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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’s 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 environments.

Keywords: UAV, Tracking, WSN, SINR, RPR, Noise, heuristic

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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 network-centric operation environments 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, Walmart, 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 flight 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 threa tened by the use of these flying machines. Through this resolution, it is considered that regardless of their sizes, the question of iden tifying 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.

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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 have autonomous flight capabilities [1]. Basicall y, an efficient off-line path planning could help to ensure a permanent localization and tracking of the drone. Moreover, the predetermined trajectory unable to avoid obstacles and eventual collisions with other drones, and also to optimize certain functionalities in certain environment. However, mission nature, battery capacity, drone characteristics and hovering capabilities strongly influence the path planning strategy [2]. 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 its 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 [3], 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 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 area size. For the drone path planning, a heuristic adaptive scheme based on Dijkstra’s 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 kinematic system issues has been widely studied and has been addressed using different approaches and techniques. Thus, several approaches exist for computing paths given some input variables of the environment. In general, the two most popular techniques are deterministic, heuristic-based algorithms [4], [5], [6] and probabilistic, randomized algorithms [7] and [8]. 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 and the environment and the air traffic will be the key factors to be considered to avoid collisions [9]. However, we do not aim to provide an exhaustive list but we will be limited to provide the most relevant work related to the path planning regarding to the nature of the objectives, problems formalization, and solving methods.

The author in [10] presented a framework to compute the minimum cost cooperative route between a heterogenous package delivery team composed of a truck and micro drones. They abstracted the problem on a graph and formulated the issue as a discrete optimal path planning problem. In the same context of heterogenous teams, the authors in [11] 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 [9] and [12] presented three-dimensional path planning solutions.
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 flying area is represented by a rectangle with a length of $x_{\text{max}}$ and a width of $y_{\text{max}}$. We suppose that the drone $D_{\text{one}}$ 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 partial or noisy environment with the existence of a certain number of noise nodes $N_{\text{noise}} = \{N_{N1}, N_{N2}, ..., N_{Nn}\}$ deployed within $A$ and uses the wireless infrastructure as an access network. We also consider that the drone has a limited flight autonomy $Y$ 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 is supposed to be located in the center of the considered cell. The transition cost between two neighbor cells depicts a certain reliability of communication, i.e., a certain probability that the communication is not interrupted and has a specific 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 identification, 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 define $c_{ij}$ the cost of using the arc going from cell $i$ to cell $j$. The flow going that way is denoted by a binary variable, noted as $x_{ij}$, where

$$x_{ij} \in \{1, 0\}, \text{ if the drone moves from cell } i \text{ to cell } j$$

$$0, \text{ otherwise.}$$

The cost of a path represents its reliability and it is set to the product of the $RPR$ of each cell forming the resultant path:
Path cost = \prod_{i=1}^{n} \prod_{j=1}^{n} \text{RPR}_{ij} \cdot x_{ij} \quad (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 represented as follows:

\[
\text{minimize } \sum_{i \in A} \sum_{j \in A} c_{ij} x_{ij} \quad (3)
\]

and

\[
\text{maximize } \prod_{i=1}^{n} \prod_{j=1}^{n} (\text{RPR}_{ij}) x_{ij} \quad (4)
\]

where, as defined 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 energy consumed between the start point \(O\) and the destination \(D\). Basically, we should find 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) and the path \(b\) (0.9, 0.1, 0.9, 0.1, 0.9) 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 benefit of this choice is to have the communication rupture spaced out on the time rather than having a long time with no communication.

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 modified 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 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 \(K = \{\text{RPR}_1; \text{RPR}_2; \ldots; \text{RPR}_n\}\) with \(\text{RPR}_1, \text{RPR}_2, \ldots, \text{RPR}_n\) are the Receiv ed Packet Rate at the cells \(c_1, c_2, \ldots, c_n\) forming the path \(K\) and \(\overline{K} = [\overline{K}_1; \overline{K}_2; \ldots; \overline{K}_{n-1}]\), where \(\overline{K}_i = (\text{RPR}_i + \text{RPR}_{i+1})/2\).

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:

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

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: \(\overline{a} = [0.9, 0.9, 0.9, 0.5, 0.1, 0.1]\) and \(f(a) = 0.33\), and \(\overline{b} = [0.5, 0.5, 0.5, 0.5, 0.5, 0.5]\) and \(f(b) = 0.5\). Since we need to maximize the function \(f\), the path \(b\) will be selected.
Finall y, in addition to the last objectiv es, we add
a new constrain t related to the UAV’s maximal fligh
distance:
\[ \sum_{i \in E} \sum_{j \in E} c_{ij} x_{ij} < \delta, \]  
(6)

where \( \delta \) is the maximum energy that the UAV could have.

3.3. Path computation

Different shortest path algorithms exist like A*,
Dijkstra, Bellman-F ord 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 find the shortest path
with high communica tion reliability and high packet
reception.

As introduced in our problem formulation section,
our objectiv es are first to minimize the traveling
distance and to maximize the tracking probability
between the start point and the destina tion point. The firsts
objectiv e correspond to the classical Dijkstra algorithm.
On the other hand, for the second objective we are
dealing with probabilities. We have to find the shortest
path where the product of the probabilities \( RPR \) of the
visited cells that constitute a given path is maximized.
More over, 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 \( t \), we build step by step
a set of \( P \) marked cells. For each marked cell \( c_i \),
the cost is equal to the product of the Receiv ed 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 \( c_i \). We repeat until exha usion unmatched 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
destina tion with the respect of the drone autonom y. To
this end, if the length of the optimal path is greater than
the drone autonom y 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 \( \epsilon \), where \( \epsilon \) 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:**
- \( G \rightarrow \) The graph \( G \)
- \( RPR \rightarrow \) The Receiv ed Packet Rate map
- \( c_o \rightarrow \) The origin cell
- \( c_d \rightarrow \) The destination cell

\begin{algorithm}
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 \( F \neq \emptyset \) do
9: choose \( c_i \leftarrow \text{max}\{P[c_i]\} \)
10: \( F \leftarrow F - \{c_i\} \)
11: for each cell \( c_i \in \text{neighbors}(c_i) \) do
12: if \( P[c_j] < P[c_i] \times (RPR(c_i)) \) then
13: \( P[c_j] \leftarrow P[c_i] \times (RPR(c_i)) \)
14: \( \Pi[c_j] \leftarrow c_i \)
15: end if
16: end while
17: return Path
18: end function
\end{algorithm}

Algorithm 2 Near Optimal Paths

**Input:**
- \( G \), \( RPR \), \( c_o \), \( c_d \)

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

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 instrumen ts. It is therefor e
important to carefully manag e 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 fligh to achieve a
real y interesting autonom y for entertainmen t 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 flight, the quad-copter may evolve following its roll, pitch and yaw axes and also in translation in all directions, Fig 4. Basicalliy, 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, Fig 5. Motion is achieved 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 flight 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 consequently, 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 flow 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 element 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 specific to the tested propeller at a specific rotation speed and cannot be used for other types of propellers. Basic drone manoeuvres include take-off, hovering, changing altitudes, and landing. This manoeuvre requires different rotors and propeller rotation speeds. To our knowledge, the best method to approximate drone power consumption 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 figure 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 finally $mg$ is the weight of the quadrotor.

In the following, the Boucher formula is used. In fact, the latest was used to compute the flight altitude and the power consumption for a real quadcopter drone type of Phantom 3 Advanced. The results were very close to the ones presented by the manufacturer:

$$P_p = K \left(\frac{Diam}{12}\right)^4 \cdot \frac{Pitch}{12} \cdot \left(\frac{N_t}{1000}\right)^3$$  \hspace{1cm} (7)

with $P_p$ in Watt, $Diam$ and $Pitch$ in inch, and $N_t$ in $tr/min$. $K$ is an adjustment parameter which depends on the propeller type, (APC: 1.11, Graupner: 1.18, Zinger: 1.31, Top flight 1.31, etc.).

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

- the power supplied by the propeller $P_p$ in watts;
- the thrust of the propeller in Kg:

$$T_p = 4.9 \cdot Diam^3 \cdot Pitch \cdot N_t^2$$  \hspace{1cm} (8)

- and the speed of air passing through the propeller in Km/h:

$$S_{air} = 60 \cdot Pitch \cdot N_t$$  \hspace{1cm} (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:

$$Pitch = \pi \cdot Diam \cdot Tang(\alpha)$$  \hspace{1cm} (10)

- The power consumed by the propeller

$$P_C = P_p \cdot C_e \cdot R_e$$  \hspace{1cm} (11)
The drone flight endurance can be expressed as in [17], and by ignoring the consumed power at the idle state we get:

\[ F_{\text{Endurance}} = \frac{B_C}{P_C} \]  

(12)

where \( R_e \) and \( C_e \) are the rotor efficiency and the controller efficiency, generally fixed at 75% and 98% respectively, \( \alpha \) 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 flight can be expressed as:

\[ E_{\text{Mvmt}} = \int P_C(t) dt \]  

(13)

Finally, using the last equation we can derive the energy \( e_{ij} \) required for a drone to fly from cell \( i \) to cell \( j \).

4. Results

In this section, we evaluate our proposed algorithm. Two main objectives were fixed first, to ensure a maximum tracking of the drone along with its flight while the second one was to minimize the energy required to travel along the path in accordance with the drone flight 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 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...
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 fly closer from the BS station to ensure a permanent tracking and localization. However, this is not the case in reality. Thus, the figures 6, 7, 8, 9 and 10 illustrate 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 interference 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 figures 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 coverage by setting the number of noise nodes to 50 nodes and the drone altitude to 60m. We compare for all these points the resulted paths with Dijkstra’s shortest path in terms of length and RPR. The comparisons are illustrated in the figures 14 and 15. Indeed, the gap is important in term of RPR. For the computed paths, the

Table 1. Simulation parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Area</td>
<td>X = Y = 1000 m</td>
</tr>
<tr>
<td>Cell radius (constant)</td>
<td>a = 5m</td>
</tr>
<tr>
<td>BSs</td>
<td>10</td>
</tr>
<tr>
<td>Noise nodes</td>
<td>10, 20, 30, 40, 50</td>
</tr>
<tr>
<td>UAV altitude</td>
<td>60m</td>
</tr>
<tr>
<td>D</td>
<td>200 bytes</td>
</tr>
<tr>
<td>( P_t )</td>
<td>20 dBm (100 mW)</td>
</tr>
<tr>
<td>Background noise power</td>
<td>-72dBm</td>
</tr>
<tr>
<td>Path loss type</td>
<td>Two Ray Ground Ref.</td>
</tr>
<tr>
<td>Antennas Gains</td>
<td>Ge = Gr = 10 dBi</td>
</tr>
<tr>
<td>Carrier Frequency</td>
<td>2.4 GHz</td>
</tr>
</tbody>
</table>
difference varies from 0.15 to 0.55 even for a path with length closer to Dijkstra a 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.

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

Finally, the figure 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...
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, 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 identification, localization and tracking are the main concerns then 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.

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