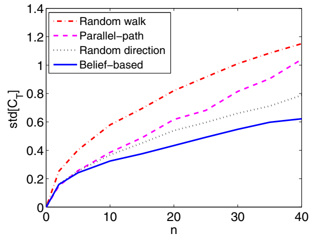
B. Temporal Coverage

We now analyze the temporal coverage performance of the different movement approaches. We assume perfect sensing ($p = 1$). As mentioned above, the temporal coverage of a given point can be greater than 1 due to the redundancies in the mobility paths. The redundancy can be caused by multiple concurrent-coverages (i.e., overlapping coverages between different mobile nodes) or due to the movement path of a single node. For example, random walk tends to create paths that are concentrated in certain areas, resulting islands of coverage areas.

Figure 5 shows (a) the mean value and (b) the standard deviation of the temporal coverage values $C_T(i,j)$ over all points (i,j) as a function of the number of nodes n. Observe that the average temporal coverages for all movement models are similar. However, the standard deviations differ significantly. Random walk results in a high standard deviation; this means that some areas are covered very well whereas others are not covered at all (e.g., coverage islands have formed). Belief-based movement achieves a low standard deviation; this represents a more uniform coverage of the area. As the belief-based movement model has the lowest mean and the lowest



(a) Mean value

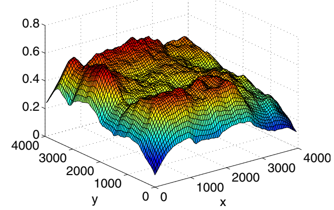


(b) Standard deviation

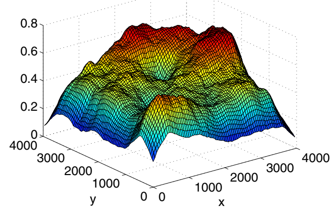
Fig. 5. Temporal coverage as a function of the number of nodes

deviation, it can cover a given area more efficiently than the other approaches.

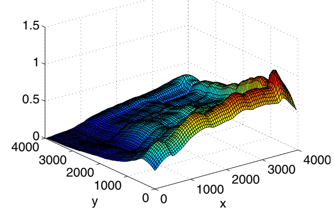
This result can also be observed in Figure 6. It shows the temporal coverage of $n = 10$ nodes after a mission duration of $\tau = 1300\,\mathrm{s}$. While a large portion of the area is covered for all approaches, the non-uniformity or imbalance of the coverage duration is high for parallel-path movement and random walk. This implies that if the redundancy could be reduced, the given area can be covered in a shorter time, when the sensing capability is good. When sensing is not good, on the other hand, redundancy is necessary for better coverage as presented in the previous section.



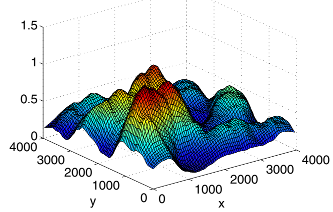
(a) Belief-based movement approach



(b) Random direction mobility



(c) Parallel path movement



(d) Random walk

Fig. 6. Temporal coverage of mobility models ($\tau = 1300\,\mathrm{s}$ and $n = 10$)

VI. Conclusions and Outlook

This paper was driven by the goal to design a self-organizing networked system of unmanned vehicles equipped with sensors, whose mission is to efficiently cover a certain area. We showed that belief-based movement of mobile sensors is a promising approach for such missions and outperforms other random approaches in terms of spatial and temporal coverage.

While the general applicability of a belief-based movement approach was shown in a case study with specific parameters, more work is needed to generalize the results and tradeoffs to draw firm scientific conclusions. Extensions will be made to the belief-based approach. While in this paper nodes exchanged only their current location, further work will investigate the performance if more information, such as direction or history, is exchanged. The ultimate goal is to come up with a distributed yet high-performance movement approach that can be tuned based on known parameters of the system.

Acknowledgment

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