Connectivity versus Area Coverage in Unmanned Aerial Vehicle Networks

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***Abstract*—We investigate the area coverage and connectivity of an autonomous, unmanned aerial vehicle (UAV) network, whose goal is to monitor and sense a given area of interest in an efficient manner. To this end, we propose a connectivity-based mobility model that aims to sustain connectivity between the UAVs and the ground station. We compare coverage and connectivity performance of the proposed scheme with a coverage-based mobility scheme in several scenarios. Results illustrate the trade-off between achieving good spatial coverage and staying connected.**

***Index Terms*—UAV networks, wireless sensor networks, mobility, coverage, connectivity**

I. Introduction

Unmanned ground and aerial vehicle networks have initially been utilized in military applications, where the network is envisioned to provide battlefield assistance, surveillance, target detection and tracking capabilities in possibly hostile environments. Recently, use of unmanned aerial vehicles (UAVs) in civil applications has been considered with increasing interest, especially to monitor areas that are inaccessible by or dangerous for humans and to deliver information to and from areas with no infrastructure.

In this work, we consider a set of networked small UAVs equipped with sensors (e.g., cameras). The aim of this network is to monitor a certain area and provide an overview image. It is likely that the area the vehicle network operates in is not known a priori or changes dynamically.

Two of the main challenges of interest of such networks are achieving spatial coverage in an efficient manner (i.e., *area coverage*) and establishing and maintaining communication links between UAVs and/or between UAVs and the ground station due to mobility (i.e., *connectivity*). Intuitively, there is a trade-off between area coverage and connectivity. For a given number of UAVs, an area of interest can be sensed (covered) faster if the sensing overlap between the UAVs is minimized. On the other hand, the UAVs might need to fly closer to each other to stay connected and to be able to deliver the sensed data, e.g., to the ground station. In this work, we propose a probabilistic mobility model for a network of UAVs, where each UAV autonomously decides its path, taking into account only communication requirements. More specifically, with the *connectivity-based* mobility model, the UAVs adapt their direction such that they maintain a communication link to the ground station and/or their neighbors.

To illustrate the trade-off between area coverage and connectivity, we compare the performance of the new model with a previously proposed coverage-based mobility model [1], which takes into account area coverage constraints only. We numerically investigate several scenarios, for a single-hop network as well as a multi-hop network. We also provide results for a UAV network used in a campus scenario, where the objective is to take snapshots of a given area and deliver the data to the ground station. Our results show that especially for sparse networks (i.e., with small number of UAVs or UAVs with short transmission ranges) the trade-off is significant. This indicates that both connectivity and area coverage requirements need to be taken into account while planning the paths of UAV networks. Our current focus is on integrating the constraints from both objectives into our path design.

The remainder of the paper is organized as follows. In Section II background on mobility models and coverage problem in wireless networks and robotics is summarized. The proposed connectivity-based mobility model is presented in Section III. Results are given in Section IV and the paper is concluded in Section V.

II. Related Work

A. Coverage and Connectivity in Wireless Sensor Networks and Robotics

Coverage problem in wireless sensor networks is of great importance and has been investigated by several researchers. In static wireless sensor networks, in general, coverage problem is treated as a node-activation and scheduling problem [2], [3]. 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 detection probability, or covering each point in the area by at least k sensors. In addition, there are studies that take into account not only the event (or network) coverage, but the connectivity of the wireless network as well [2]. While deciding which sensor nodes should be active at a given point in time, coverage and connectivity requirements are met.

Recently, it has been shown that mobility, while complicating the design of higher layer algorithms, can improve network performance, for instance, in terms of capacity and coverage [4], [5]. Optimum mobility patterns for certain applications are proposed, such as mobile target tracking and chemical detection using both ground and aerial vehicles. Mobile robots with swarming capability operate cooperatively and aim to achieve a global goal have also been considered [6], [7].

In robotics, several mobility models have also been developed. In many of these models, 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 a certain distance. Gas expansion model [8], for example, mimics the way gas particles are spread to vacuum when they are allowed to expand. This model, again, uses attraction and repulsion forces between robots to maximize the dispersion while maintaining the communication. Similar models have also been proposed using an artificial force or potential fields for the robots to cooperatively move [9], [10].

In addition, there are several planning strategies proposed for ground robots [11], [10], delivery systems, autonomous high-speed, fixed-wing UAV networks with less strict energy requirements [12], or mobile sensor networks [6] with different objectives and constraints. Applications range from snow removal, lawn mowing, floor cleaning, to surveillance, mobile target tracking, chemical or hazardous material detection and containment, or to any combination of localization and navigation problems (see [7], [13], [14]). While some algorithms use prior information and have exact or partial decomposition of the areas, some use sensor-based information in unknown environments to make navigation decisions. Algorithms exist that try to minimize the path traveled or time or energy required to achieve a goal.

Moreover, an increasing number of path planning and swarming algorithms for UAVs have recently been proposed, whose success relies on the availability of communication links between UAVs [15]–[18].

B. Coverage-based Mobility Model

In this section, we provide a brief overview of the coverage-based mobility model proposed in [1]. Coverage-based mobility model makes use of the local physical topology information. The objective is to achieve coverage of a geographical area using a mobile sensor network; e.g., a UAV network. Since the objective is to achieve coverage, it is desirable to reduce the overlap between the covered areas by different UAVs and use the limited number of UAVs efficiently (especially, if the UAV network will be used for a time-critical application.).

In the model, we assume that there is a force between UAVs that causes them to *repel* each other. The forces at the time of decision are illustrated in Fig. 1, where UAV 1 is moving toward right. The magnitude of the force that each UAV applies to others is inversely proportional to the distance between the UAVs, i.e., the closer the UAVs get the stronger they *push* each other. We also assume that each UAV knows its current direction (e.g., from an on-board GPS module). As a rule, a force with a magnitude inversely proportional to the UAV's sensing range is applied to it in the direction of movement to avoid retracing the already covered areas by the UAV (see $\vec{F}_{11}$ in Fig. 1). Each UAV computes the resultant force acting on them and update their direction accordingly (see $\vec{R}_1 = \sum_j \vec{F}_{j1}$ in Fig. 1).

III. Connectivity-based Mobility

We propose a mobility model that takes communication requirements into account. The algorithm is self-organizing in the sense that the UAVs use only local information, they can be heterogeneous with different capabilities, they can enter and leave the system at will. The area of interest can also

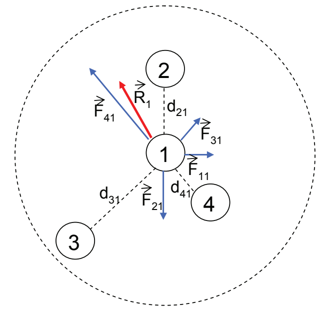


Fig. 1. Illustration of forces on UAV 1, where the dashed circle is the sensing range of UAV 1, which is moving toward right.

Algorithm 1 Connectivity-based Mobility

Input: Area of interest, sensing period (t_s), transmission range (r), sink location, current direction ($\vec{\theta_c}$)
Output: Next direction of UAV i: $\theta(i)$

1) If i is connected to the sink (via single or multi-hop link), compute the location of i and its neighbors after t_s.
   - If still connected, return $\theta(i) = \theta_c(i)$.
   - If not connected:
     - If next hop is the sink, $\theta(i)$ is randomly chosen toward the coverage area of the sink (see Fig. 2(a)).
     - If not, update $\theta(i)$ such that i is within the range of the next hop (see Fig. 2(b)).
2) If i is not connected to the sink, check if it has any neighbors.
   - If at least one neighbor exists, compute locations after t_s.
     - If i still has at least one neighbor, return $\theta(i) = \theta_c(i)$.
     - If not, update $\theta(i)$ such that i moves toward its neighbor with longest estimated connection duration (see Fig. 2(c)).
   - If no neighbors, return $\theta(i) = \theta_c(i)$.

be dynamic and the proposed algorithm can adapt to it. The goal of the UAV network is to sense a given area, while the UAVs maintain connectivity to the sink (i.e., the ground station) and/or their neighbors. Due to the probabilistic nature of the algorithm, disconnections from the sink can occur, but likelihood of isolated UAVs is low. The method is summarized in Algorithm 1. The parameters used in the algorithm running at each UAV are defined in Table I. Each UAV senses its neighbors every t_s seconds; it computes its location at the end of next sensing period given its current heading; and decides if it needs to change direction. The information exchanged between UAVs consists of current location and direction. We denote the UAV of interest as UAV i.

Every t_s seconds, UAV i first checks whether it is within the transmission range of the sink (i.e., whether the sink is a neighbor). If yes, it checks whether it would still be within range after t_s seconds given its current direction $\theta_c(i)$. If it determines that it would not leave the sink coverage, it does not change its direction. Otherwise, it changes its direction randomly toward the transmission range of the sink (illustrated in Fig. 2(a) for UAV i, where $\theta(i)$ is the next direction).

If the sink is not a neighbor, UAV i checks if it has a multi-hop route to the sink. If yes, it computes next location of itself and its neighbors and determines whether it would still be connected to the sink. If a route still exists, it keeps

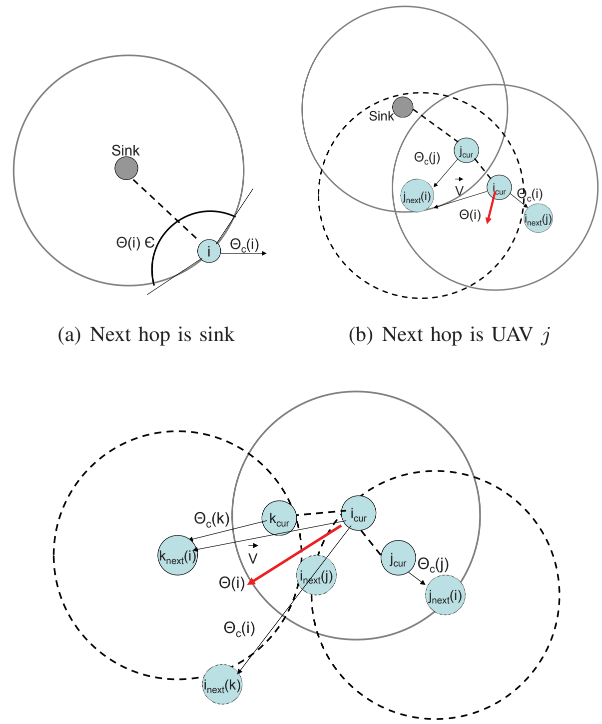
TABLE I
ALGORITHM PARAMETERS

Parameter	Definition
t_s	sensing period
r	transmission range
$\theta_c(i)$	current direction of UAV i
$\theta(i)$	next direction of UAV i
i_{cur}	current location of UAV i
$i_{\text{next}}(j)$	location where UAV i loses connection to UAV j
$\vec{V}$	vector from i_{cur} to $x_{\text{next}}(i)$, where $x = \begin{cases} \text{next hop UAV in route from UAV } i \text{ to sink,} & i \text{ connected to sink} \\ \text{UAV that stays connected the longest to UAV } i\text{,} & \text{otherwise} \end{cases}$

its direction. Note that UAV i knows only the location of its own neighbors. Hence, it can only rely on local information to determine the existence of a route at the next sensing time. If it detects that it will not have a connection at the next step, it changes its direction such that it stays connected to the next hop UAV (UAV j in Fig. 2(b)). To this end, it computes the vector $\vec{V}$ from its current location (i_{cur}) to the point UAV j would leave its transmission range ($j_{next}(i)$). UAV i then computes the resultant vector by adding a unit vector in direction $\theta_c(i)$ to unit vector $\frac{\vec{V}}{\|\vec{V}\|}$ (see Fig. 2(b)). The angle of the resultant vector is the next direction of UAV i, $\theta(i)$. The motivation is to extend connection time, while changing the direction gracefully (since turning requires energy).

Finally, if UAV i does not have a route to the sink, it tries to stay connected to a neighbor to avoid isolation. First, it checks whether if it would be connected to at least one neighbor UAV at the end of t_s seconds at the current headings. If yes, it does not change its direction. If not, it computes the duration it would be connected to each of its neighbors, and determines the neighbor that would stay connected the longest if they would keep their current heading. Then, it follows the procedure of the previous case to determine its new direction (see Fig. 2(c)). In Fig. 2(c), UAV i has j and k as its neighbors, whose current locations are i_{cur}, j_{cur}, and k_{cur}, respectively. From their current directions, i determines that it would leave the transmission range of both UAVs at the end of t_s seconds and that k would stay longer in its transmission range (i.e., $\|i_{\text{cur}} - i_{\text{next}}(k)\| > \|i_{\text{cur}} - i_{\text{next}}(j)\|$).Then, it computes its next direction $\theta(i)$ as the angle of the resultant vector calculated by adding the unit vector in direction $\theta_c(i)$ and $\frac{\vec{V}}{\|\vec{V}\|}$, where $\vec{V}$ is from i_{cur} to $k_{next}(i)$.

If a UAV becomes isolated (i.e., because t_s is too long, the transmission range of the sink is too short, or the UAV speed is too high), it does not change its direction until it reaches the boundary or it meets another UAV. The behavior at the boundary is such that each UAV changes its direction randomly toward the area of interest. The sensing period t_s is a design parameter and can be optimized to avoid disconnections for a given application and UAV network.



(a) Next hop is sink

(b) Next hop is UAV j

(c) No route to sink: direction update based on neighbors

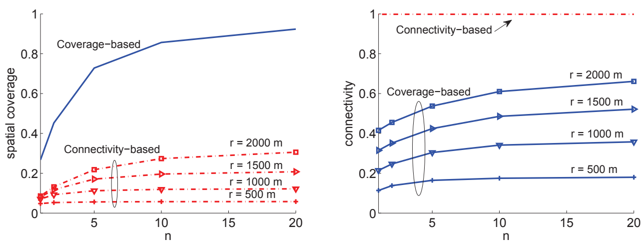
Fig. 2. Direction change illustration of UAV i. The solid and dotted circles are the current and next transmission ranges of the UAVs, respectively.

IV. RESULTS AND DISCUSSION

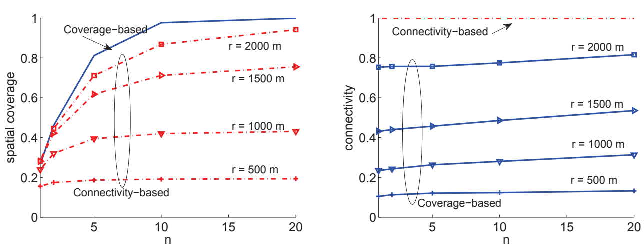
In this section, we compare the spatial area coverage and connectivity performance of the proposed mobility models via Monte Carlo simulations. The spatial coverage is defined as the percentage of the area of interest that is sensed in a given amount of time. Connectivity is defined as the percentage time the UAVs are connected to the sink averaged for all UAVs. First, we use a square area with side length 4000 m without obstacles. The travel time of the UAVs is assumed to be 1000 s, and their velocity is fixed to 5 m/s. The sensing range of the UAVs is set to 500 m and the sensing period for direction change is 2 s. The performance is computed for different number of UAVs (n) and transmission ranges (r). The UAVs start their mobility path above the ground location, which is placed either at the corner or center of the observation area. The location of the ground station is expected to influence the coverage of the connectivity-based scheme and connectivity of the coverage-based scheme.

We study two systems: single-hop and multi-hop. The single-hop system allows only direct links between the UAVs and the ground station. In the multi-hop system, the UAVs are connected to the ground station via a shortest-hop route. While a single-hop system might be considered too simple or unrealistic, analysis of such a system carries value in determining the impact of available information on the performance.

Figure 3 shows coverage and connectivity of the single-hop system versus n, when the ground station is located in the corner ((a)-(b)) and in the center ((c)-(d)), respectively. The location of the ground station affects the coverage for the connectivity based scheme by a scaling factor only. Since the sensing range is fixed, spatial coverage of the coverage-based model is not affected by the transmission range. For connectivity-based mobility, spatial coverage gets better as the transmission range increases. This is because the UAVs can better spread out and the overlap between their sensing coverage decreases (Fig. 3(a),(c)). Spatial coverage of the connectivity-based model can be approximated by $\frac{1}{4}\frac{\pi r^2}{4000^2}$ and $\frac{\pi r^2}{4000^2}$ for the case the ground station is in the corner and center, respectively. Coverage-based mobility spreads better as the number of UAVs increase, whereas connectivity-based mobility is not significantly influenced by the number of UAVs. This is expected since the UAVs only consider their position and multi-hop links do not exist. In terms of connectivity, we see a reversal of performance (see Fig. 3(b),(d)). The connectivity-based model is not affected by the transmission range as opposed to the coverage-based model. Connectivity of the latter improves with increasing transmission range and is not influenced by the number of UAVs. These results imply that collaboration in terms of coverage is fruitful and collaboration in terms of connectivity can improve performance. To illustrate this, we next investigate a multi-hop system.



(a) Spatial coverage over n (b) Connectivity over n

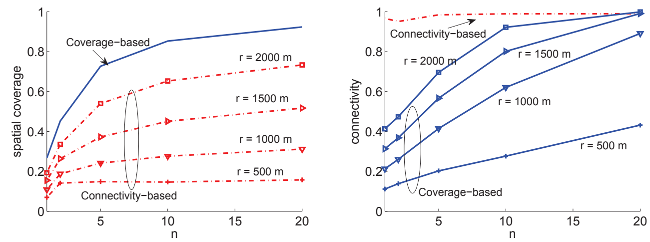


(c) Spatial coverage over n (d) Connectivity over n

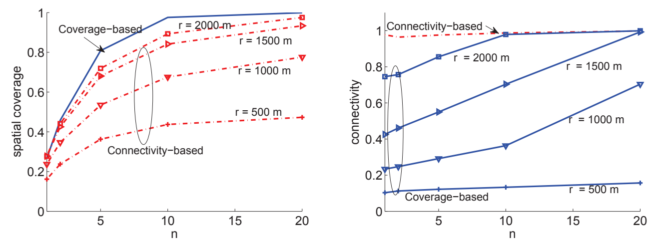
Fig. 3. Single-hop system: Spatial coverage and connectivity over number of UAVs, when ground station is (a)-(b) in the corner and (c)-(d) in the center.

Figure 4 shows the spatial coverage and connectivity performance of the two schemes for a sink located at the corner ((a)-(b)) and at the center ((c)-(d)). The spatial coverage of coverage-based scheme and the connectivity of the connectivity-based scheme is not influenced by the multi-hop capability. On the other hand, we observe significant improvement in terms of spatial coverage of the connectivity-based scheme due to the improved spreading. Similarly, the connectivity of the coverage-based scheme improves approximately linearly with the number of UAVs when the transmission range is sufficiently large. The connectivity of this scheme is still dependent on the sink location. Allowing multi-hop communication brings the performance of the two schemes closer to each other. Our current focus is on determining the optimum spatial density that maximizes coverage, such that the connectivity is sustained throughout flight.

Next, we study the performance of the multi-hop system in a campus scenario. Figure 5 illustrates the system under study. The green polygon represents the area of interest and the red polygons are forbidden areas (i.e., no flight zones). We set the simulation parameters based on received signal strength measurements collected during a flight over campus (see Fig. 6(a)). The test setup consists of an access point located at the start-point (lower-right corner of the observation area) and a single quadrotor UAV, both equipped with 802.11a wireless interfaces and two dipole antennas (for details of the tests the reader is referred to [19]). Based on the measurements, we compute the best-fit path loss coefficient to be $\alpha = 2.6$. Using this path-loss coefficient, we can also compute the theoretical path loss map over the campus (see Fig. 6(b)). The yellow rings on the figure correspond to the maximum range for different data rates (i.e., inner to outer circle: 54 Mbps, 36 Mbps, 24 Mbps, and 6 Mbps). The corresponding maximum transmission ranges are 67 m, 126 m, 164 m, and 278 m, respectively. For both schemes, the UAVs follow the boundary rule when they are close to the forbidden areas.



(a) Spatial coverage over n (b) Connectivity over n

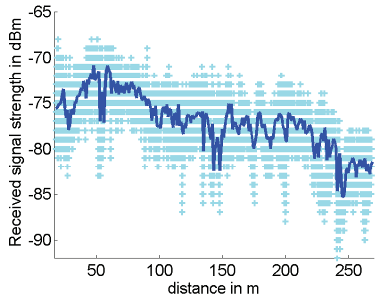


(c) Spatial coverage over n (d) Connectivity over n

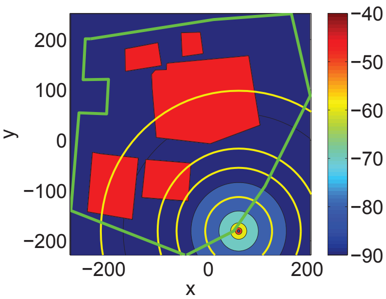
Fig. 4. Multi-hop system: Spatial coverage and connectivity over number of UAVs, when ground station is (a)-(b) in the corner and (c)-(d) in the center.

Fig. 5. System under investigation

Figure 7 shows the spatial coverage and connectivity performance of the two schemes for the campus scenario. The highest transmission range corresponds to the lowest data rate.

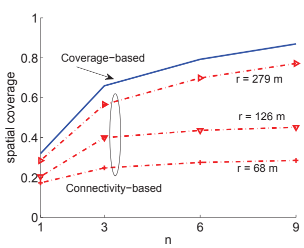


(a) Received signal strength measurements over campus

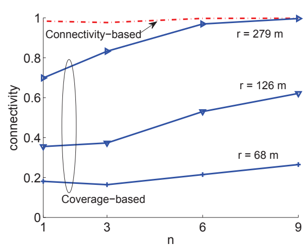


(b) Path loss map of campus: $\alpha = 2.6$

Fig. 6. Experimental and theoretical path loss over a campus area



(a) Spatial coverage over n



(b) Connectivity over n

Fig. 7. Multi-hop system: Spatial coverage and connectivity over number of UAVs

At this rate, the coverage-based scheme would not result in disconnections when the number of UAVs is higher than 6. With this number of UAVs, a high coverage can also be achieved. The observed trends are similar to the no obstacle case. The linear relation is not preserved due to the direction changes around the obstacles.

V. Conclusions

We proposed a novel connectivity-based mobility model for a UAV network monitoring and sensing a given area of interest. The main objective of the model is to sustain connectivity to the ground station during flight. To illustrate the trade-off between achievable area coverage and connectivity, we compared the performance of the proposed scheme with a coverage-based mobility scheme for several scenarios. Our results showed that to achieve good spatial coverage, while staying connected; a certain spatial density is required. If not enough UAVs are available, a combination of the connectivity and coverage-based schemes is expected to be more beneficial. Our current focus is on determining the optimum spatial density and investigating combining methods for the two schemes utilizing their advantages.

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