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UAV-based Data Gathering using An Artificial Potential Fields Approach

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Abstract—The recent advances in wireless sensors and Unmanned Aerial Vehicles have created new opportunities for environmental control and low cost aerial data gathering. In this paper, we propose to use an Unmanned Aerial Vehicle (UAV) for data gathering. Basically, we have proposed a method for UAV path planning based on virtual forces and potential fields. In addition, and more importantly, we present a new approach to compute the attractive forces of the potential field.

I. INTRODUCTION

The latest technological advances in wireless communications have allowed the development of wireless sensors with low energy consumption. These small devices are interconnected to form wireless sensor networks and are then deployed in an area of interest to handle specific tasks. These networks are useful in many fields such as: military, environmental, industrial and medical applications[2] [4]. Recent progress has led to the development of increasingly efficient sensors that can now handle increasingly complex data. The expected contribution of these elements makes it possible to envisage autonomy and a direct interaction with the environment thus offering the users a set of increasingly complex actions / reactions. The richer this interaction is, the more relevant the services to the users are. This type of sensor, however, brings their share of constraints, mainly due to hardware limitations as well as the types of information processed.

One of the consequences of the proliferation of wireless sensors is the development of flying equipment (also called drones or UAVs) at low cost and which can be used for a multitude of civilian or military applications. This new type of wireless sensor can be used in a variety of applications such as vehicle tracking, traffic management, fire detection, and assistance of crisis response teams [18] [15] [1]. These mobile wireless sensors are able to fly autonomously at different altitudes and are generally equipped with units to monitor the environment and communicate to exchange data with other drones, ground sensors or even central stations. Among the possible applications are the collection and dissemination of data in environments that are difficult to access or hostile. Indeed, one or more drones can be used as a mobile data collection sink to navigate an area where wireless sensors are

already deployed. In this case, the objective of the drone(s) is to collect information in an efficient and coordinated manner [7] [8].

UAV path Planning has been used (combined) with many other methods such as Genetic Algorithms [13], A* Algorithms [12] and the Artificial Potential Field (APF) [16]. The APF method is commonly used in path planning because of its concise mathematical description and the suitability for the real time control [14] [6].

In this paper, we are interested in the use of a potential field method for data collection in wireless sensor networks. We follow on from the idea proposed by [16]. Indeed, in this approach they use a robot that is in charge of collecting WSN data. Each sensor is a source of an attractive force that attracts the robot. The robot will then have to move towards the node that emits the strongest signal (i.e., the sensor node containing the most data). The aim of our work is to collect the maximum amount of data while limiting the energy consumption of the drone (its flight time).

The remainder of this paper is organized as follows. Section II shows a state of the art on the different studies already proposed for the use of the potential field method for UAV guidance. Sections III and IV describe the system and the platform proposed for UAV data gathering. Tests and results are reported in Section V. Finally, Section VI concludes this paper.

II. THE STATE OF THE ART

The artificial potential field (APF) for robot obstacle avoidance was first used by Khatib [11]. Briefly, this method consists in providing the workspace with an artificial potential field, in which the obstacles are represented by repulsive forces that push the robot back and prevent it from colliding with these obstacles. While the destination point is modeled by an attractive force that helps the UAV to reach the goal. The state of the art for UAV path planning using APF presents different uses of this method [3].

Target tracking is one of the application uses of the APF method. These approaches are designed to find a known number of targets that are in motion in a workspace. In [5]

the authors present a system to track a moving target using a swarm of UAVs under the influence of an artificial potential field. In their approach, they choose one UAV as the leader of the group, this leader being endowed with virtual attractive force to keep the swarm together. Each member of the group has repulsive forces to prevent from colliding together. The swarm of UAVs is under the influence of the moving target which is endowed with an attractive force to help the leader to reach the target position. [19] presented a dynamic target tracking and obstacle avoidance system using a drone. This system is based on Potential Fields and it is extended to take into account not only the relative position of the target but also to modify the velocity of the UAV so that it will be able to pursue it.

The second use cases of potential fields are to help the robots (or UAVs) to reach a set of goal locations. In [14] the authors use the method of potential fields for the path planning of their drone. They update the method by an additional control force that helps the UAV get out from a local minimum. At first, the authors bring together in one block obstacles that are geographically close to one another to avoid the drone getting blocked between them. In a second step, they define virtual points equipped with attractive forces that help the UAV to avoid local minima points. In [12] the authors present an autonomous navigation system for UAVs. Their method is based on a combination of virtual potential fields and the A* algorithm. Virtual forces are used to set up the environment (define obstacles and goals) while the A* algorithm is used to optimize the path. Thus, they study the performances of their different algorithms (the hierarchical A* 3D Algorithm, the A* 3D and the receding Horizon A* 3D) in terms of processing time and distance traveled by the UAV. Another study [6] presents a UAV path planning method using an artificial potential field updated by optimal control theory. They use an improved APF method enhanced by introducing additional control forces, based on performance constraints (the speed and acceleration), the space constraint (the UAV needs to avoid the obstacles) the dynamic constraints (the relation between the force, the acceleration, the speed and the position) and the boundary condition (the path is represented by a starting point and a target point). Therefore, the constrained optimization problem is translated into an unconstrained optimization problem.

Finally, the APF method can be used to explore an area in order to map the environment. Another contribution [10] presents a cooperative research algorithm where drones explore the environment to search for several unknown targets while avoiding the obstacles. They aim to minimize the searching time. The authors in [18] present the different parameters to be taken into account when using potential fields for search and rescue operations. Their study is mainly based on time, i.e., they aim to reduce the time of discovery of a target (of a victim in a natural disaster for example). In a separate study [16] propose a potential field approach for collecting data from sensor networks using mobile robots. They consider a capture field consisting of m sensor nodes and a robot

R whose function is to circulate in the workspace in order to collect the captured data. The authors consider that each sensor node is a source of an attractive potential function, which leads to choosing the radial basis function (RBFs) centered on each sensor node, this choice is motivated by the possibility to determine the region of influence of each of the forces. The cost function that the authors use is based on the amount of data harvested; specifically, the robot goes to the nodes with the least available space. When the robot is in the communication space of a node, the available space is equal to the capacity of the node from which the space occupied by the captured data is deduced, adding to this the amount of data transferred to the robot. On the other hand, when the robot is far from a sensor node, the remaining space is equal to the initial space minus the space occupied by the sensed data. Once the forces have been calculated, the direction vector to be followed by the robot is obtained by adding all the vectors to the same vector of the strongest attractive force

III. PROBLEM DEFINITION

In the following, we consider a drone D , and a set of m sensors $N = (s_1, s_2, \dots, s_m)$ deployed within a sensing area A . In addition, we assume that there is no obstacles in the considered area. The drone is represented by its coordinates $q_d = (x_d, y_d, z_d)$. We do consider that the sensor nodes are on the ground, each node is represented by its coordinates on a 3D plane $s_i = (x_i, y_i, z_i)$, in our case, the coordinate of the 3rd dimension of all the nodes is equal to "0".

Each sensor node has several sensors (temperature, humidity, etc.) and is able to communicate with the other sensor nodes as well as with the drone through a wireless communication device with a communication range r_i . The sensor nodes have a limited storage capacity denoted as $C_i : \forall i \in m$. We consider that each sensor is able to capture the environmental data with a capture frequency denoted as $g_i : \forall i \in m$ (different frequencies for each node of the network). Thus, the amount of data collected by a sensor node at a time t is represented as $d_i(t) = g_i * t$.

As introduced earlier, in this paper we extend the work proposed by Pereira and al. Thus, as in [16], in this work we aim to collect as much data as possible while minimizing both the time needed to collect this data and the drone's traveling time. To achieve this goal, our UAV will have to go towards the region presenting the maximum data to harvest or the areas that contain the nodes having the least available storage space. The remaining space c_i for each sensor node is estimated with respect to the data transfer frequency h_i as well as the distance between the sensor nodes and the drone as depicted in the following:

$$c_i(t) = \begin{cases} C_i - d_i(t) + h_i * t & \text{for } \|q_d - q_i\| < r_d \\ C_i - d_i(t) & \text{otherwise} \end{cases} \quad (1)$$

Thus, the amount of data stored by each sensor node is then equal to the capacity of this node from which we subtract the

remaining storage space. The following formula summarizes this property:

$$D_i = [C_i - c_i], 1 \leq i \leq m \quad (2)$$

As in [16], we use potential fields to direct the drone. We considered that we have only attractive forces, and the drone will be attracted by the point that emits the greatest force of attraction. However, unlike [16], in this case, we do not consider that the sensor nodes are the sources of attractive forces but all possible points within the sensing area A . For seek of simplicity, we discretized this space into small hexagonal cells, and the center of each cell is considered as being a possible position of the drone. In this case, the center of the cell is considered as a possible the source of an attractive force.

According to the last considerations, each point of the area A is than a possible destination of the drone. If the drone is placed on this point, we have to compute the amount of data that could be collected by the drone. In this paper, we assume that the amount of data available at each cell is equal to the sum of data available at each sensor located at a maximum range of r_d from that cell. Formally, the amount of potentially harvested data in each cell is computed by the following equation:

$$Q_{data}(k) = \sum_{j \in V_k} D_j \quad (3)$$

where V_k is the set of neighboring cells of cell k and D_j is the amount of data present in each cell.

IV. POTENTIAL FUNCTIONS

As defined previously, the Virtual Potential Fields (VPF) method consists of an artificial potential field that models the workspace. The obstacles are modeled by repulsive forces while the goal(s) is represented by attractive force. In this paper, we consider that our workspace is represented by a potential function where the drone is attracted by the cells containing the maximum amount of data. We make use of the Radial Basis Function [17] defined for each cell of the capture field. With this feature, we can manage the intensity of the strength of each cell and its radius of influence. The function used is of the form:

$$\phi_k(q_d) = \alpha_k e^{-\frac{1}{2P_k^2} \|q_d - q_k\|^2} \quad (4)$$

where, k denote the k^{th} hexagonal cell. α_k is the maximum amplitude of the function. P_k is the basis radius. q_d refer to the drone's position. q_k are the coordinates of the center point of the hexagons.

In this case, we can define the gradient of the function as following:

$$\nabla \phi_k(q_d) = -\alpha_k \frac{\|q_d - q_k\|}{P_k^2} e^{-\frac{1}{2P_k^2} \|q_d - q_k\|^2} \quad (5)$$

The basis radius of this function must be defined so that the area with the most amount of data has the largest basis radius and areas with less data have a smaller basis radius; the

computation of the basis radius of each zone P_k is shown by the following equation:

$$P_k = \varepsilon[Q_{data}(k)] \quad (6)$$

In addition, the amplitude of the function must also be proportional to the amount of data present in the cell, and therefore proportional to the base radius. For this, as in [16], we have used a parameter b that links these two parameters (α_k and P_k) ad following:

$$\alpha_i = p_i^b \quad (7)$$

As we can see, as the amount of data increases, the basis radius and the magnitude of the function increase, which increases the force of attraction on the drone.

After computing the strength of each cell, the drone must then move to the area that has the largest basis radius (the greatest force of attraction). It will have to follow a vector v :

$$v = \max(\nabla \phi_i(q_d)) \quad (8)$$

Finally, by following the vector with the maximal force, the drone harvests the data that is on its way to the destination point. The quantity of data collected at a time t is equal to the sum of the data found on the path of the drone.

V. TEST AND RESULTS

In this section, we evaluate the performance of our approach. Our aim is to collect the maximum amount of data while minimizing both the time needed to collect this data and the drone's traveling time. The first step is to divide the network into hexagonal cells, as shown in Figure 1. The second step is to define and compute the potential functions of each cell and, finally, that the drone follows the greatest force.

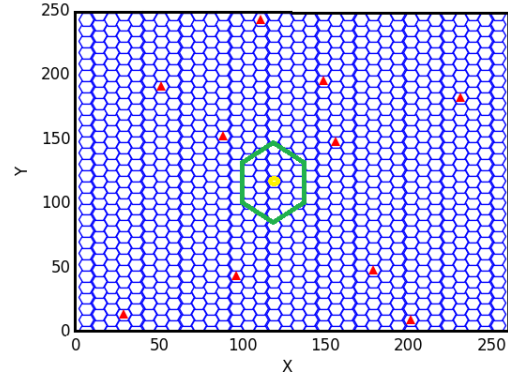


Fig. 1: Representation of the division of the sensing area into hexagonal cells

We have conducted some tests, considering an area of 250m x 250m which we divided into a set of hexagonal cells of 34x29 cells. We deployed sensors using the Random Poisson Process over the sensing area. The drone was initially positioned at coordinate (0.0,0.0). Finally, we consider 50 sensor nodes randomly deployed in A .

TABLE I: Characteristics of CC2420

parameter	Value
Communication Range	20 m
Battery Capacity	1000 mAh
Voltage	3.3V
Tx_Current	17.4mA
Rx_Current	18.4mA
Data Packet Length	26 Bytes
Buffer size	1000kbyte

We consider that all the sensor nodes have the same communication range, the same initial energy (battery capacity) and the same initial storage capacities. Regarding the energy consumption model, we used the energy values of the CC2420 family [9]. Table I illustrate the characteristics of the considered sensors.

In order to evaluate the performances of our approach, we compare our results with the performances achieved using the approach proposed by Pereira et al. in [16]. We computed the amount of data collected by the drone when using each of the two methods. Figure 2 shows the amount of data collected over time.

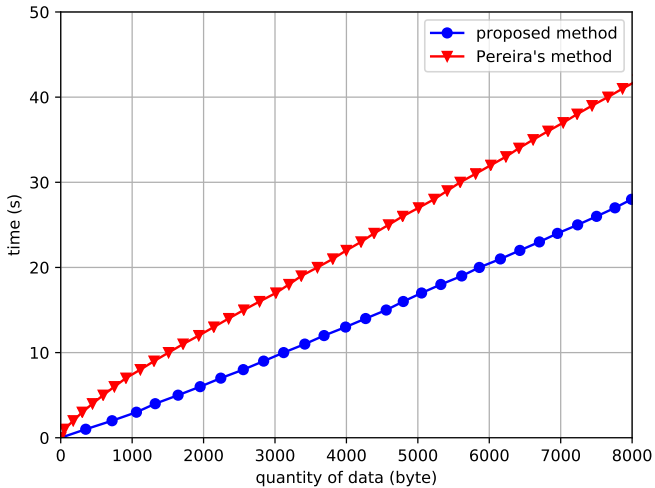


Fig. 2: Time Versus Amount of Data

We note that our method offers better results than Pereira’s method in terms of data collection time. Over a time interval of 20 seconds, for example, we find that when we use Pereira’s method, the amount of data collected is equal to 3500 Bytes while in the same using our approach we were able to harvest 5900 Bytes. This is due to the fact that the drone is moving towards areas where we can collect the data of more than one sensor node, whereas with the Pereira method, the drone is moving towards a sensor node and collects only that node’s data.

In figure 3, we plot the amount of data collected versus the distance traveled by the drone for both our approach and Pereira’s approach. We can clearly see that when the drone travels small distances, the performances of both algorithms

are quite similar. Indeed, by traversing up to 1000 m, both methods allow the drone to harvest about 2000 Bytes. However, when the drone travels a longer distance, the amount of data collected using our approach is much greater. For example, for a flight of 5000 m, the drone harvests 10000 Bytes using our method while with the other method it harvests only 5900 Bytes.

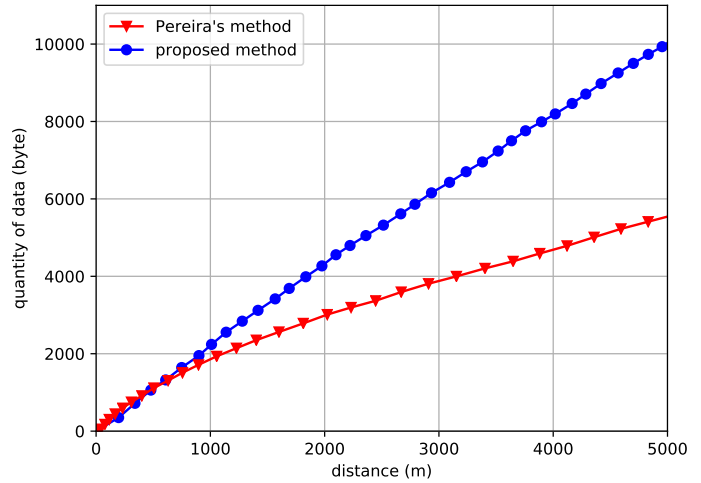


Fig. 3: Distance Versus Amount of Data

In Figure 4 we plot the distances traveled by the drone to collect different amounts of data. As we can see, using Pereira’s method the drone need to cover a greater distance to collect the same amount of data as our algorithm. More precisely, for a small amount of data 1000 Byte, the drone travels almost the same distance for both methods. However, when we increase the amount of data to collect, we find that using Pereira’s method, the drone travels more than twice the distance traveled using our method.

Finally, we carried out a second series of simulations when we varied the number of sensor nodes within the network (from 10 sensors to 100 sensors), and we computed the distances required to collect the data. The obtained results are plotted in Figure 5. As we can see, increasing the number of sensors leads to a decrease in the traveled distance. For example, using Pereira’s method and for 10 sensor nodes, the drone has to travel nearly 16 km to collect 8000 bytes while for 50 sensor nodes the distance is reduced to 9 km. On the other hand, using our method and for 10 sensors, the drone need to travel 10 km to harvest this amount of data. While using 50 sensor nodes, the distance is reduced by more than a half. Comparing the two methods, we find that our method gives better results in terms of the distance necessary to collect different amounts of data using different numbers of nodes

To conclude, according to our simulations, we found that our method provides an improvement in performance compared to the method proposed by [16], in terms of distance traveled and amount of data collected.

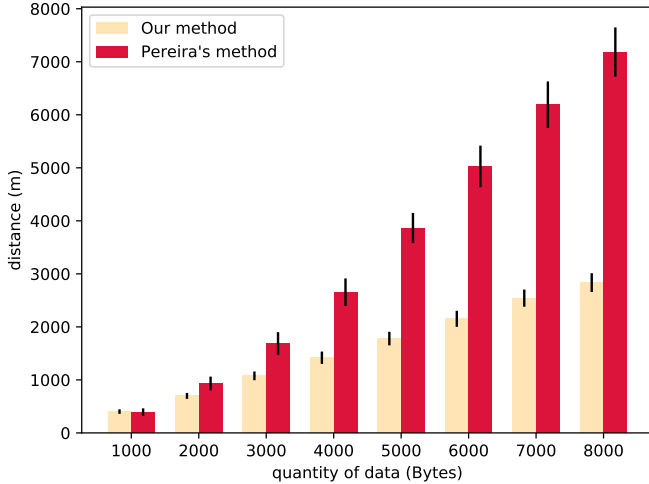


Fig. 4: Histogram of comparison between the distance traveled by the drone to collect different quantities of data

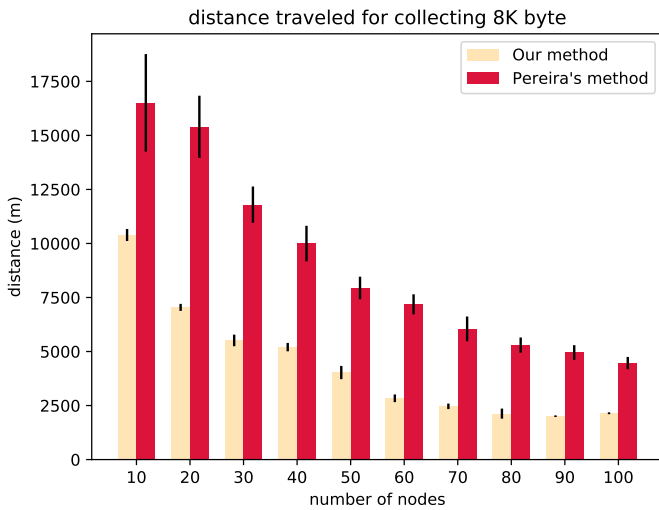


Fig. 5: Number of deployed sensors vs Traveled distance

VI. CONCLUSION

In this paper, we presented a simple potential field-based model for collecting data using a drone. We use as our starting point the idea used by Pereira et al. [16]. However, we extend this work by considering that each cell in the area apply an attractive force on the drone, not only the deployed sensors. We compared our results with those obtained with Pereira's method and we obtained better performance in terms of data collection time. In other words, for the same period of time our method collect more data. The second advantage of our approach is that it leads to a significant reduction in the distance that the drone must travel.

In future work, we intend to extend this approach by deploying several drones to collect the data. This will introduce

a new challenge to this problem since we also need to consider repulsive forces in order to avoid collisions between drones.

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