Drone Package Delivery: A Heuristic approach for UAVs path planning and tracking

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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 benefit of UAVs include reduced costs and no warfighter risk. In fact UAVs use is increased by time, especially under the concept of the network-centric operation environment and under the concept of revolution in military affairs. 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 of fligh security and air traffic management which have to balance safety and public concerns against the potential economic benefit

By virtue of their small size, mini drones are difficult to be detected and to be tracked. 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 emphasized 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.
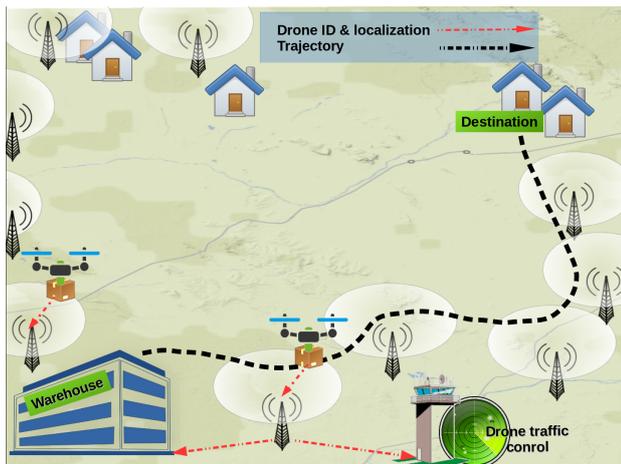
Figure 1. Drone package delivery

It is obvious that path planning is one of the most crucial tasks for mission definitio and manag emen t of the aircr aft and it will also be an importan t requiremen t for UAVs tha t has autonomous fligh capabilities [1]. Basicall y, an efficien t off-line path planning coul d help to ensure a permanen t localiza tion and tracking of the drone. Moreov er, the predetermined trajectory unable to avoid obstacles and eventual collisions with other drones, and also to optimize certain functionalities in certain environmen t. How ev er, mission na ture, ba ttery capacity , drone char acteristics and hov ering capabilities strongl y inf uence the pa th planning str ategy [2]. The oper ational problem tha t this w ork address is enabling the governmen t authorities in charg e of fligh saf ety to iden tify, loca te and to track drones. Usuall y the area is larg e and the detection and localiza tion time to fin the UAV is the critical par ameter tha t shoul d be minimized. To this end and in order to make this possible, we presen t in this paper a newl y approach based on the expl oita tion of the available wireless netw ork cov erage. This approach relies on a pow erful inter action, or collabor ation betw een the UAVs and the oper ators. Cooper ation in such environmen t implies tha t the drone periodicall y send its iden tific tion, localiza tion, speed and other inf orma tion to the remote oper ators through the available wireless netw orks. The sol ution we aim to presen t provide or inf orm of the optim um and the near optim um pa ths tha t the drone shoul d foll ow to ensure a reliable comm unica tion and high packet deliv ery rate depending on its ba ttery autonom y.

In our previous w ork [3], we form ula ted the problem as an Integer Linear Problem. Moreov er, we expressed in an anal ytic manner the packet loss rate of tracking messag es depending on the UAV loca tion and the wireless netw ork cov erage. By sol ving the ILP problem using CPLEX, we were being able to anal yze how the radio cov erage as well as the threshold d on the packet success rate, impact the number of possible sol utions

and the trajectory of the UAV. Unf ortuna tel y, due to the computa tional complexity the proposed approach was not able to provide a pa th planning solution for a larg e area. In addition, the packet success rate was computed by considering onl y the radio channel and without an y MAC la yer oper ations.

Our curren t investig ations focus on the complexity issue raised for larg er area size. For the drone pa th planning, a heuristic adaptiv e scheme based on Dijkstr a algorithm is presen ted to cope with the problem of scalability . The fligh pa th of drone is optimized in order to improv e its connectivity to the available terrestrial wireless netw ork and consequen tl y its localiza tion, iden tific tion and tracking. Moreov er, the sol ution is proposed to yiel d a simple but effectiv e and fast sol ution and tested under a more realistic scenario char acterized with a noisy environmen t.

2. State of the art

Path planning for kinema tic system issues has been widel y studied and has been addressed using di fferen t approaches and techniques. Thus, sev er al approaches exist for computing pa ths giv en some input variables of the environmen t. In gener al, the tw o most popu-lar techniques are deterministic, heuristic-based al go-rithms [4], [5], [6] and probabilistic, randomized al go-rithms [7] and [8]. The choice of the al gorithm to use depends on the type of problem to be sol ved. Although, the robotic bibliogr aph y on this subject is very rich, it's not the case for the UAV's one.

For the autonomous fligh of drones, pa th planning is one of the most crucial and importan t issues to sol ve. Now ada ys, the applica tion of UAV is extending from high- altitude fligh to very low-altitude, where the impact of the terr ain, the en vironmen t and the air traffic will be the key factors to be considered to avoid collisions [9]. How ev er, we do not aim to provide an exha ustiv e list but we will be limited to provide the most relev an t w ork rela ted to the pa th planning reg arding to the nature of the objectiv es, problems formaliza tion and resol ving methods.

The author in [10] presen ted a fr amew ork to compute the minim um cost cooper ativ e route betw een a heterog eneous packag e deliv ery team composed of a truck and micro drones. They abstr acted the problem on a gr aph and formula te the issue as a discrete optimal pa th planning problem. In the same context of heterog eneous teams, the authors in [11] presen ted a pa th planning problem involving an UAV and a ground vehicle for in tellig ence, surv eillance and reconnaissance missions. The addressed problem is similar to the ring-star problem and the hier archical ring netw ork problem.

On the other hand, the authors in [9] and [12] presen ted three dimensional pa th planning sol utions

for unmanned aerial vehicles. The firs solution is based on interfered fuid dynamic system, while the second approach uses linear progrmming where obstacle avoidance and target tracking are linearized to generate a linear progrmming model in a relative velocity space. Dealing with adversarial environmens, the authors in [13] and [14] presented solutions for unmanned aerial vehicles path planning in uncertain an adversarial environmen t in sight to reach a given targt, 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 predictive model control.

Another importan t work is [15], which contains concise summaries. It 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 [16] 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 flexibl and adaptive.

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

3. Path planning problem formulation

3.1. Problem statement and system description

In this paper, we are considering a package delivery service using UAVs. Basically, a UAV has to deliver a package from a depot or warehouse to a predetermined destination or consumer. The main objective of this paper is to provide an off-line path planning that aims to minimize the delivery delay with respect to the UAV's residual energy constraint while ensuring an optimum tracking of the UAV's at the operator side.

In this frame, the system is modeled as 2D area A without any obstacle. The projection of the fying 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 environmen t with the existence of a certain number of noise nodes $N_{oise} = \{N_{N1}, N_{N2}, ...N_{Nn}\}$ deployed within

A and uses the wireless infrastructure as an access network. We also consider that the drone has a limited fligh autonomy Υ and is 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 cells of the same dimension. This implies discrete position for the UAV, which then is supposed to be located in the center of the considered cell. 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 specifie Reception Packet Rate RPR. In this paper, the OMNeT++ 4.61 simulator and the INET framework were used to generate both the signal-to-interference-plus-noise ratio $SINR$ maps and the Received Packet Rate for all possible transitions in A.

Our goal is to determine a path or a set of paths that maximize 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, the drone generates a message of size d bits containing its identifiction, position and speed. The on-board wireless interface tries to send each generated message to the remote UAV monitoring and controlling system via the set BS while the jamming nodes attempt 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 even 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.

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, where the valuation of an arc is comprised between 0 and 1, indicating the reception packet rate (RPR) on that arc.

Finally, we defin c_{ij} the cost of using the arc going from cell c_i to cell c_j. The fow going that way is denoted by a binary variable, noted as x_{ij}, where

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

(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:

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

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 first two objectives for our drone path planning problem are reported as follows:

$$\text{minimize} \sum_{i \in A} \sum_{j \in A} c_{ij} x_{ij} \qquad (3)$$

and

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

where, as define earlier, c_{ij} is the cost of the arc going from cell c_i to cell c_j. In this paper, we consider c_{ij} as the amount of energy consumed by the drone on that arc,

The objective functions (3) and (4) represent respectively the minimization of the energy consumed by the drone and the maximization of the tracking probability between the start point O and the destination D. Basically, we should fin the shortest possible path, in terms of consumed energy, that passes through the cells with highest Received Packet Rate, see Fig 2.

In addition to the last two objectives, we also add a third objective that aims to minimize the tracking time loss of the drone, by avoiding passing through several adjacent cells with low RPR. For example, as illustrated in Fig 3, if we have to choose between the path a (0.9, 0.9, 0.9, 0.1, 0.1, 0.1) and the path b (0.9, 0.1, 0.9, 0.1, 0.9, 0.1) with the same length and the same average packet delivery ratio, than we have to privilege the solution b rather than a. The privilege of the solution b is motivated by the fact that we have fewer adjacent cells with low packet delivery probability. The main benefi of this choice is to have the communication rupture spaced out on the time rather than having a long time with no communications.

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 is obtained by taking the average of the two initial adjacent cells of the selected path. Thereafter, the subset is modifie by shifting it forward, excluding the first cell and including the next cell in K. This creates a new subset of numbers $\overline{K}$. 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 averages on a shifted window is interesting in the case when we use prediction
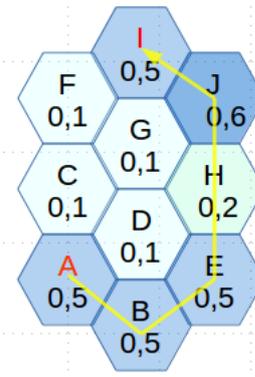

Figure 2. Example of a path from the origin A to the destination I where the shortest path with high packet delivery rate is (A, B, E, H, J, I)
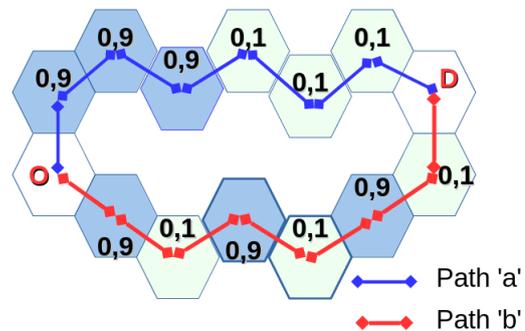

Figure 3. example of paths with the same cost

algorithms. Basically, we need to compute an average data based on the most recent results in order to create forecasts. Indeed, 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 $c_1, c_2, ...c_n$ forming the path K and $\overline{K} = \{\overline{K}_1; \overline{K}_2; ....\overline{K}_{n-1}\}$, where $\overline{K}_i = (RPR_i + RPR_{i+1})/2$.

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:

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

Thus, by applying the formulas 5 on the previous paths $a = \{0.9, 0.9, 0.9, 0.1, 0.1, 0.1\}$ and $b = \{0.9, 0.1, 0.9, 0.1, 0.9, 0.1\}$ we will get: $\overline{a} = \{0.9, 0.9, 0.5, 0.1, 0.1\}$ and $f(a) = 0.33$, and $\overline{b} = \{0.5, 0.5, 0.5, 0.5, 0.5\}$ and $f(b) = 0.5$. Since we need to maximize the function f, the path b will be selected.

Finally, in addition to the last objectives, we add a new constraint related to the UAV's maximal flight distance:

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

where δ is the maximum energy that the UAV could have.

3.3. Path computation

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

As introduced in our problem formulation section, our objectives are firs to minimize the traveling distance and to maximize the tracking probability between the start point the destination point. The firs objective correspond to the classical Dijkstra algorithm. On the other hand, for the second objective we are dealing with probabilities. We have to fin the shortest path where the product of the probabilities RPR_i of the visited cells that constitute a given path is maximized. Moreover, each time a cell is added to a path, the product of the probabilities decreases. In this case, our algorithm firs 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 vertexes.

In addition to 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 above function f for a better drone tracking result.

Algorithm 1 Optimal Path algorithm

Input:
  G ▷ The graph G
  RPR ▷ The Received Packet Rate map
  c_o ▷ The origin cell
  c_d ▷ The destination cell

1: **function** OPTIMAL PATH(G, RPR, c_o, c_d)
2:      **for** each cell $c_i \in G$ **do**
3:          $P[c_i] \leftarrow 0$
4:          $\Pi[c_i] \leftarrow nil$
5:      **end for**
6:      $P[c_o] \leftarrow 1$
7:      $F \leftarrow G$
8:      **while** $F \neq \varnothing$ **do**
9:          choose $c_i \leftarrow max\ P[c_i]$
10:        $F \leftarrow F - \{c_i\}$
11:        **for** each cell $c_j \in neighbors(c_i)$ **do**
12:            **if** $P[c_j] < P[c_i] * (RPR(c_j))$ **then**
13:              $P[c_j] \leftarrow P[c_i] * (RPR(c_j))$
14:              $\Pi[c_j] \leftarrow c_i$
15:            **end if**
16:      **end while**
17:      **return** $Path$
18: **end function**

Algorithm 2 Near Optimal Paths

Input:
  G, RPR, c_o, c_d
1: Path = Optimal Path(G, RPR, c_o, c_d)
2: **if** length(Path) $> \delta$ **then**
3:      **for** each cell $c_i \in Path$ **do**
4:          $RPR(c_i) \leftarrow \epsilon$
5:      **end for**
6:      Path = Optimal Path(G, RPR, c_o, c_d)
7: **end if**

3.4. Energy Consumption Model

In this section we estimate the energy consumed by each drone according to its characteristics.

The main challenge for the construction of rotary-wing drones is to maximize its autonomy for a given mass, while providing the power needed for propulsion and for the embedded instruments. It is therefore important to carefully manage the available energy and the path planning with each other to have the best overall. In fact, recent progress achieved on Lithium battery type allowed the electric flight to achieve a really interesting autonomy for entertainment or local missions, but still far from being effective for longer trips and missions.

In this paper, we consider a quad-copter which is a drone with four rotors at the ends of a cross. The four rotors provide the vertical force (Thrust) that allows the unit to rise. In fligh , the quad-copter may evolve following its roll, pitch and yaw axes and also in translation in all directions, fi 4. Basicall y, the dynamic model of quad-rotor can be seen as a system where the spatial evolution's are the outputs and the voltage of each engine are the inputs, fi 5. Motion is achiev ed by changing the rotation speed of one rotor or more. Thus, to control the roll of the UAV, it is sufficient to act on the rotational speeds of the motors 2 and 4. In the same way, the pitch of the UAV is controllable by acting on the motors 1 and 3.

Furthermore, maintaining a stable fligh requires an equilibrium and a balance of all forces acting upon a drone. Weight , lift , thrust and drag are the acting forces on a drone. These Forces are vector quantities having both a magnitude and a direction and consequen tly, the motion of the drone through the air depends on the relative magnitude and direction of these forces. A general derivation of the thrust force equation shows that the amount of thrust generated depends on the mass f ow through the rotors and the change in rotation speeds of the four propellers.

In fact, several methods exist in the literature allowing to have an order of magnitude of the power of a propeller , such as the blade elemen t theory (BET) and the Froude theory. Even if these methods can provide a more precise result, they are based on a certain number of coefficients which cannot be computed only after empirical tests, like Thrust Coefficient, Torque Coefficient, Power Coefficient, etc... In addition, the obtained coefficients are specifi to the tested propeller at a specifie rotation speed and cannot be used for other types of propellers. Basic drone manoeuvres include take-o ff, hovering, changing altitudes, and landing. This manoeuvre requires different rotors and propeller rotation speeds. To our knowledg e, the best method to approxima te drone power consum ption is to use formulas that connect power to rotor rotation speed, propeller diameter and pitch like the one proposed by Abbott , Young, Boucher , and Aguerre.

As illustrated in figur 4, $\Omega_1, \Omega_2, \Omega_3, \Omega_4$ are the rotation speed of the propellers; T_1, T_2, T_3, T_4 are the Forces generated by the propellers; and final y mg is the weight of the quadrotor;

In the following, the Boucher formula is used. In fact, the latest was used to compute the fligh autonom y and the power consum ption for a real quadcopter drone type of *Phantom 3 Advanced*. The results were very close to the ones presen ted by the manufacturer:

$$P_p = K * \left(\frac{Diam}{12}\right)^4 * \frac{Pitch}{12} * \left(\frac{N_t}{1000}\right)^3 \qquad (7)$$
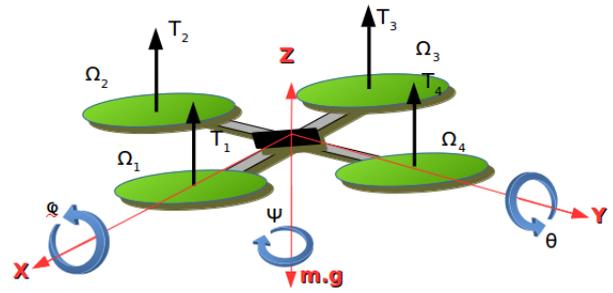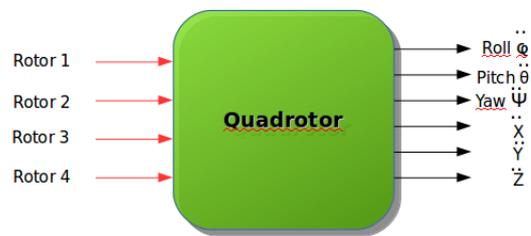

Figure 4. Dynamics involved in the quadcopter

Figure 5. Dynamic Model of quadrotor

with P_p in Watt, $Diam$ and $Pitch$ in inch, and N_t in tr/mn. K is an adjustmen t par ameter , which depends on the propeller type, (APC: 1.11, Graupner: 1.18, Zing er: 1.31, Top flite 1.31, etc..).

To link the aerodynamic properties of the propeller to the pow er and the engine speed, we will need three formulas:

- the pow er supplied by the propeller P_p in watts;

- the thrust of the propeller in Kg:

$$T_p = 4.9 * Diam^3 * Pitch * N_t^2 \qquad (8)$$

- and the speed of air passing through the propeller of in Km/h:
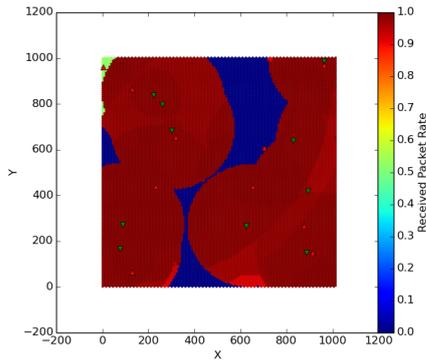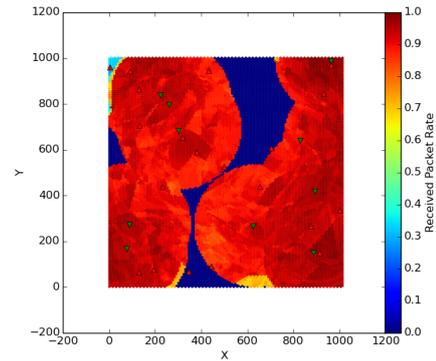
$$S_{air} = 60 * Pitch * N_t \qquad (9)$$

where $Diam$ is the propeller diameter in meter, $Pitch$ in meter and N_t is the number of thousands revolutions per minute (rpm). In addition to the last formulas, we also need to compute:

- The pitch:

$$Pitch = \pi * Diam * Tang(\alpha), \qquad (10)$$

- The pow er consumed by the propeller

$$P_C = P_p * C_e * R_e \qquad (11)$$

Figure 6. RPR with 10 noise nodes at h=60m

Figure 7. RPR with 20 noise nodes at h=60m

- The drone fligh endurance can be expressed as in [17], and by ignoring the consumed power at the idle state we get:

$$F_{Endurance} = B_C/P_C \qquad (12)$$

where R_e and C_e are the rotor efficiency and the controller efficiency, generally fixe at 75% and 98% respectively, α is the attack angle of the propeller, B_C the Capacity of the battery, P_C is the Power consumed by the propeller.

Since the power is the rate of doing work, it is equivalent to the amount of energy consumed per unit time. If work is done quickly, more power is used and if work is done slowly, very little power is used. Thus, the energy consumed by the propellers to ensure the thrust forces required for the fligh can be expressed as:

$$E_{Mvmt} = \int P_C(t)dt \qquad (13)$$

Finally, using the last equation we can derive the energy c_{ij} required for a drone to fy from cell i to cell j.

4. Results

In this section, we evaluate our proposed algorithm. Two main objectives were fixed firs, to ensure a maximum tracking of the drone along with its fligh while the second one was to minimize the energy required to travel along the path in accordance with the drone fligh autonomy and the capacity of its battery. In addition to the last objectives we also consider a third objective which is to minimize the number of adjacent cells with low RPR.

In this case, we assess our proposed the algorithm in case of different scenarios. We start, using the OMNET++ simulator, by generating 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
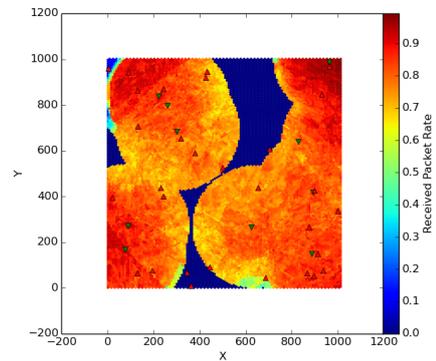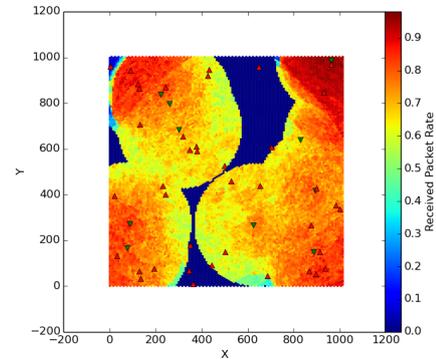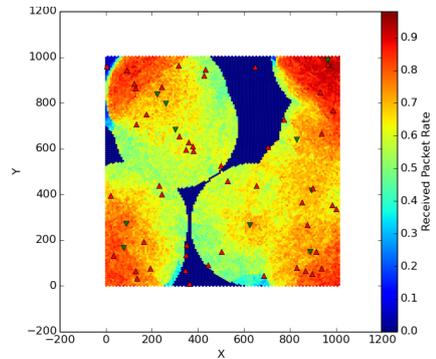

Figure 8. RPR with 30 noise nodes at h=60m

Figure 9. RPR with 40 noise nodes at h=60m

Figure 10. RPR with 50 noise nodes at h=60m

Table 1. Simulation parameters

Area	X = Y = 1000 m
Cell radius (constant)	a = 5m
BSs	10
Noise nodes	10, 20, 30, 40, 50
UAV altitude	60m
D	200 bytes
P_t	20 dBm (100 mW)
Background noise power	-72dBm
Path loss type	Two Ray Ground Ref.
Antennas Gains	Ge = Gr = 10 dBi
Carrier Frequency	2.4 GHz

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.

For an ideal environment with no interference and noise, the drone shall fligh closer from the BS station to ensure a permanent tracking and localization. However, this is not the case in reality. Thus, the figure 6, 7, 8, 9 and 10 illustrates the received packet rate in a noisy environment. It shows clearly that more noise nodes (red dots) are present more we have low *RPR*. We can also notice that for the received packet rate, the results are better in the edge of the area, this even for the same *SINR*. This can be explained by the fact that these sub-areas are less subject to physical radio errors because of the position of the receiver who will experience fewer physical collisions and busy channel state.

Figures 11a and 11b represent respectively the shortest path with highest *RPR* at 60m of altitude with the presence of 20 and 50 noise nodes. We compared our algorithm to the shortest path using the well-known Dijkstra algorithm since to the best of our knowledge there is no other work similar to our work in the literature. We also illustrate, in figure 11c, the set of paths that we generated by our algorithm to compute the optimal path and optimizing our third objective.

To understand the impact of increasing the interferences on the path length and *RPR*, we varied the number of the nodes simulating the noisy environment. We set the drone altitude to 60m and we measure the length of the optimal paths and their respective *RPRs*. As we can observe in figur 12 and 13, if we increase the number of noise nodes, we gradually decrease the quality of the signal and subsequently the *RPR* and the path length also decrease. In fact, in case of good radio coverage, the drone tends to be attracted to the cells with higher *SINR*, which represent the BS locations. On the other hand, when we degrade the *SINR*, the drone tends to take the shortest path to its destination.

In order to evaluate the efficiency of our solution, we tested the proposed algorithm for a thousand random destination points in an environment with low signal
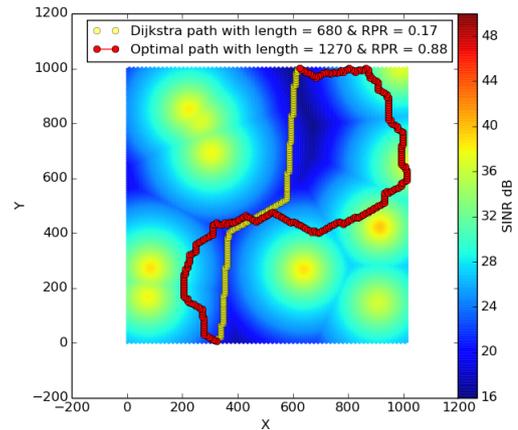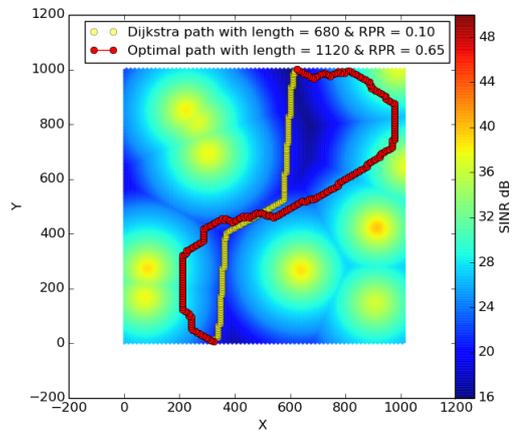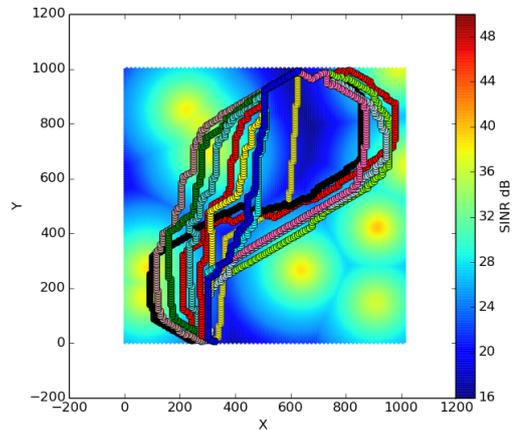

(a) noise nodes= 20

(b) noise nodes= 50

(c) set of near Optimal paths

Figure 11. Optimal and near optimal paths, h=60m

coverage by setting the number of noise nodes to 50 nodes and the drone altitude to 60 m. We compare for all these points the resulted paths with Dijkstra's short path in terms of length and *RPR*. The comparisons are illustrated in the figure 14 and 15. Indeed, the gap is important in term of *RPR*. For the computed paths, the
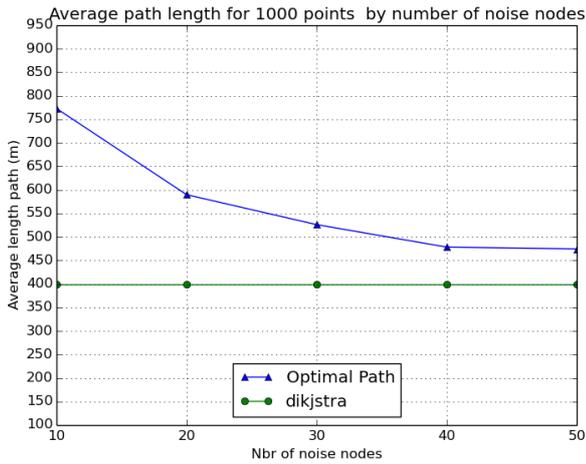
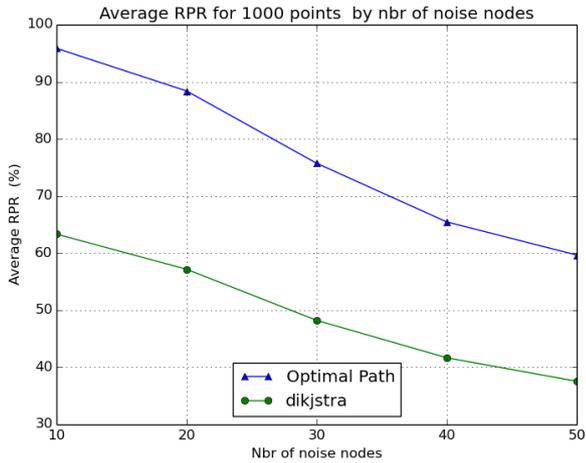**Figure 12.** Path lengths with different number of noise nodes, h=60m

Figure 13. Received Packets Rate with different number of noise nodes, h=60m

Figure 14. Difference between optimal and Dijkstra path length, nbr paths = 1000
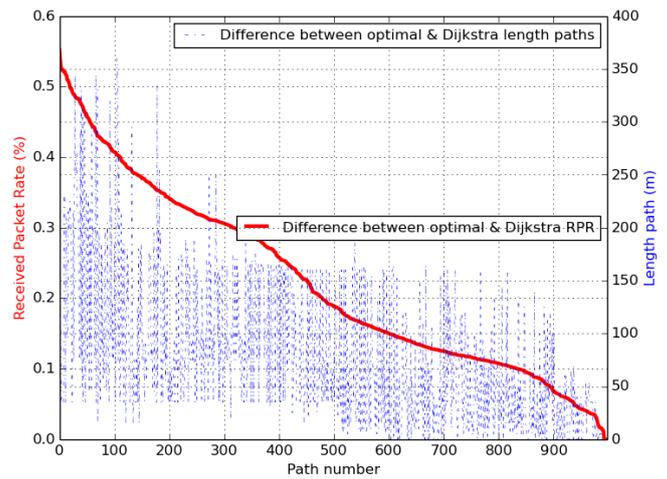
Figure 15. Difference between optimal and Dijkstra RPR, nbr paths = 1000

difference varies from 0.15 to 0.55 even for a path with length closer to Dijkstra short path length.

In figure 16 and 17 we illustrate the impact of the drone speed on the packet received rate and the consumed energy. The results were obtained using the Omnet++ simulator. We vary the drone speed from $10\,m/s$ to $18\,m/s$, which are the most common drone speeds, and we compare the simulator results to the theoretical ones. We can notice that the RPR remains almost the same for drone speed varying from $10\,m/s$ to $13\,m/s$. However, this rate decrease once the drones exceed the speed of $14\,m/s$. Almost 10% of the tracking capability is lost due to the drone's speed. In addition to the same payload, a drone will consume about a double in terms of energy when increasing the speed from $10\,m/s$ to $18\,m/s$. This consumption is due to the increased rotational speed of the propellers.
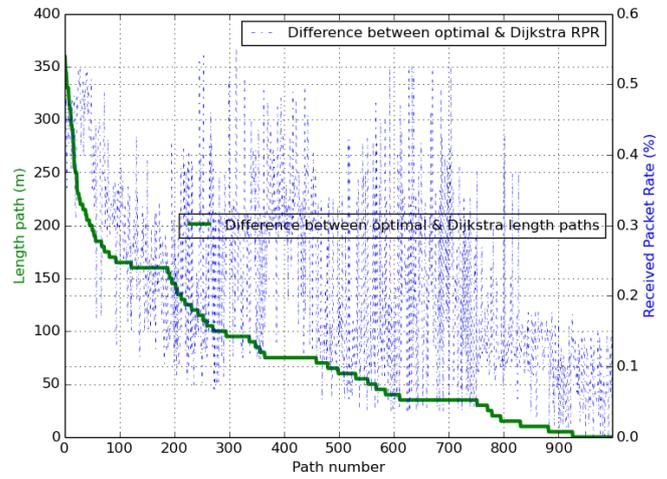
Finally, the figur 18 summarizes and illustrates clearly the advantage of our proposal in terms of drone localization and tracking. In fact for two drones starting from the same point and flying to the same destination at the same altitude, the capacity of tracking the drone at the controller side is different. As we can see, the tracking capability of the drone following the path generated by our algorithm reaches 88%, while for the one following the Dijkstra shortest path the tracking capability is about 14%.

5. Conclusion

In this paper, we propose a path planning algorithm for UAV. Our approach doesn't only generate one single
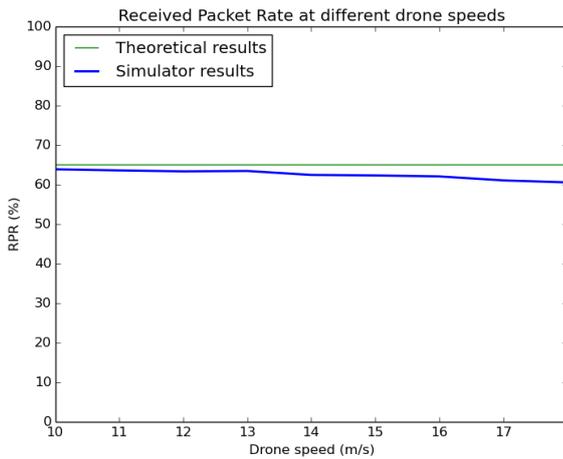
Figure 16. Received Packet Rate at different drone speeds, noise nodes = 50

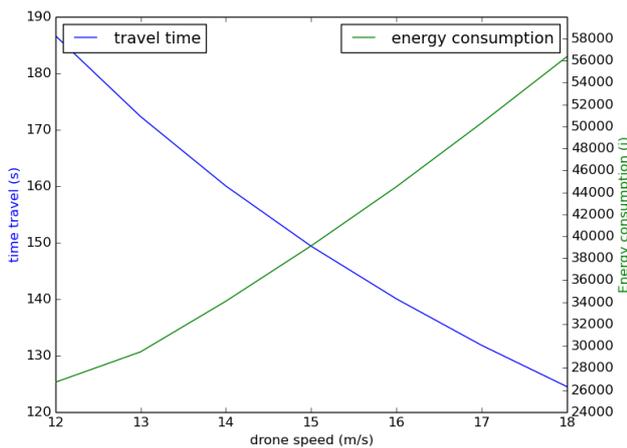**Figure 18.** Optimal path Vs Dijkstra shortest path tracking

Figure 17. Energy consumption at different drone speeds

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 fligh autonomy. Therefore, we 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 identific tion, localization and tracking are the main concerns than we can choose the longer path which insures a high communication probability and if the UAV energy autonomy is a priority than the we need to choose the suitable path length according to the battery duration.
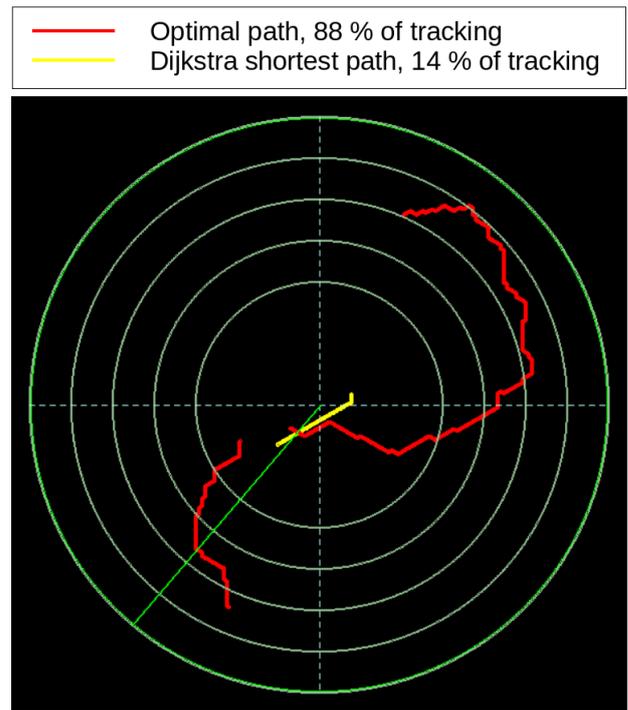
Torquay, Devon, UK. Website:

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