Maximizing Search Coverage Using Future Path Projection for Cooperative Multiple UAVs with Limited Communication Ranges

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Abstract. In this chapter, we present Future Path Projection (FPP) as a novel method for multiple Unmanned Aerial Vehicles (UAVs) with limited communication ranges to cooperatively maximize the coverage of a large search area. For multiple cooperative UAVs to perform an effective search mission, the critical status and sensor information collected by each UAV must be shared with all other UAVs in the group. In an ideal environment where there is no communication limitation, all involved UAVs can share the necessary information without any constraints. In a more realistic environment, UAVs must deal with limited communication ranges. The communication range limitation, however, introduces a challenging problem for multiple UAVs to effectively cooperate. In the proposed method, each UAV constructs an individual probability distribution map of the search space which reflects predictions of the future paths of UAVs as they move beyond their communication ranges. The probability distribution map describes the likelihood of detecting targets within the search space. The overall, collective UAV search patterns are governed by decisions made by each UAV within the group, based on each individual probability distribution map. We show that the collective search patterns generated by cooperative UAVs using the proposed method significantly improve the search area coverage when compared to similar search patterns produced by other mitigation strategies designed to overcome the communication range limitation. We validate the effectiveness of the proposed path projection method using simulation results.

Keywords: cooperative, unmanned aerial vehicles, limited communication, future path projection.

1 Introduction

Significant research has been conducted on mobile multi-agent systems directed at solving problems such as target search [1], target observation [2], and cooperative transportation [3]. Of particular interest is the development of multi-agent systems composed of Unmanned Aerial Vehicles (UAVs) capable of covering vast areas using a wide range of sensors. These systems are ideal for applications such as surveillance, reconnaissance, rescue, and emergency site monitoring [4].

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For an increasing number of applications, multiple UAV systems provide superior performance compared to single UAV systems by taking advantage of the redundancy, robustness, and cooperation potential of multiple systems. However, to gain the advantages of no centralized control unit, cooperation intrinsically requires some degree of communication between UAVs [5]. In practice, the cooperation potential is often not fully achieved due to restricted communication capabilities, such as limited communication ranges. Moreover, the bigger the volume of information a cooperative algorithm requires to be transferred between UAVs, the greater will be the necessary communication bandwidth. In most protocols, increased bandwidth usage ultimately leads to communication delays. When UAVs operate based on delayed information about the states of other cooperating UAVs, the environment, or the status of the global mission, the entire system performance can be degraded or its stability compromised [6], [7].

Recently, strategies that aim at mitigating the impact of communication limitations on the cooperation performance of multi-agent systems have been the focus of significant research activity. Current efforts can be generally classified into two groups: uninterrupted communication strategies that restrict the mobility of the fully connected cooperating UAVs; and unrestricted mobility strategies that provide the agents with freedom of movement but temporarily increase the volume of information exchanged when two or more UAVs happen to fly within communication range of each other.

An example of an uninterrupted communication strategy can be found in [8], where a formation control framework is applied to a set of multiple agents with the goal of balancing the intent of each unit to contribute to the collective mission and the requirement to maintain a single communication network by restricting any single agent from moving beyond the communication range of the group. Another such strategy is introduced in [9], where occasional non-local interactions determined by an acute angle switching algorithm are shown to generate mobile networks that robustly preserve system-wide connectivity while seeking to cover a number of regions of interest. Approaches such as these have the benefit of allowing agents to operate under a single network. If the volume of exchanged information is not prohibitive, it allows for all agents to share a common knowledge database during the entire mission. However, to achieve and maintain a single network, the mobility of each individual agent becomes limited, which can compromise the performance of the group.

In unrestricted mobility strategies, individual performance is not compromised. However, cooperation performance is generally affected negatively since, for the lack of a system-wide network, the UAVs must operate without access to a common knowledge database. Without such information, the capability of a UAV to effectively cooperate with the team becomes limited. Therefore, unrestricted mobility strategies focus on techniques that provide additional information when communication opportunities occur as two or more UAVs fly within a communication range of each other. Typical approaches involve the sharing of information in the form of past states and/or past sensor readings. In practice, the frequency and duration of such encounters tend to decrease with smaller communication ranges, the use of a smaller number of agents, and/or larger mission areas. With only short intervals to transmit the knowledge accumulated between encounters, greater bandwidth is necessary, which can lead to the negative outcomes previously outlined.

In this chapter we propose a novel unrestricted mobility strategy called Future Path Projection (FPP) that aims to mitigate the adverse effects of operating a cooperative control algorithm under scenarios with limited communication ranges. Our work suggests that the FPP strategy outperforms the existing approaches without limiting UAV mobility or increasing the volume of information shared among UAVs during their sporadic encounters. This is accomplished by having each UAV draw a probabilistic projection of the future paths of the other UAVs based on their operational behavior as they move beyond the communication range.

To compare the effectiveness of the proposed FPP strategy, we implemented two other strategies. The first is an uninterrupted communication strategy in which UAVs have their mobility restricted by an algorithm that sets maximum UAV-to-UAV distances in order to generate a flexible, reconfigurable chain structure that maintains the connection among all UAVs and the ground station. The second strategy represents a classical unrestricted mobility strategy, which we named Past Path Sharing (PPS). Similar to the proposed FPP strategy, the PPS data exchange takes place only when two or more UAVs happen to fly, based on their independent decentralized goals, within each other's communication ranges. Unlike the FPP strategy, in the PPS strategy, UAVs operate based only on deterministic past data (as opposed to probabilistic extrapolations of future behavior), but require increased data transfer rates in order to share both current and past data.

To measure the impact on the capability of multiple UAVs to cooperate under different communication ranges and to quantify the level of success of the different mitigation strategies, we challenge a set of UAVs to perform a search for mobile ground targets over a wide area using short range sensors. An efficient solution for this task requires UAVs to cooperate by coordinating their flight paths in order to provide coverage [10] by scanning the entire search area at least once and by revisiting every section as often as possible and with similar frequencies. In this manner, total area coverage and its evolution through time become two measures of the degree of cooperation of a team of UAVs.

For the experiments, we make use of the approach introduced in [11] and [12]. This algorithm seeks to maximize the likelihood of detecting a mobile ground target, and, therefore, maximize the coverage efficiency, by providing a cost function which each UAV uses to determine its next waypoint. The key characteristic of this cost function that directly impacts the efficiency of the group coverage is its ability to balance each UAV's intention to fly towards the location where the probability of detecting a target is greater, to fly away from other UAVs in order to maximize the spread of the search, and to remain inside the designated search area. Although the algorithm requires only that the position information be exchanged between UAVs, as the communication range is reduced and UAVs have fewer opportunities to exchange information, the cost function will not be able to account for information obtained by all other UAVs and, therefore, the collective search will not be as effective. More importantly, the lack of knowledge on the positions of UAVs outside the communication range deteriorates the accuracy of the target detection probability map carried by each individual UAV. The decrease in the spreading of UAVs and in the accuracy of the individual probability distribution maps makes it easy to discern the connection between the communication range, the degree of cooperation, and the ultimate sweep coverage efficiency of the group.

This chapter is organized as follows. In Section II, the prototype search algorithm is described and a series of simulation results demonstrate the negative impact of running it under progressively smaller communication ranges without any mitigation strategy. Section III describes the uninterrupted communication strategy, and Section IV introduces two unrestricted mobility strategies: PPS and the proposed FPP. In this section, both independent and comparative simulation results are provided for all three mitigation strategies. Section V closes the chapter with some final observations and conclusions.

2 Cooperative Decentralized Search Algorithm

In this chapter, we assume a target is detected when the distance between a UAV and the target is less than a given detection range. If the targets of interest are stationary, it is possible to measure the effectiveness of the search effort by the total area covered by the sensors onboard all involved UAVs and by how fast this coverage was achieved. Once the entire area is covered, the probability of detecting such targets becomes one. However, since our interest is in mobile targets, another relevant factor is how often each location is revisited.

In order to demonstrate the impact of a limited communication range to a mobile target search effort, we implemented the cooperative, decentralized search algorithm introduced in [11]. As a distributed approach, cooperative search patterns are generated by having each UAV determine its own flying path based on the group dispersion pattern, the search history of the immediate neighborhood, and the fuel consumption necessary for possible maneuvers. These factors are captured in search cost C_s shown in Equation (1). By evaluating C_s for different locations around its current position, a UAV continuously flies in the direction of the location with the minimum search cost.

$$C_S = (1 - P(i,j)) \left(\frac{1}{\sum(D_k)} + \frac{1}{\sum(D_l)} \right) |\Delta\phi_{\mathrm{UAV}}|. \tag{1}$$

Equation (1) is composed of four decision variables. The sum of the distances from a UAV to its peers and the sum of the distances between a UAV and the search area boundaries are represented by $\sum(D_k)$ and $\sum(D_l)$, respectively. The change in the heading angle required to reach a particular location is represented by $\Delta\phi_{\mathrm{UAV}}$. Finally, P is the probability matrix defined over the search area, and each element $P(i,j)$ corresponds to the probability of detecting a target in cell

i, j of the search area. Before the search starts, P is initialized with the same value for all cells, which is a function of the number of targets and the size of the search area. As a UAV flies over a cell, subjects to its sensors, and does not detect a target; the probability of a target existing in the cell drops to zero. However, as we consider mobile targets, as a UAV moves away from a visited cell, the probability of a target existing in an already searched cell gradually increases over time, making it more attractive to be revisited as time goes by.

Assuming unlimited communication range and bandwidth, by minimizing C_S each UAV attempts to fly to destinations that offer a greater probability of detecting a target (i.e., areas that have not been inspected for longer times), while maximizing distances from other UAVs, therefore maximizing the coverage of the overall search area. At the same time, each UAV also tries to remain inside the search area and maintain a constant heading, thereby minimizing fuel consumption. Note, however, that for each UAV to maintain an accurate representation of the current probabilistic distribution of the target locations in the matrix P, each UAV must know the positions of all other UAVs participating in the search effort at all times. As can be expected, when a limited communication range is considered, each UAV operates on an incomplete, inaccurate, individual probability distribution matrices P^k (where k stands for each UAV's identification number) that can differ greatly from the true probability distribution matrix P, unless some mitigation strategy is applied.

To demonstrate the impact of limited communication ranges on the performance of the cooperative search when no mitigation strategy is implemented, simulation results were collected where six UAVs attempt to cover a rectangular area of 150 km by 112.5 km. Each UAV is equipped with a sensor that is assumed to detect a target with probability one if the target is within 5 km of the UAV, and probability zero if the distance is larger. The UAVs fly at 100 km/h and calculate the cost C_S every 10 seconds at seven points equally spaced around its current location. The UAV then chooses the point with minimum C_S as its next waypoint, but its actual heading change is limited by a maximum turn rate of 2 degrees per second to simulate actual UAV dynamics limits. Since no mitigation strategy is implemented, UAVs receive only the current position information of other UAVs within their communication range, positions which are then incorporated into each individual target detection probability matrix P^k. During each simulation run, the six UAVs were launched sequentially at five minutes intervals and allowed to fly for six hours in order to allow long-term effects to be observed. All results presented in this chapter pertain to averages over 10 simulations for each scenario considered. A snapshot of a typical run showing both the *true* collective probabilistic distribution map P and the individual P^k built by one of the UAVs can be seen in Figure 1.

As previously mentioned, since the target is mobile, the probability of a target moving into an area that has already been searched increases over time, making it more likely to detect a target when the same location is searched again. However, since typically the speed of ground mobile targets is less than the speed of the UAVs, it is safe to assume that the probability of finding a target in a location

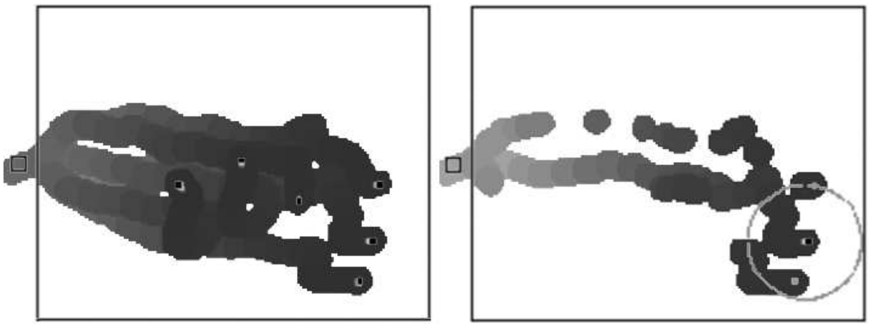

Fig. 1. Starting from an airfield (small square on the left), six UAVs (dark squares) attempt to search the designated area (wide rectangle). The complete probability matrix P is overlaid over the search area in the left frame, where the lighter the area, the greater the probability of detecting a target. The individual probability matrix P^1 built by UAV Number 1 is shown in the right frame. The circle around the UAV Number 1 indicates its maximum communication range.

that has not yet been searched will at all times be greater than a previously visited location. Therefore, instead of measuring the success of the cooperative effort as the time to locate a particular target, no targets were simulated and the degree of success of the effort is measured by observing the evolution over time of the percentage of the total area that has been searched at least once by at least one UAV. We refer to this quantity as the aggregated coverage, shown in Figure 2 as the average result of 20 simulations for each scenario. As expected, the aggregated coverage of the team decreased as the communication range was reduced, reflecting the failure of the UAVs to efficiently cooperate due to the increased disparities between each individual target detection probability map and the true probability map P. At the end of a six hour simulation run, UAVs without any communication range limitations achieved an average aggregated coverage of 98.0%, while UAVs that operated with a 20 km communication range achieved only 90.6%, those that were restricted to a 15 km communication range achieved 73.8%, and those that were restricted to a 10 km communication range achieved only 67.7%.

3 Uninterrupted Communication Strategy

The goal of this control strategy is to allow each UAV to freely move as long as a constant communication chain linking all UAVs and the ground station is maintained. In this manner, even though at times a UAV may not be able to reach a desired location within the search space, the preserved communication ensures that the true collective target detection probability map P is available to all UAVs. Since the only critical information to be transferred within the network is the position and heading of each UAV and the estimated position of

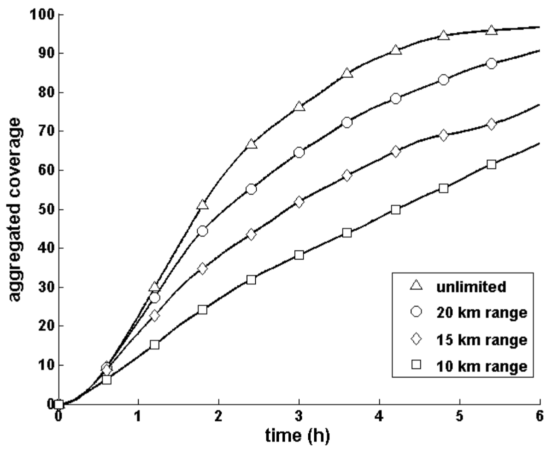

Fig. 2. Evolution of aggregated search coverage over time for scenarios with no communication limit (triangles), a 20 km communication range (circles), a 15 km communication range (diamonds), and a 10 km communication range (squares). No mitigation strategy applied.

detected targets, we assume that a single communication link between UAVs is capable of handling all the bandwidth required.

Before we introduce the modified search algorithm that will prevent UAVs from breaking the network connectivity while searching an area, we must first establish a network ranking system. The purpose of this ranking scheme is to allow each UAV to know which communication link is critical to maintain its communication with the ground station and, by extension, all other deployed UAVs. To determine its rank, each UAV must first calculate the distances between itself and the ground station, as well as all other UAVs within its communication range. If, for a particular UAV, the distance to the ground station is less than the distance to any other UAV with a lower or equal rank, then a direct link to the ground station is established and such UAV gains rank one. On the other hand, if a subset of UAVs with lower or equal ranks is closer to its location than the ground station, the UAV in question assumes a rank equal to one plus the rank of the UAV that is closer to its present location. An example of a possible configuration is shown in Figure 3. For this ranking scheme to accurately represent the necessary number of hops required for a UAV to communicate with the ground station, it is necessary that the UAVs perform periodic rank changes one at a time. For this reason, a token passing control mechanism is implemented to guarantee that the rank change occurs in a sequential manner. Since all UAVs are launched from the vicinity of the ground station, all are initialized with rank one. With each UAV periodically ranked according to the previously discussed procedure, a new term, $N(d)$, is introduced to the search cost as shown in Equation (2), defining the modified search cost $C_S^{'}$.

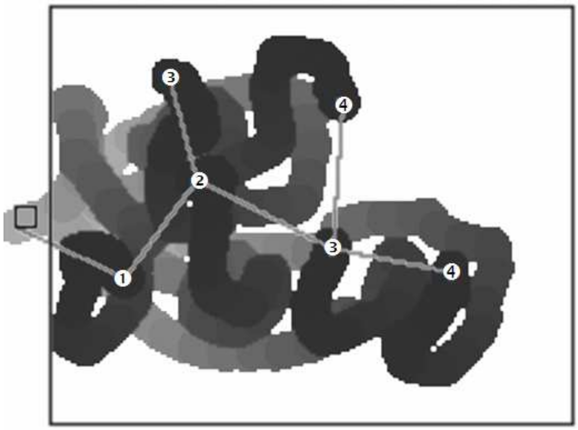

Fig. 3. A snapshot of the uninterrupted communication strategy managing a network of UAVs with a 40 km maximum communication range. The lines connecting the UAVs indicate the current information paths connecting all six UAVs and the ground station. The numbers over the UAVs are their dynamically adjusted ranks.

$$C_S^{'} = (1 - P(i,j)) \left(\frac{1}{\sum(D_k)} + \frac{1}{\sum(D_l)} \right) |\Delta\phi_{UAV}|(1 + N(d)). \tag{2}$$

The purpose of $N(d)$ is to prevent a UAV from choosing a heading that will cause a break in the communication network while preserving most of the search mobility autonomy. As shown in Figure 4, the value of the term N changes depending on the value of d, the distance from a UAV to the closest UAV with smaller rank (or distance to the ground station if the UAV's rank is one). For a distance d beyond the communication range cr, the cost factor $N(d)$ starts at a very large number γ and linearly increases with d as shown in Equation (3). For $N(d)$ between zero and the point α, $N(d)$ is zero and therefore imposes no restriction to the search process. The region between α and cr generates a softer early response region that provides gradual cost impact to a UAV in order to allow it to plot feasible flight trajectories that allow it to remain within the communication range. To minimize the mobility restrictions imposed by this strategy, the value of α is platform dependent and should be set as high as admissible by the dynamics of the UAV. The values that $N(d)$ assumes within this region are given by Equation (3).

$$N = \begin{cases} 0 & \text{, if } d \le \alpha \\ min\left[\gamma, tan\left(\frac{(d-\alpha)*\pi}{2*(cr-\alpha)}\right)\right] & \text{, if } \alpha < d \le cr \\ \gamma(1 + d - cr) & \text{, otw.} \end{cases} \tag{3}$$

Performing simulations with the same parameters used in the previous section, using this uninterrupted communication strategy the average final aggregated coverage was 95.0% for a maximum communication range of 50 km and 89.7%

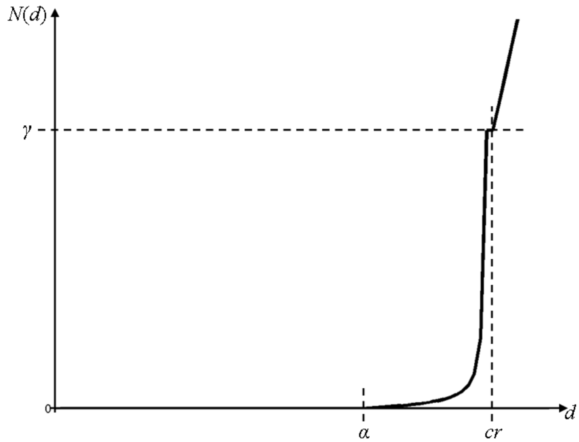

Fig. 4. Shape of $N(d)$ curve for arbitrary α, cr, and γ

for a range of 40 km. For communication ranges of 30 km and smaller, even if the algorithm resorts to a single line of UAVs stretching from the ground station, it is not geometrically possible to reach full aggregated coverage given the dimensions of the search area. If attempted, an aggregated coverage of 34.8% is reached for the 20 km communication range scenario, and only 8.45% for the 10 km one.

4 Unrestricted Mobility Strategies

For the search of vast areas with multiple UAVs subject to limited communication, a different set of strategies provides unrestricted search mobility by allowing communication to occur only sporadically when the search paths of two UAVs, determined by the original search cost introduced in Section II, happen to be close enough to allow data to be transferred. Due to the sporadic characteristic of the communication, all UAVs do not have access to the status of the complete search coverage effort of the group. If the content of the communications among UAVs is limited to their current positions and headings, as implemented in the previous section, it is clear to see that as the communication range is reduced, each individual probability distribution map $P^k(i,j)$ will become increasingly different from the other individual maps as well as from the true collective probability distribution map P. Two strategies, PPS and FPP, are proposed to mitigate the loss of search efficiency, caused by the disparities between each individual probability map, while still maintaining full mobility for the minimization of C_s. Both are described in detail in the following subsections.

4.1 Past Path Sharing

The PPS strategy approaches the problem by taking advantage of the chance encounters between UAVs to share past knowledge in order to improve the accuracy of their respective individual probability maps $P^k(i,j)$. Ideally, the most complete and accurate knowledge would be attained if the communicating UAVs could share their entire individual probability maps $P^k(i,j)$. However, in order to provide the minimum level of local accuracy, such maps become very large matrices in order to represent entire search areas, resulting in a severe increase in communication bandwidth requirements. Instead, in the proposed PPS, during such chance encounters each UAV transmits within each communication interval its current position and a set of past known visited positions (by itself or others) along with the time they were visited, which is then transformed by the receiving UAV into modifications in its own $P^k(i,j)$.

Although this approach requires an increase in the amount of information transferred between UAVs, the size of the set of past locations and sensing times transferred within each interval can be adjusted according to the bandwidth limitations of the communication network. Furthermore, after a packet of data is successfully sent, the next packet includes the UAV's updated current position and the next set of past values that pertain to even more distant instants in time. In this manner, even for scenarios that require low bandwidth, the accuracy of the individual $P^k(i,j)$ of the communicating UAVs is periodically improved throughout the time the UAVs remain within communication range of each other.

In order to store and provide the past information, each UAV maintains a table of past visited positions. Each line of the table pertains to a particular moment in time and contains the positions of the individual UAV and the positions of all other UAVs with known positions, leaving empty the cells for which no knowledge is available. Knowledge of a UAV position can be gained either directly by receiving position data from a communicating UAV, or indirectly through the sharing of tables among communicating UAVs. With a set frequency, synchronized among all UAVs, all cells of the table are shifted down, the oldest line at the bottom of the table is discarded, and the current known positions are added to the top of the table.

In actual implementation, when two UAVs happen to fly within the communication range of each other, each exchanges packets containing its current position, heading, and lines from the table, starting from the top (most recent) and moving to the bottom with each communication opportunity. Note that as the communication range decreases with respect to the overall search area, less knowledge can be obtained and shared, causing the tables to become increasingly sparse, a situation in which the communication toll can be reduced by the sharing of only non-empty cells. Also, increasing the maximum length of the table allows more knowledge to be stored from times further in the past while requiring additional memory usage by each UAV. This also allows more information to be exchanged when the UAVs' flight paths happen to remain close to each other for extended periods.

To demonstrate the impact of the PPS method on the final coverage capabilities of the group, the strategy was implemented in the same simulation environment used in the previous sections. Figure 5 shows a snapshot of the coverage as a UAV updates its map with past positions of a UAV within its communication

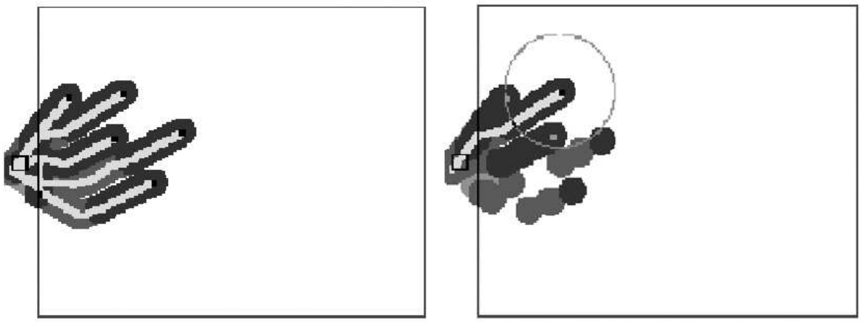

Fig. 5. A simulation snapshot for the PPS strategy. The left frame shows the total P, and the right frame shows the P^k of one of the UAVs where past information on locations visited by other UAVs are being obtained through communication with its neighbors.

range. As we vary the communication range, an aggregated coverage of 95.0% was reached when a 20 km communication range was available, while only 78.2% was achieved at the 10 km communication range.

4.2 Future Path Projection

Different from the PPS strategy, which required some level of additional communication load, in the FPP strategy it is not necessary that any information, other than their current positions and headings, be exchanged between UAVs during their chance encounters. In the PPS strategy, past information is used with the goal of making each individual $P^k(i,j)$ approach the collective probabilistic map P. On the other hand, FPP focuses on the instant when one UAV departs from the communication range of another and modifies its $P^k(i,j)$ based on the chance of the departing UAV visiting areas in the future, given the last received position and heading. This process is illustrated in Figure 6.

Since UAVs are subject to dynamic limitations on their turn radius, and since the original search cost C_S has as one of its goals to maintain the same heading in order to conserve fuel, it is reasonable to assume that the more likely path of a UAV is in the direction of its final received heading. To also incorporate the course changes that can occur due to the other factors within C_S, the projected path fans out from the last received heading direction with a likelihood that is inversely proportional to the required angular change in the heading. Finally, since the projection becomes less accurate the further it extends into the future, the likelihood that an area is visited in the future also is reduced proportional to its distance from the last received position. The end result is the cone shape shown in Figure 6 with maximum likelihood (intensity) in the area immediately ahead of the point of last communication and with gradually reduced likelihood as either the angle of the heading, or the distance from the position of last communication is increased over time.

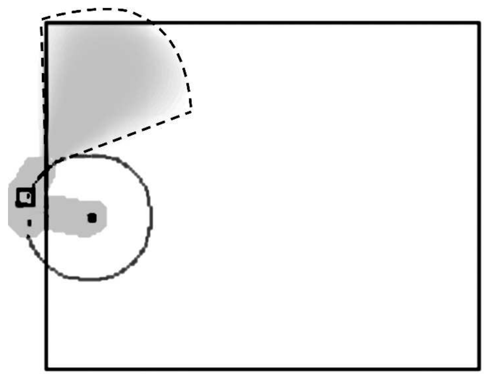

Fig. 6. As one UAV departs from the communication range of another, the FPP strategy augments P^k with a probabilistic projection (dotted line area in the picture) of the departing UAV's future path

A simulation with the same parameters used for the test of PPS was conducted using FPP. In this simulation, the FPP strategy was allowed to extend the projection up to 60 km away from the point at which communication was lost with an included angle of 30 degrees. At the end of the six hours of simulation, the application of the FPP mitigation strategy resulted in a comparable 93.9% average aggregated coverage for the 20 km communication range scenario, and a vastly superior response of 92.1% for the 10 km communication range scenario. All coverage values for both the PPS and FPP cases were obtained from the aggregated effective coverage represented by P, as opposed to the individual perception of the target detection probability map of each P^k.

Having introduced all three mitigation strategies, Figure 7 shows a comparison of the evolution of the aggregated coverage over time for a more demanding scenario where communication only takes place between UAVs less than 10 km apart. For reference, Figure 7 also displays the performance of the cooperative decentralized search algorithm operating with unlimited communication range and with the restricted communication range but without any mitigation strategy. As expected for communication ranges at or below 30 km, the uninterrupted communication strategy performs even worse than when no mitigation strategy is applied, since at this range the network, although flexible, is geometrically incapable of stretching over the entire area without losing communication with the ground base. Applying both PPS and FPP strategies in parallel over the same Pk map resulted in a performance level between the full communication and no mitigation strategy scenarios, with FPP providing a superior average aggregated coverage throughout the entire six hours. When PPS and FPP were applied simultaneously, the end result was statistically identical to the result when FPP was applied alone, suggesting that if FPP is applied at this communication range there is no benefit from increasing the communication bandwidth usage to implement PPS.

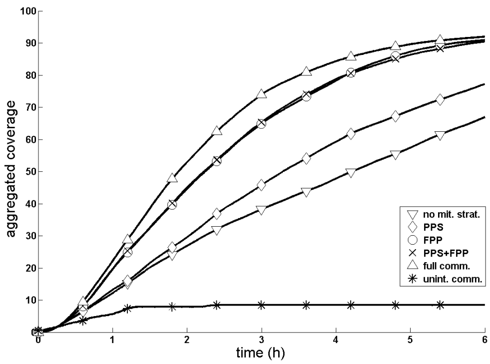

Fig. 7. Comparison of the performance of the cooperative sweep search with a 10 km maximum communication range using the different mitigation strategies: uninterrupted communication (asterisk), PPS (diamond), FPP (circle), and the combination of PPS and FPP (×). For reference, curves from the system operating without any mitigation strategy (down-facing triangle) and with full communication (up-facing triangle) are also provided.

Figure 8 shows results equivalent to when a 20 km communication radius was applied. As before, the uninterrupted communication strategy under-performs since the very limited communication range still prevents it from achieving full coverage. Comparing the performance of PPS and FPP, we notice that at this communication range FPP outperforms PPS until approximately three and half hours after the search starts. After that point, PPS provides superior aggregated coverage. This behavior can be explained by the fact that in the beginning of

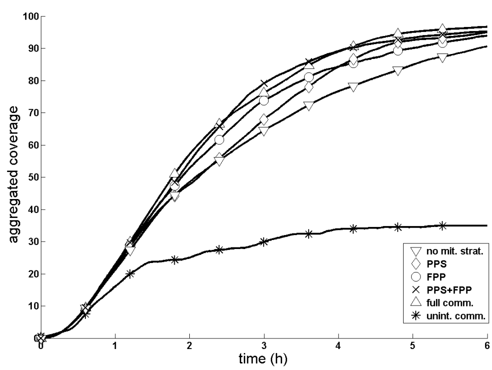

Fig. 8. Comparison of the performance of the cooperative sweep search with a 20 km maximum communication range using the different mitigation strategies: uninterrupted communication (asterisk), PPS (diamond), FPP (circle), and the combination of PPS and FPP (×). For reference, curves from the system operating without any mitigation strategy (down-facing triangle) and under full communication (up-facing triangle) are also provided.

the simulation UAVs are less likely to deviate from the paths predicted by FPP based on their knowledge of the search area since they all depart from the same airbase. In such situations, the choice of future waypoints will be directly influenced by the projection of future paths of its neighbors, whereas knowledge of a neighbor's past positions will only impact the decision making of a UAV when it changes course and if it approaches the vicinity of such locations. Different from the results for the shorter communication range, at 20 km the benefit of combining both PPS and FPP strategies becomes evident as the end result shows the rapid initial increase in the aggregated coverage brought by FPP and the ultimately superior result of PPS. This result suggests that combining the two techniques can be significantly advantageous on scenarios with extremely constrained communication ranges. Nevertheless, it is important to note that any usage of PPS comes with an increase in the bandwidth demand, which may not be acceptable due to the negative consequences mentioned earlier in the chapter.

5 Conclusion

In this chapter, we showed the validity and effectiveness of the FPP strategy to update search maps which are used by a set of cooperative UAVs to collectively, in a probabilistic context, maximize the coverage of a large search area under communication range limitations. The unique search problem involves mobile ground targets emitting radio frequency signals that can turn on and off. The nature of the targets demands a search technique that causes the cooperative UAVs to not only efficiently cover the search area, but also to revisit areas previously searched with unexpected frequencies and patterns. The proposed method has been shown to be effective in maintaining good search coverage with a wide variety of communication ranges, demonstrating its value especially when the communication range for each UAV is relatively small. We presented a comparative study on the performance of the proposed method against two other methods to accommodate the communication limitation problem, one based on an uninterrupted communication principle and the second on an uninterrupted mobility principle. Using the search task as a testbed, we demonstrated that the proposed FPP algorithm managed to provide a group of decentralized UAVs operating under a limited communication range with a degree of cooperation comparable to the one attained under the assumption of unlimited communication range.

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