A Heuristic Path Planning Approach for UAVs Integrating Tracking Support Through Terrestrial Wireless Networks

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Abstract. In this paper we propose a new approach based on a heuristic search for UAVs path planning with terrestrial wireless network tracking. In a previous work we proposed and exact solution based on an integer linear formulation of the problem. Unfortunately, the exact resolution is limited by the computation complexity. In this case, we propose in this paper a new approach based on a heuristic search. More precisely, a heuristic adaptive scheme based on Dijkstra algorithm is proposed to yield a simple but effective and fast solution. In addition, the proposed solution can cover a large area and generate a set of optimum and near optimum paths according to the drone battery capacities. Finally, the simulation results show that the drone tracking is sustainable even in noisy wireless network environment.

1 Introduction

For decades, Unmanned Aerial Vehicles (UAVs) are widely used in modern warfare for surveillance, reconnaissance, sensing, battle damage assessment and attacking. The benefits of UAVs include reduced costs and no warfighter risk. Recently, technological advances in micro controllers, sensors, and batteries have dramatically increased their utility and versatility and yet, a new horizon is open for civilian uses. This began with limited aerial patrols of the nation's borders, observation and aerial mapping, disaster response including search and support to rescuers, sports event coverage and law enforcement. Although the market is almost nonexistent today, this is most likely in the civil field that drones are expected to play the largest role. Recently, those flying machines have also been destined to the commercial market and have gained much attention. In fact, a forthcoming plans for commercial drone use have been recently announced by a number of companies around the world such, Amazon, Wallmart, DHL, and Zookal which are investing in mini drones development for variety of tasks, including freight and package delivery to consumers. The introduction of drones in civil applications raises new challenges to the government authorities in charge

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of flight security and air traffic management which have to balance safety and public concerns against potential economic benefit (Fig. 1).

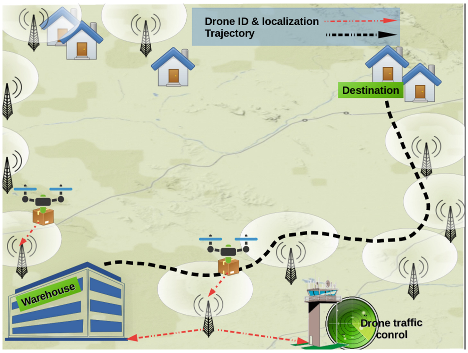


Fig. 1. Drone package delivery

By virtue of their small size, mini drones are difficult to be detected and to track. In this frame, the European Parliament adopted a resolution on the use of drones, which requires Member States to implement various regulations to ensure the safety of the airspace and to ensure the privacy of citizens threatened by the use of these flying machines. Through this resolution, it is considered that regardless of their sizes, the question of identifying is essential, and emphasizes the need to provide appropriate solutions in terms of locating and tracking. In other words, this new report aims to ensure the traceability of all UAVs, but also operators and owners as a sine qua non-conditions for any use.

It is obvious that path planning is one of the most crucial tasks for mission definition and management of the aircraft and it will also be an important requirement for UAVs that has autonomous flight capabilities [1]. The operational problem that this work address is enabling the government authorities in charge of flight safety to identify, locate and to track drones. Usually the area is large and the detection and localization time to find the UAV is the critical parameter that should be minimized. To this end and in order to make this possible, we present in this paper a newly approach based on the exploitation of the available wireless network coverage. This approach relies on a powerful interaction, or collaboration between the UAVs and the operators. Cooperation in such environment implies that the drone periodically send his identification, localization, speed and other information to the remote operators through the available wireless networks. The solution we aim to present provide or inform of the optimum and the near optimum paths that the drone should follow to ensure a reliable communication and high packet delivery rate depending on its battery autonomy.

In our previous work [2], we formulated the problem as an Integer Linear Problem. Moreover, we expressed in an analytic manner the packet loss rate of tracking messages depending on the UAV location and the wireless network coverage. By solving the ILP problem using CPLEX, we were being able to analyze how the radio coverage as well as the threshold on the packet success rate, impact the number of possible solutions and the trajectory of the UAV. Unfortunately, due to the computational complexity the proposed approach was not able to provide a path planning solution for a large area. In addition, the packet success rate was computed by considering only the radio channel and without any MAC layer operations.

Our current investigations focus on the complexity issue raised for larger size of the area A. For the drone path planning, a heuristic adaptive scheme based on Dijkstra algorithm is presented to cope with the problem of scalability. The flight path of drone is optimized in order to improve its connectivity to the available terrestrial wireless network and consequently its localization, identification and tracking. Moreover, the solution is proposed to yield a simple but effective and fast solution and tested under a more realistic scenario characterized with a noisy environment.

2 State of the Art

Path planning for a kinematic system issues has been widely studied and have been addressed using different approaches and techniques. Thus, several approaches exist for computing paths given some input variables of the environment and in general, the two most popular techniques are deterministic, heuristic-based algorithms [3–5] and probabilistic, randomized algorithms [6,7]. The choice of the algorithm to use depends on the type of problem to be solved. Although, the robotic bibliography on this subject is very rich, it's not the case for the UAV's one.

For the autonomous flight of drones, path planning is one of the most crucial and important issues to solve. Nowadays, the application of UAV is extending from high-altitude flight to very low-altitude, where the impact of the terrain, the environment and the air traffic will be the keys factor to be considered to avoid collision [8]. However, we do not aim to provide an exhaustive list but we will be content to provide the most relevant work related to the path planning regarding to the nature of the objectives, problems formalization and resolving methods.

The author in [9] presented a framework to compute the minimum cost cooperative route between a heterogeneous package delivery team composed of a truck and micro drones. They abstracted the problem on a graph and formulate the issue as a discrete optimal path planning problem. In the same context of heterogeneous teams, the authors in [10] presented a path planning problem involving an UAV and a ground vehicle for intelligence, surveillance and reconnaissance missions. The addressed problem is similar to the ring-star problem and the hierarchical ring network problem.

On the other hand, the authors in [8,11] presented three dimensional path planning solution for unmanned aerial vehicles. The first solution is based on interfered fluid dynamic system, while the second approach uses linear programming where obstacle avoidance and target tracking are linearized to generate a linear programming model in relative velocity space. Dealing with adversarial environments, the authors in [12,13] presented solutions for unmanned aerial vehicles path planning in uncertain an adversarial environment in sight to reach a given target, while maximizing the safety of the drone. They proposed a path planning algorithm based on threats probability map, which can be built from a priori surveillance data and from a mechanism based on a model predictive control.

Another important work is [14], which contains concise summaries and focused on dynamic problems and discussed a family of heuristic algorithms for path planning in real-world scenarios such as A*, D*, ARA* and AD*. Finally, it is worth mentioning the research done by [15] that can be considered one of the few papers dealing with path planning strategies destined for a based UAVs network. The authors compared deterministic and probabilistic path planning strategies for autonomous drones to explore a given area with obstacles and to provide an overview image. The results showed that although the deterministic approach could provide a solution it requires more knowledge and time to generate a plan. However, the probabilistic approaches are flexible and adaptive.

To the best of our knowledge, none of the above works have investigated UAV path planning problem assuming that UAV uses terrestrial wireless networks to transmit its locations.

3 Path Planning Problem Formulation

3.1 Problem Statement and System Description

In this paper, we are considering a package delivery services using UAVs. Basically, a UAV has to deliver a package from a depot to a predetermined destination or consumer. In this frame, the system is modeled as 2D area A without any obstacle. The projection of the flying area is represented by a rectangular with length of x_{max} and a width of y_{max}. We suppose that the drone D_{rone} keeps the same altitude h from the starting point O to the destination D. A set of wireless receivers or Base stations $BS = \{BS_1, BS_2, ...BS_n\}$ is deployed randomly at different altitudes in order to provide a wireless access infrastructure. In addition, we assume a partially noisy environment with the existence of a certain number of noise nodes $N_{oise} = \{N_{N1}, N_{N2}, ...N_{Nn}\}$ deployed within A and use the wireless infrastructure as an access network. We also consider that the drone has a limited flight autonomy Υ and equipped with a wireless interface in order to communicate with the other Base stations. The latter has a short sensing range compared to the size of the region of interest. Moreover, we consider that A is discretized into C hexagonal Area Units (AU) of the same dimension. The transition cost between two neighbor cells depicts certain reliability of communication, i.e. a certain probability that the communication is not interrupted and has a specified Packet Reception Rate PRR.

Our goal is to determine a path or a set of paths that optimize the drone localization and tracking using a wireless network, such as cellular or IEEE 802.11x technologies. For this purpose, we assume that after each period T drone generates a message of size D bits containing its identification, its position and speed. The on-board wireless interface tries to send each generated message to the remote UAV monitoring and controlling system via the BS while the jamming nodes attempt to exhaust and to overload the network by sending messages in a continuous and unpredictable manner to the BS. For that reason, a message can be corrupted or lost due to possible interference and collisions. The opportunity to transmit also depends on the radio coverage, the capacity of the related wireless technology and the drone's location.

The basic concept in building the probability map in this paper is different to the probability grid-based in our previous work. Thus, in this paper, the OMNeT++ 4.61 simulator and the INET framework were used to generate the Received Packet Rate and the signal-to-interference-plus-noise ratio $SINR$ maps. Thereby, for each cell C the Received Packet Rate RPR is computed as the proportion of received messages over generated ones and the values of the $SINR$.

3.2 Problem Formulation

In order to describe the proposed mathematical model that represents the optimum path planning problem, it is useful to introduce the following notations and definitions.

First, we model the problem with the help of a directed and valued graph G consisting of n hexagonal cells c, where the valuation of an arc is comprised between 0 and 1, indicating the packet error delivery on that arc. The unit cost for using the arc going from node i to node j is c_{ij}. The flow going that way is denoted by a binary variable x_{ij}

$$x_{ij} = \begin{cases} 1, & \text{if the drone moves from } AU\, i \text{ to } AU\, j \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

The cost of a path represents its reliability and it is set to the product of the RPR of each cell forming the resulted path.

$$Path_{cost} = \prod_{i=1}^{n} \prod_{j=1}^{n} RPR_{ij} * x_{ij} \tag{2}$$

As, the RPR_{ij} is comprised between $]0, 1]$, this means more we add a new cell to the path more the path cost is low. Thus, the mathematical formulation of the optimal drone path planning problem is reported as follows:

$$\text{minimize} \sum_{i \in A} \sum_{j \in A} c_{i,j} x_{ij} \tag{3}$$

and

$$\text{maximize} \prod_{i=1}^{n} \prod_{j=1}^{n} (PRR_{i,j}) x_{ij} \tag{4}$$

The objectives functions (3) and (4) represent respectively the distance or the delivery delay that should be minimized between the start point O and the destination D and the drone tracking possibility that should be maximized, by passing through cells with highest Received Packet Rate.

In addition to the last two objectives we add a last objective that aims to minimize the tracking time loss of the drone, by avoiding to pass through several adjacent cells with low RPR. Basically, we need to maximize a given cost function noted as f. For example, as illustrated in Fig. 2, if we have to choose between the paths a (0.9, 0.9, 0.9, 0.1, 0.1, 0.1) and b (0.9, 0.1, 0.9, 0.1, 0.9, 0.1) with the same distance and the same average packet delivery ratio, than the score function f has to privilege the solution b rather than a. The privilege of the solution b is motivated by the fact that we have less adjacent cells with low packet delivery probability. The main benefit of this choice is to have the communication rupture spaced out on the time rather than having a long time with no communication.

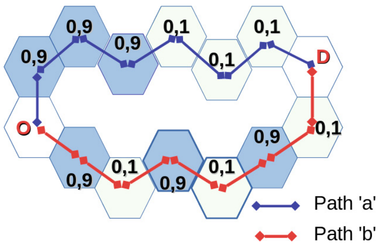


Fig. 2. Example of paths with the same cost

To this end, we need to analyze the cells data in terms of RPR values and their positions in the path by creating series of averages of different subsets of the full path. Basically, given K a path and the subset size equals to 2, the first element of the moving average is obtained by taking the average of the initial fixed subset of the number series. Then the subset is modified by shifting forward, excluding the first number of the series and including the next number following the original subset in the series. This creates a new subset of numbers $\overline{K}$, which is averaged. This kind of mathematical transformation is also used in the signal processing in order to mitigate the higher frequencies and to retain only the low frequencies or the contrary. The principle of moving averages is interesting, especially when it comes time to make predictions. Basically, this is about to calculate an average data based on the most recent results in order to create forecasts. Thus, it is assumed that the most recent data are more important or more meaningful than older data.

Let's consider $f(K)$ the score function and K is the path to analyze, where $K = \{RPR_1; RPR_2; ....RPR_n\}$ with RPR_1, RPR_2,... RPR_n are the Received Packet Rate at the cells c_1, c_2, ...c_n constituting the given path k and $\overline{K} = \{\overline{K}_1; \overline{K}_2; ....\overline{K}_{n-1}\}$ where $\overline{K}_i = (RPR_i + RPR_{i+1})/2$. Finally, since the geometric average is less sensitive than the arithmetic average to the highest or lowest values of a series, we propose the following cost function:

$$f(K) = \sqrt[n-1]{\prod_{i=1}^{n-1} \overline{K}_i} \tag{5}$$

In addition to the last objectives we add a constraint related to the UAV's maximal flight distance:

$$\sum_{i \in A} \sum_{j \in A} c_{i,j} x_{ij} < \delta \tag{6}$$

where δ is the maximum distance that the UAV could perform, taking in account UAV autonomy, speed and package weight.

3.3 Path Computation

Different shortest path algorithms exist like A*, Dijkstra, Bellman-Ford and others. Our proposal is based and adapted from Dijkkstra algorithms. The latest is one of the most common and effective algorithms used to search the shortest path between two vertices in a graph in terms of distance. For our case, we adapt the Dijkstra algorithm to find the shortest path with high communication reliability and high packet reception.

Since we are dealing with probabilities, the best way to find the shortest path with high Received Packet Rate is to seek for a path where the product of the probabilities RPR_i of the visited cells that constitute a given path is maximized. This also guarantees that if each time a cell is added to a path, the product of the probabilities decreases.

In this case, our algorithm first starts by initializing the cost of the origin cell c_o to 1. The cost of the remaining cells is set to 0. Starting from the origin point, we built step by step a set of P marked cells. For each marked cell c_i, the cost is equal to the product of the Received Packet Rate probabilities of all predecessors cells. At each step, we select an unmarked vertex c_j whose cost is the highest among all vertexes not marked, then we mark c_j and we update from c_j the estimated costs of unmarked successors of c_j. We repeat until exhaustion unmarked vertices.

Based on the above algorithm, we also derived a set of near optimal paths. In fact, the solution was extended to compromise localization data delivery rates and distance between the starting point and the destination with the respect of the drone autonomy. To this end, if the length of the optimal path is greater than the drone autonomy or simply, the operator would to have multiple choice of short paths, then we re-execute the function above until we get the desired solution and for each execution we set the RPR of the cells of the obtained path to ϵ, where ϵ is a small non-null value. This allows us to generate a new path totally different from the previous one. All these paths can then be compared using the cost function f.

4 Results

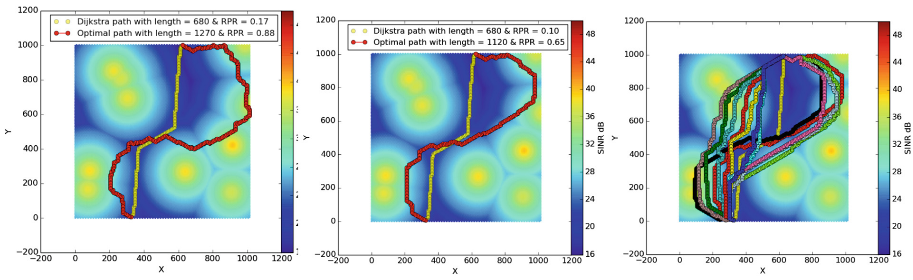
In this section we evaluate our proposed algorithm to generate optimal and near optimal paths for a drone to deliver packages from a start point to a given destination. Two main objectives were fixed, first, to ensure a maximum tracking and localization time of the drone along with its flight while the second one was to minimize the length of the path in accordance with the drone flight autonomy and the capacity of its battery. Thus, we assess the algorithm in different scenarios. Using `OMNET++` simulator, we generate the RPR map for a given altitude and in the presence of a given number of nodes using the wireless network. Basically, in order to increase the packet losses we can increase the altitude of the drone or the number of nodes acting as noisy nodes. In the following, we provide some results according to the simulation parameters summarized in the Table 1.

Table 1. Simulation parameters

Area	X = Y = 1000 m
AU radius (constant)	a = 5 m
BSs	10
Noise nodes	10, 20, 30, 40, 50
UAV altitude	60 m
D	200 bytes
P_t	20 dBm (100 mW)
Background noise power	−72 dBm
Path loss type	Two ray ground reflection
Antennas gains	Ge = Gr = 10 dBi
Carrier frequency	2.4 GHz

Figure 3a and b represents respectively the shortest path with highest RPR (optimal path) at 60 m of altitude with the presence of 20 and 50 noise nodes. Since the problem is new and there is no other similar algorithm in the literature, we compare the resulted paths to the shortest path using the well-known Dijkstra algorithm.

The set of paths illustrated in the Fig. 3c represents the near optimal paths calculated by our algorithm. As indicated in the Fig. 4, our proposed solution is able to provide other paths, called near optimal paths shorter than the optimal one but eventually with less important RPR. It is clear that even for the shortest near optimal path with a distance almost equal to the Dijkstra short path length, the RPR is even important. The relationship between path length and RPR is shown in Fig. 4. It proves the efficiency of our solution to find more than one optimal paths with different lengths and RPRs. More the path is longer more the RPR is important.



(a) noise nodes= 20 (b) noise nodes= 50 (c) set of near Optimal paths

Fig. 3. Optimal and near optimal paths, $h = 60\,\mathrm{m}$

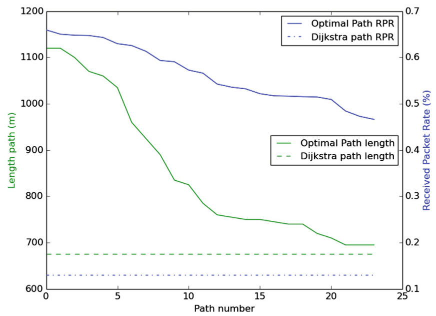


Fig. 4. Near Optimal paths with respective length and RPR

To understand more the impact of the noisy environment on the path length and quality, we varied the number of the nodes simulating the noisy environment, we fixed the drone altitude to 60 m and we measure the length of the optimal paths and their respective RPRs. If we increase the number of noise nodes, we gradually decrease the quality of the signal and subsequently the RPR and the path length decrease too as shown in the Figs. 5 and 6.

It's clear that bad quality of the signal and a noisy environment cause a low RPR; But how it can affect the path length? This can be explained as follows: with an excellent radio coverage, the drone tends to be attracted to the cells with higher SINR, which represent the BS locations. And as we go along with a bad or a noisy radio coverage, the drone tends to take the shortest path to its destination.

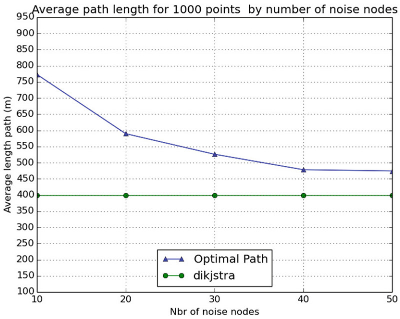


Fig. 5. Path lengths with different number of noise nodes, h = 60 m

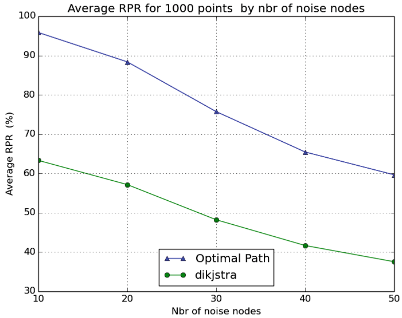


Fig. 6. Received packets rate with different number of noise nodes, h = 60 m

5 Conclusion

In this paper, we propose a path planning algorithm for UAV. Our approach doesn't only generate one single optimal solution but a number of other near optimal paths with a trade-off between length distance and probability of localization determined by the drone flight autonomy. Therefore, the operator who is in charge of tracking the drones for package delivery missions can choose the best path suited to the need of localization and tracking but also to the capability of the UAV in terms of energy autonomy. More precisely, if identification, localization and tracking is the main concern than he can choose the longer path which insures a high communication probability and if the UAV energy autonomy is a priority than the operator has the possibility to choose the suitable path length according to the battery duration.

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