Sampling-Based Positioning of Unmanned Aerial Vehicles as Communication Relays in Underground Environments

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Abstract

In this paper, we address the problem of using repeater drones as a relay chain to maintain communication between a ground station and a main drone responsible for exploration. We propose a sampling-based solution for dynamical positioning of the relay chain. Our method is fully decentralized, scalable and is able to deal with the case when the trajectory of the main drone is unknown. Simulation results are provided to show the performance of the proposed algorithm together with suggestions for further improvement.

1 Introduction

In the last years, the use of Unmanned Aerial Vehicles (UAVs) have found application in different environments that are dangerous or unaccessible by humans. Examples can be the inspection of disaster sites, search and rescue missions, and forest fire monitoring. Usually, during a mission it is required for the UAV to maintain connectivity with the ground station (GS), in order to enable real time transmission of the collected data, which has several advantages. For instance, it allows for in-flight change of mission trajectories, it enables collection of data in case of mission failure, and allows for "suicidal drones" that can potentially fly twice as far.

In our scenario, we are interested in using a UAV (leader) to explore unknown underground mines, where keeping constant communication with the GS is often unfeasible due to the presence of obstacles. In addition, the communication ranges may also be limited, especially for the small-size UAVs allowed to fly in mines. In order to ensure the continuous transmission of data, we try to keep a reliable communication link between the leader and the GS by introducing a team of UAVs acting solely as communication relays.

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In this paper, we propose an autonomous positioning strategy that allows each repeater drone to maintain optimal communication with its target (the leader or the following drone in the relay chain). We assume that the trajectory of the leader is unknown, and the repeaters continuously try to reach their optimal position. In addition, the inside of the mine is initially unexplored, and becomes accessible for the repeaters only after the leader collects the necessary data. The implemented method is decentralized and scalable. In fact, each repeater will autonomously try to find its own optimal (or sub-optimal) position with a technique based on sampling, constantly adapting to the new position of its target. The motivation for this method is twofold: first, the computation of an optimal solution can be expensive; secondly, to the best of our knowledge there is no such approach that can position a dynamic relay chain for LOS communication without direct control over the leader trajectory.

The paper is organized as follow: In section 2 we describe different approaches for the optimal positioning of relay systems, highlighting the different assumptions and applications. In section 3 we present the theoretical background of the implemented method. In section 4 the details of our strategy for the positioning of the repeater drones are given, and finally in section 5 our results are summarized. Also, we provide some consideration for further development and improvement.

2 Related Work

There are several possible scenarios where a chain of repeater drones can be used to guarantee real-time communication with the GS. Depending on the specific applications and assumptions, different approaches for optimal drone positioning have been proposed. In (Ladosz et al., 2016) the UAVs are used as communication relay nodes to improve the connectivity and communication performance of several ground nodes. The assumption is that both the mission trajectories and the urban maps are known a priori. Therefore, the proposed solution uses the Particle Swarm Optimization (PSO) algorithm (Poli et al., 2007) for optimal UAV positioning, and the optimization is based on three different communication performance metrics.

A different application can be found in (Burdakov et al., 2009) where the chain of repeater drones is used for surveillance tasks. In particular, the leader has to survey a distant target with a position which is known in advance. The solution method is centralized, i.e. the coordination of the drones is performed by the GS, and full information about the environment is available. To find the optimal positions, a discrete graph of the environment is first generated, then the positions are obtained by solving the all hops optimal path (AHOP) graph search problem (Guérin and Orda, 2002). In (Schouwenaars et al.) a mixed integer linear programming (MILP) approach is adopted for online connectivity-constrained trajectory planning for autonomous helicopters through cluttered environment. The problem formulation takes into account the line of sight (LOS) constraint as well as the presence of obstacles and unexplored areas (thus unaccessible). With MILP, both centralized and decentralized solutions are possible. However, the leader has a known goal, and cooperates with the repeaters in order to ensure feasibility of the mission. Finally, in (Dixon and Frew, 2009) and (Dixon and Frew, 2012), the coordination of the drones in the communication chain is achieved using a decentralized mobility control algorithm, where each drone estimates the communication objective function gradient with stochastic approximation techniques. Even though this method seems promising, it is not clear if the drones are able to efficiently find their position in case of continuous change of signal source. In addition, the evaluation and propagation of the received signal is hard to simulate.

In our solution, we deal with the fact that both the environment and the trajectory of the leader are unknown. The adopted method is fully decentralized and based on LOS constraint between adjacent drones in the communication chain.

3 Background

3.1 Collision Avoidance

One popular approach for collision avoidance in autonomous robotics is the use of artificial potential fields. They are commonly used in swarm behavior algorithms where the distance between agents should be kept small, but the agents should not collide. Also, it can be used in unison with planning algorithms to, locally, avoid collision between agents and obstacles. The idea is to fill the agents workspace with an artificial potential field and let the agent be attracted to intermediate target positions and repelled from objects and other agents (Ge and Cui, 2002).

Positioning will be considered with in later sections, therefore only repulsive fields are dealt with in this section.

For agent a_i, denote the position with $\boldsymbol{p}_i$ and velocity with $\boldsymbol{v}_i$. Let $\mathcal{A}$ be the set of all agents, such that $a_i \in \mathcal{A}$ for $i = 1, \dots, L$, and let $\mathcal{O}$ be the set of all obstacles and the unknown area.

In general, potential fields are scalar fields dependent on obstacles and other agents positions. The generic form for the repulsive potential for agent a_i is

$$U_{rep}(\boldsymbol{p}, \boldsymbol{v}) = \sum_{j \neq i} f(\boldsymbol{p}, \boldsymbol{v}, \boldsymbol{p}_j, \boldsymbol{v}_j) + \sum_{o \in \mathcal{O}} g(\boldsymbol{p}, \boldsymbol{v}, \partial o) \tag{1}$$

where ∂o denotes the boundary of the obstacle o. The repulsive force can then be derived by taking the negative gradient of the potential (Ge and Cui, 2002).

$$\boldsymbol{F}_{rep}(\boldsymbol{p}, \boldsymbol{v}) = -\nabla_{\boldsymbol{p}} U_{rep}(\boldsymbol{p}, \boldsymbol{v}) - \nabla_{\boldsymbol{v}} U_{rep}(\boldsymbol{p}, \boldsymbol{v}) \tag{2}$$

3.2 System Connectivity

In many UAV applications such as search and rescue, surveillance, and area mapping, there is a strong need for a high quality communication link for sending a continuous stream of data. The most outstanding factors in wireless communication systems are considered the range and that there is line of sight (LOS) between transmitter and receiver (Burdakov et al., 2009).

The LOS problem with restricted range can be defined as a geometric connectivity problem, with the system constrains defined below.

First, we say that two points $\boldsymbol{p}_i$ and $\boldsymbol{p}_j$ are in line of sight if the line between them does not intersect any obstacles (or unexplored area), such that

$$\boldsymbol{p}_i + \lambda(\boldsymbol{p}_j + \boldsymbol{p}_i) \notin \mathcal{O}, \quad 0 \leq \lambda \leq 1 \tag{3}$$

Also, two agents a_i and a_j are defined to be within communication range if the distance between them is smaller than the shortest broadcast range of the two agents, denoted $d_{b,ij}$:

$$||\boldsymbol{p}_i - \boldsymbol{p}_j|| < d_{b,ij} \tag{4}$$

There is system connectivity if all subsequent agents a_i and a_{i+1} are within range and in line of sight, such that equation (3) and (4) holds for $i = 1, \ldots, L-1$.

3.3 Positioning

In the case of controlling the leader, an approach based on mixed integer linear programming (MILP) can be used for trajectory optimization (Schouwenaars et al.). In this scenario, a cost function J can be introduced, together with different constraints such as the ones in equation (3) and (4). At time t up until a limited horizon of T time steps, the objective can be formulated as to minimize the cost function:

$$\begin{aligned} J = &\sum_{k=t}^{T-1} \ell_{L,k}(\boldsymbol{p}_L(k)) + \\ &\sum_{i=1}^{L-1} \sum_{k=t}^{T-1} \ell_{i,k}(\boldsymbol{p}_i(k)) + \\ &\qquad \ell_{L,T}(\boldsymbol{p}_L(T), \boldsymbol{p}_f) \end{aligned} \tag{5}$$

where the first term is the stage cost for the leader, motivating it to get closer to the target position. The second term is the stage cost for the relay drones and the last term is a terminal penalty for the leader, for example to promote going faster to the goal or saving battery/fuel. The constraints can be formulated in terms of binary variables and the problem can be solved with optimization software like CPLEX. Further details regarding the constraints of the optimization problem can be found in (Schouwenaars et al.).

4 Method

4.1 Problem Formulation

The scanning leader drone has the objective of going into an environment (e.g. an underground mine) and map the area. Thus, the trajectory of the leader is not predefined, and evolves while the data is collected. To increase the range of communication, a set of relay drones are introduced when the leader is out of range from the ground station or when it is about to loose LOS. It is assumed that the leader is not controlled by the same system as the relay drones, instead it is controlled by a semi-autonomous system supervised by the ground station. At some point during scanning of the environment we have L agents a_i, where $i = 1$ is the ground station, and $i = L$ is the scanning leader drone so that $L \geq 2$.

The goal is to keep system connectivity as defined in section 3 by equation (3) and (4).

4.2 Our solution

With inspiration from the MILP optimization formulation, we use a utility function (instead of a cost function) to evaluate positions. Since the mine exploration is time constrained due to the limited battery life of the drones, we prefer not to change the leader plans, and choose a decentralized approach where each drone only considers the consecutive drone in the relay chain. This leads to independent utility functions $u_i(t)$ for each drone i at time t. Another advantage is that the system can be completely parallelized with independent computations for each drone.

For obstacle avoidance, a force is directly introduced instead of a potential as in (Balch and Arkin, 1998). For static obstacles and unexplored area we use:

$$\boldsymbol{F}_{obst} = \begin{cases} 0, & d > S_o \\ G_o \dfrac{S_o - d}{S_o - R_o} \hat{n}, & R < d < S_o \\ \infty, & d \leq R \end{cases} \tag{6}$$

where S_o is a sphere of influence of the obstacles, R_o is a "radius" of the obstacle o, d is the distance from the drone's center to the obstacle and G_o is a gain parameter. The unit vector $\hat{n}$ is the direction from the obstacle to the the drone defined as

$$\hat{n} = \frac{\boldsymbol{p}_i - \boldsymbol{p}_o}{||\boldsymbol{p}_i - \boldsymbol{p}_o||} \tag{7}$$

The force from other drones has an equivalent form, but with other parameters. Furthermore, in the relay chain we introduce priorities so that drone i always avoids collision with drone $j > i$. This has the advantage of not slowing down the drones already in the relay chain, and also reducing the risk of loosing LOS due to collision avoidance maneuvers.

In our simulations, we discretize the space and sum the force vectors from each cell on the boundary of the obstacles or unexplored areas, together with the repulsive force coming from nearby drones.

Our objective for the positioning is a function of two distances, since we use a decentralized approach there is no need to take the distances to all drones into consideration. First, we use the distance d_1 from the straight line connecting the two drones with signal to the nearest obstacle or unexplored area. Second, the distance d_2 is to the "target" drone with position $\boldsymbol{p}_t$, i.e. the one that we want to keep LOS with. The distances can be seen in figure 1 and are defined by:

$$d_1 = \min_{o \in \mathcal{O}} \|r\| \tag{8}$$

$$r = (\boldsymbol{p}_o - \boldsymbol{p}_i) - \frac{(\boldsymbol{p}_o - \boldsymbol{p}_i)^T(\boldsymbol{p}_t - \boldsymbol{p}_i)}{||\boldsymbol{p}_t - \boldsymbol{p}_i||^2}(\boldsymbol{p}_t - \boldsymbol{p}_i) \quad (9)$$

$$d_2 = ||\boldsymbol{p}_t - \boldsymbol{p}_i|| \quad (10)$$

We set up a utility function that provides an evaluation score for a position $\boldsymbol{p}_i$ at time t:

$$u_i(t) = h(d_1, d_2) \quad (11)$$

In practice we tried multiple functions, with the best performing once being two simple ones:

$$u_i(t) = w_1 d_1 + w_2 d_2 \quad (12)$$

$$u_i(t) = w_1\sqrt{d_1} + w_2\sqrt{d_2} \quad (13)$$

where w_1 and w_2 are two weights that can be tuned to produce the desired behavior.

For the positioning, we use a sampling based approach instead of solving the exact optimization problem. We sample feasible points close to the the current position, that are in LOS and within communication range. Then we evaluate these points using the utility function defined in equation (11), and simply pick the sampled point with the highest score as the next target position.

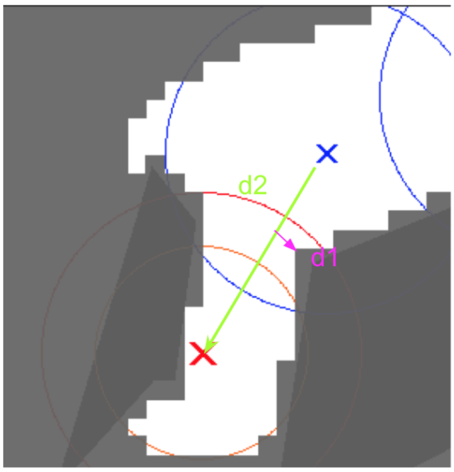

Figure 1: Distances d_1 and d_2

5 Results and Conclusions

To simulate the behavior of the relay chain, we use a 2D simulation environment where the trajectory of the leader is predefined but not provided to the repeaters. The model used for the drones motion is the "dynamic point", i.e. control signal is provided as an acceleration, velocity and acceleration are bounded, and the drone is modeled as a point in space without orientation. To steer a drone to its target position, a PD-controller is used.

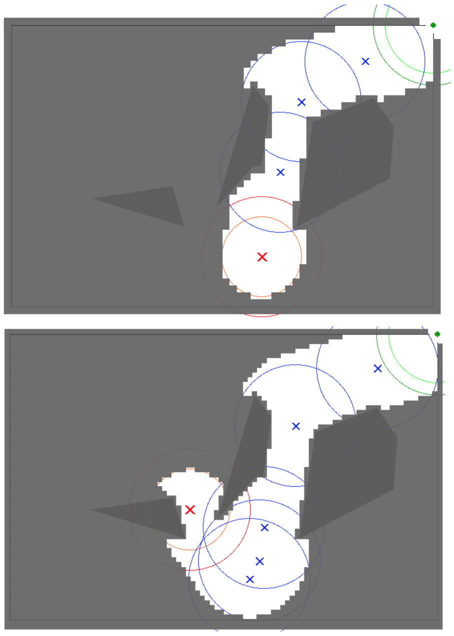

Figure 2: On the top: desired behavior. On the bottom: undesired behavior

In trivial situations, our algorithm is able to position the relay chain in an adequate manner (figure 2 top). However, there are many situations in which the positioning is far from optimal and the connectivity of the relays becomes redundant (figure 2 bottom). Most importantly, there are some corner cases where the line of sight is lost. This is partially due to the non-optimality of our approach, but also to the complexity of underground environments. In fact, since the leader acts independently, in some cases it might be impossible to avoid loosing line of sight.

The most important part of the proposed sampling algorithm is the utility function used to evaluate the sampled positions. Further exploration and analysis of such functions could drastically improve the performance. In particular, taking into account the velocity of the target may allow for estimation of its position in the near future, which could prevent the loss of line of sight in many situations. Thus, further work should mainly be focused on improving the utility function, and eventually extend the simulation to take into account signal propagation and diffraction.

Finally, it would be interesting to introduce high level coordination for the whole relay chain in order to allow for "intelligent" maneuvers. Some examples could be restoring formation in case of the loss of a relay drone, or a dynamic substitution of repeater in case of low battery. One way to do this could be by the use of Behavior Trees, and would most likely lead to an increase in the robustness and reliability for the whole system.

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References

Tucker Balch and Ronald C Arkin. Behavior-based formation control for multirobot teams. *IEEE transactions on robotics and automation*, 14(6):926–939, 1998. ISSN 1042-296X.

Oleg Burdakov, Patrick Doherty, Kaj Holmberg, Jonas Kvarnström, and Per-Magnus Olsson. Positioning unmanned aerial vehicles as communication relays for surveillance tasks. In *Robotics: Science and Systems*, 2009.

Cory Dixon and Eric W Frew. Maintaining optimal communication chains in robotic sensor networks using mobility control. *Mobile Networks and Applications*, 14(3):281–291, 2009. ISSN 1383-469X.

Cory Dixon and Eric W Frew. Optimizing cascaded chains of unmanned aircraft acting as communication relays. *IEEE Journal on Selected Areas in Communications*, 30(5):883–898, 2012. ISSN 0733-8716.

Shuzhi Sam Ge and Yun J Cui. Dynamic motion planning for mobile robots using potential field method. *Autonomous robots*, 13(3): 207–222, 2002. ISSN 0929-5593.

Roch Guérin and Ariel Orda. Computing shortest paths for any number of hops. *IEEE/ACM Transactions on Networking (TON)*, 10(5): 613–620, 2002. ISSN 1063-6692.

Pawel Ladosz, Hyondong Oh, and Wen-Hua Chen. Optimal positioning of communication relay unmanned aerial vehicles in urban environments. In *Unmanned Aircraft Systems (ICUAS), 2016 International Conference on*, pages 1140–1147. IEEE, 2016. ISBN 1467393347.

Riccardo Poli, James Kennedy, and Tim Blackwell. Particle swarm optimization. *Swarm intelligence*, 1(1):33–57, 2007. ISSN 1935-3812.

Tom Schouwenaars, Andrew Stubbs, James Paduano, and Eric Feron. Multi-Vehicle Path Planning for Non-Line of Sight Communication.