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Potential field based receding horizon motion planning for centrality-aware multiple UAV cooperative surveillance

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A B S T R A C T

In this paper, we propose a two-layer control framework for the cooperative surveillance problem using multiple Unmanned Aerial Vehicles (UAVs). The framework consists of a network topology control layer and a motion planning layer. The former regulates the network topology and maintains the network connectivity. The latter plans the motion of UAVs using the distributed receding horizon optimization. The model of the cooperative searching problem is built based on the probability of targets and the detection history of UAVs over the region. The forgotten factor is introduced to drive the UAVs to revisit the areas that have been searched before. Furthermore, the tradeoff between the coverage enhancement and the network performance is achieved by taking into account the centrality of communication links in the deletion of communication links. The potential field design in the receding horizon optimization is presented to obtain the optimal motion of UAVs without violating the collision avoidance and network connectivity constraints. Simulation results demonstrate the feasibility of the proposed methods by analyzing the effects of the forgotten factor and the centrality of communication links.

1. Introduction

In recent years, the Unmanned Aerial Vehicles (UAVs) have been employed in the military and civil applications more widely due to the improvement of the autonomy. Multiple UAVs can perform complex missions more efficiently in comparison with a single UAV. Multi-UAV cooperation also improves the robustness and flexibility [1–4]. One major application of multiple UAVs in the battlefield is the cooperative surveillance and monitoring. In general, the surveillance region is divided into cells. The probability of targets or the uncertainty level of states is associated with the cells to represent the prior information [5–7]. The probability of targets and uncertainty level of states may be time varying because of the movement of the targets [3,5].

The sufficient information sharing in the group is quite indispensable for the cooperation and information fusion [7], and thus, the network connectivity must be preserved. The potential function method is a traditional way to preserve the connection and avoid collision for continuous-time systems [8–11]. For discrete-time systems, the agent can choose control inputs from the allowable set (known as the connectivity constraint set) so that the connectivity can be maintained in the next step [6,12]. However, both the methods cannot deal with the kinematic constraints of the UAVs well, such as the range of velocity and the minimum turning radius.

While preserving connectivity, the flexible network topology would enormously improve the efficiency of the surveillance [8,9]. The agent removes the redundant communication links through local communication without violating the global connectivity condition in [8] where the potential function method is adopted to disperse the agents for the coverage enhancement. The properties of the relative neighborhood graph are developed to preserve the connectivity in the deployment of mobile sensors in [13]. The agents estimate the global network topology through the local communication and achieve agreement on the deletion of the communication link based on the distributed auction mechanism in [9,10].

The deletion of redundant communication links may enhance the coverage, yet would also affect the information sharing in the network, especially the “important” links. Therefore, it would be beneficial taking the importance of the communication link into account when the decision on the deletion of the link is made. The method based on the betweenness of the edge is proposed in [14] for topology control in wireless sensor networks. The comparison with other methods has also been made to demonstrate the validity of the betweenness based method. The measures of the centrality of a node represent the relative importance of the node in the network. Degree centrality, betweenness, closeness and eigen-

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vector centrality are four measures of centrality which are widely used. The definition of the centrality often implies assumptions on the information delivery mechanism [15]. The corresponding centralities can be defined based on various information delivery models [16,17]. The centrality of communication links based on the eigenvector centrality [18] is defined to represent the importance of links in this paper.

Since the receding horizon control could handle the dynamic changes of the environment and kinematic constraints of agents effectively, it is quite popular in the multi-agent cooperation problems [19–22]. The distributed model predictive control is utilized to the multi-vehicle cooperative searching problem in [19] where the greedy and cooperative distributed model predictive control are stated and distinguished, depending on whether other neighboring vehicles' objectives are considered in the optimization. The coupling objectives and constraints of the vehicles make the distributed receding horizon control much more complex in comparison with the centralized method [20–23].

In the distributed receding horizon optimization, the agent usually needs other neighboring agents' decisions in the motion planning in order to plan its optimal motion under the coupling constraints, for example, the collision avoidance. One way is that the agents update their plans in sequence: only one agent is allowed to plan its motion and share the plan results with adjacent agents at every step while other agents hold their current plans [19,22]. The iteration of the optimization can also be divided into two steps. In the first step, the agent plans its presumed motion without taking the coupling constrains into account and shares the presumed motion with its neighbors. In the second step, the presumed motions are adjusted by taking the coupling constraints into account to obtain the feasible motion. However, the method is based on the assumption that the difference between the presumed motion and the optimal feasible motion is small and the update goes fast enough [20,21]. The potential field method is utilized for coupling objectives in the distributed receding horizon control for the multiple agent stable flocking [24].

The main contributions of this paper are described as follows. Firstly, the cooperative searching model is established based on the probability of targets and the detection history of UAVs. The forgotten factor is introduced to indicate how fast the detection efforts are forgotten. In this way, the UAVs are driven to revisit the areas which have been searched before. Secondly, the consensus based methods and distributed auction mechanism is utilized for the network topology control and management. The tradeoff between the detection rewards and the network performance is achieved by taking the centrality of the communication links into account in the deletion of links. Thirdly, the potential field integrating the potential function and the constraint set is designed to penalize the motion that may violate the coupling constraints in the distributed receding horizon motion planning. Thus, the UAVs could plan the optimal motion with the coupling constraints satisfied through one round of optimization in each iteration and could update their plans in parallel.

2. Multi-UAV cooperative surveillance framework

Consider that a group of UAVs perform cooperative surveillance over a given region. There is no leader UAV in the team. Although the UAVs may have different capabilities, their roles and status are equal. Each UAV searches the surveillance region and shares the information which includes the detection information, the local states, and the local topology information with the UAVs if there exists a communication link between them. And the UAVs are called as its "neighbors". Thus, each UAV collects the information of all the UAVs in the group through exchanging information with its neighbors and makes its decisions based on the collected information. Therefore, it is necessary to maintain the network connectivity. With the connectivity preserved, the flexible topology which changes with the searching task requirements could improve the efficiency of surveillance. The changes of the communication topology (additions and deletions of the communication links) would affect the structure of the network and the information delivery. Both surveillance task requirements and the network performance should be considered in the communication topology control.

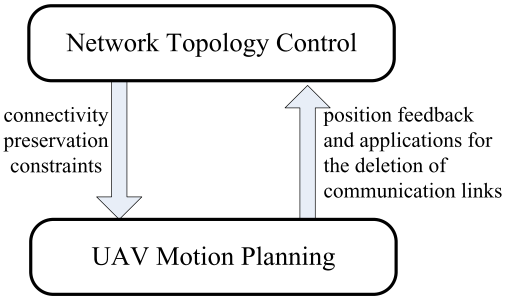

Fig. 1. Multi-UAV cooperative surveillance control framework.

The control system which consists of the topology control layer and the motion planning layer [8,9] is proposed as depicted in Fig. 1. The topology control layer obtains the global topology based on the collected local topology information. It also regulates the addition and deletion of communication links and maintains the network connectivity which imposes constraints on the motion planning. The motion planning layer guides the UAV's motion to obtain most detection rewards without violating the coupling constraints. It also provides the position feedback for the topology control layer and applies for the link deletion to the topology control layer to explore more areas.

In the topology control layer, each UAV estimates the global topology based on the collected local topology information. The consistent of the link deletion is achieved based on the distributed auction mechanism. The importance of the communication link and the estimated increase of the detection rewards are considered in the deletion of the link. While in the motion planning layer, each UAV plans its motion based on the local information in a receding horizon manner. The objective of the optimization for each UAV is to obtain the optimal path which could cause the most detection rewards in the given horizon. The coupling constraints, such as collision avoidance and connectivity preservation, would also be satisfied. The workflow in an iteration of each UAV is illustrated in Fig. 2.

3. Multi-UAV cooperative searching problem formulation

Consider that there is a group of UAVs performing cooperative surveillance tasks over an $L \times W$ rectangular region. The surveillance region is divided into $L_x \times L_y$ cells. It is assumed that each UAV knows how the region is divided and can access its own position. Denote $p_j(q)$ as the prior probability that target $j \in T$ exists in cell q, where $T = \{1, 2, \cdots, N_T\}$ is the set of targets that may exist in the region. The probability $p_j(q)$ may be time-varying because of the movement of the targets, and can also be estimated if some motion information is available. When cell q is searched by an UAV, all the targets in the cell would be detected with probabilities which are related to the UAV sensing capabilities.

The set of UAVs is defined as $U = \{1, 2, \cdots, N_U\}$. All the UAVs are assumed to fly at a constant altitude. The kinematics of the UAV $m \in U$ can be simplified as [3]: