Energy-aware Coverage Path Planning for Unmanned Aerial Vehicles*

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Abstract. Coverage Path Planning (CPP) problem is a motion planning subtopic in robotics, where it is necessary to build a path for a robot to explore every location in a given scenario. Unmanned Aerial Vehicles (UAV) have been employed in several applications related to the CPP problem. However, one of the significant limitations of UAVs is endurance, especially in multi-rotors. Minimizing energy consumption is pivotal to prolong and guarantee coverage. Thus, this work proposes energy-aware coverage path planning solutions for regular and irregular-shaped areas containing full and partial information. We consider aspects such as distance, time, turning maneuvers, and optimal speed in the UAV's energy consumption. We propose an energy-aware spiral algorithm called E-Spiral to perform missions over regular-shaped areas. Next, we explore an energy-aware grid-based solution called EG-CPP for mapping missions over irregular-shaped areas containing no-fly zones. Finally, we present an energy-aware pheromone-based solution for patrolling missions called NC-Drone. The three novel approaches successfully address different coverage path planning scenarios, advancing the state-of-the-art in this area.

Keywords: Coverage Path Planning · Energy-aware · UAV.

1 Introduction

Unmanned Aerial Vehicles (UAVs) consist of aerial platforms with no pilots onboard the vehicle. These platforms are remotely and manually operated by a human, but they also perform automated pre-programmed flights. Autonomous flights can be executed using intelligent systems integrated with onboard sensors. These vehicles have increasingly been employed in several application domains, such as surveillance, smart farming, and wildfire tracking.

Coverage Path Planning (CPP) problem is a motion planning subtopic in robotics, where it is necessary to build a path for a robot to explore every location in a given scenario [8]. UAVs can also deal with this problem, but several aspects must be considered, such as maneuverability limitations, restricted payload, and environmental conditions. Most UAVs nowadays engage in missions using

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geometric flight patterns [3]. The most employed in real-world scenarios is the back-and-forth (BF), also known as a zigzag move or lawnmower pattern. Following the same idea, one can design a spiral flight pattern (SP) where the UAV flies in circles, slowly decreasing the circle radius while flying towards the center. Both flight patterns deal with the problem in regular-shaped areas requiring very low computation. UAVs can also explore approaches classified either as a heuristic or complete. Such methods deal with irregular-shaped areas containing no-fly zones (NFZ). UAVs follow a set of simple rules guided by pheromones in the heuristic approaches when they do not have full knowledge about the area. They must use their onboard sensors to gather data while covering the scenario but do not have a coverage success guarantee. Complete methods perform exhaustive searches over a discretized grid represented as a graph, guaranteeing the coverage success by ensuring that the vehicle visits each decomposed cell.

Despite the technology progress related to control systems and energy monitoring, one of UAVs' main limitations is the endurance, due to the limited payload of the vehicles. In multi-rotors, endurance is about 25-30 min, even in more sophisticated models released in 2019 [2]. The energy consumed depends on several parameters, such as flying time, optimal speed, turns, and altitude. The number of turning maneuvers performed by these vehicles significantly impacts energy consumption, so finding a path with the minimum turns enhances its endurance. It is also possible to save energy using optimal speeds depending on the path segment's length [11].

This work aims to propose energy-aware coverage path planning solutions for regular and irregular-shaped areas containing full and partial information. We consider the impact of different aspects, such as distance, time, turning maneuvers, and optimal speed in the UAV's energy consumption.

This paper is organized as follows: in Section 2, we present the theoretical foundation. Section 3 discusses the related work. Section 4 describes the proposed energy-aware coverage path planning algorithms. Section 5 explains the simulation and real flight experiments. Section 6 presents the conclusion and future work.

2 Theoretical Foundation

The CPP problem consists of planning a path covering the entire target environment considering the vehicle's motion restrictions and sensor's characteristics while avoiding passing over obstacles. These obstacles can represent no-flight zones (NFZ) that the UAV should not consider during the planning phase.

Cellular decomposition can be used to divide the target space into smaller pieces, also known as cells, to simplify the coverage. This technique is helpful to guarantee complete coverage, one of the major concerns about the CPP. The most commonly used are exact and approximate cellular decomposition. The former consists of splitting the space into sub-areas, whose reunion precisely fills the target area, while the latter discretizes the area into a set of regular cells [8].

Coverage algorithms must consider several issues to guarantee a coverage mission's success, such as the area's complexity, the NFZ, and the cellular decomposition. Moreover, it should take into account whether the coverage is simple or continuous. In both cases, the coverage can be performed by a single or multiple vehicles. The information availability also influences the searching for a solution in coverage missions with UAVs.

Performance metrics must fulfill application requirements. The most common are path length, mission time, coverage maximization, and the number of turns. Authors usually connect such metrics with energy consumption, trying to minimize them to save energy. However, for an efficient energy-saving regarding UAVs, additional features need to be investigated as vehicle's motions and constraints, turning angles, and optimal speeds. Our approaches explore such features using an energy model to minimize the energy directly.

3 Related Work

The coverage path planning problem has been extensively addressed in the literature. Andersen [3] explores different flight patterns in rectangular areas with no decomposition. Coombes et al. [9] present an analysis of wind disturbances' effect in the mission time of a fixed-wing UAV in circular areas. Franco and Buttazzo [11] present an energy-aware back-and-forth approach for photogrammetry in regular-shaped areas. Li et al. [13] present a triple-stage algorithm exploring features such as payload and power variation. Artemenko et al. [5] propose energy-aware algorithms for smoothing paths, providing more effective turns.

In large and complex scenarios, authors usually apply an exact cellular decomposition to split the area and simplify the coverage. Li et al. [14] explore the decomposition to create paths in concave areas using a single UAV, and Torres et al. [21] used it to capture pictures of convex and concave areas for 3D reconstruction. Coombes et al. [10] propose a technique for fixed-wing UAVs exploring wind to decrease flight time. Maza and Ollero [15] present a cooperative strategy in a convex area using a team of heterogeneous UAVs. Balampanis et al. [6] explore a spiral algorithm for missions in coastal regions using multiple heterogeneous UAVs. Acevedo et al. [1] present a decentralized algorithm for partitioning rectangular areas, where short-range communication UAVs share information. Araujo et al. [4] explore continuous coverage with local priority, where the UAV can revisit previously explored areas according to the raising uncertainty or priority.

Several works present coverage solutions for precision agriculture using the approximate cellular decomposition. Valente et al. [23] and Barrientos et al. [7] propose algorithms for image mosaicing over irregular-shaped fields. Valente et al. [22] propose a meta-heuristic exploring the jazz musician's improvisation called Harmony Search. Sadat et al. [19] present a non-uniform coverage, where the UAV fly at different altitudes. Santamaria et al. [20] explore cells of different sizes. Many authors have also explored biologically-inspired approaches for the CPP problem using UAVs, including real-time search methods [16], evolutionary computation [17], and swarm intelligence [18].

4 Proposed Approaches

Our work proposes three novel energy-aware approaches for the coverage path planning problem with UAVs. The solutions consist of flight patterns, complete algorithms, and pheromone-based methods suitable for regular and irregular-shaped areas of interest. The first two methods deal with scenarios where the UAVs contain full information to perform the coverage, while the latter handles a dynamic environment with only partial information.

4.1 E-Spiral

The energy-aware spiral flight pattern algorithm (E-Spiral) consists of a sequence of maneuvers performed by the aerial vehicle to cover an area of interest using approximate circular motions. E-Spiral computes coverage paths for regular-shaped areas. Such areas comprise convex ($\forall i, \gamma_i < \pi$) and concave ($\forall i, \gamma_i > \pi$) polygons without inner no-fly zones.

E-Spiral considers application requirements, such as overlapping and resolution, to compute a photogrammetric sensing application's coverage path. The centroid point cp is computed based on the vertices of the polygon. Then, the minimum distance d_{cp} from the centroid point cp to the edges e_i is calculated. The distance d_{cp}, the width L_x and height L_y of footprint, the lateral ov_x and the frontal ov_y overlapping are employed to calculate the number of layers needed to fully cover the area. Lateral and frontal overlapping determine the distance between each layer and the distance between two consecutive waypoints.

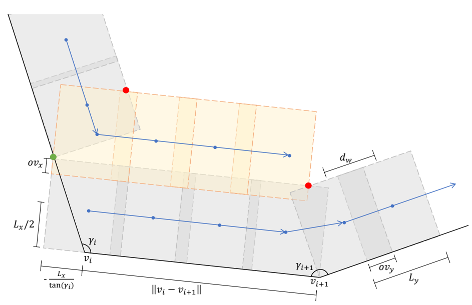

Fig. 1. E-Spiral pattern with inner layers, turning angles, and overlapping rates.

The spiral coverage path passes by the area of interest's vertices at the beginning of the mission. Turning maneuvers with different inner angles are necessary to cover the workspace fully. After the first completed layer, the vehicle starts to decrease the radius at each step, flying towards the center, as illustrated in Fig. 1. The first layer starts near v_i. The distance between the inner layers is set as $d_{layer} = L_x - ov_x$ and the distance d_w between consecutive waypoints in a straight line is set as $d_w = L_y - ov_y$. After covering an entire layer, the intersection points form the new vertices of the area of interest, and the coverage continues in the next segment.

To determine the optimal speed for each straight segment of the spiral path, we improved the energy model proposed by Franco and Buttazzo [11]. The authors exploit the energy model to compute the integral of the energy for a given distance d to find the optimal speed that minimizes the energy needed to travel that portion of the path. This optimal speed exists due to the total drag force curve, which combines the parasite drag and the induced drag. As the speed increases during steady flights, the parasite drag increases while the induced drag decreases. This behavior leads to a minimum value for the drag curve, where the optimal speed requires less power to perform the flight, saving energy.

The energy model proposed by Franco and Buttazzo [11] presents an accurate energy estimation considering back-and-forth coverage paths. The model considers that the UAV starts from zero speed, reaches and keeps a constant speed, and then decelerates until zero before the turning maneuver at the end of each straight line. In this way, we improved the energy model to deal with more complicated maneuvers, such as the ones performed during spiral paths, where the UAV decelerates until a given speed different from zero, performs the turn while moving, and then accelerates again. We evaluate the variation of speed according to the executed turning angle, performing a set of real flight experiments with an IRIS quadcopter. Knowing the vehicle's entrance speed when it performs a given angle allows us to modify the energy model when performing the integrals for the acceleration/deceleration/constant-speed phases. The optimal speed can be computed as follows:

$$E_d(v, d, \gamma) = \int_{v_{in}}^{v} P_{acc}(v)dv + \int_{0}^{t(v)} P(v)dt + \int_{v}^{v_{out}} P_{dec}(v)dv \tag{1}$$

where $v_{out} = f(v, \gamma)$ is the entrance speed when performing the next turn with angle γ. The data can be stored in a look-up table.

4.2 EG-CPP

The energy-aware grid-based coverage path planning approach (EG-CPP) generates trajectories for UAVs in irregular-shaped areas, consisting of a concave/convex polygon with obstacles and NFZ. EG-CPP improves the approach proposed by Valente et al. [23], which employs a Deep-limited search (DLS) with a backtracking procedure. The area is discretized through approximate cellular decomposition and converted to a regular graph numerically labeled by the Wavefront algorithm. It consists of a flooding algorithm that marks the neighborhood adjacency of cells, as illustrated by Fig. 2.

EG-CPP replaces the original cost function (OF) proposed by Valente et al. [23] by our improved version of the energy model proposed by Franco and Buttazzo [11] to find the minimum-cost path to perform a complete coverage. The OF is based exclusively on the sum of angles, which is unreliable and may provide more expansive paths in real measured energy while discarding promising

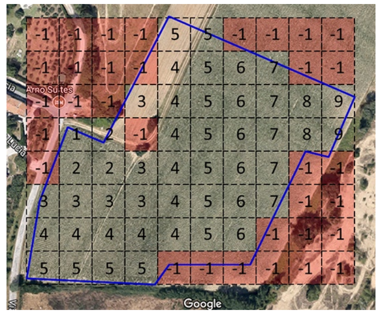

Fig. 2. Irregular-shaped area discretized into a regular grid with the starting position marked with number 1 and the surrounding neighbors with number 2, and so on. Obstacles and no-fly zones are marked with -1.

solutions during the minimization process. On the other hand, the energy model splits the path into a set of straight segments and rotations to accurately predict the energy cost. The energy-aware cost function (EF) exploits the energy model to account not only for the energy required for every turn but also for the energy needed when accelerating/decelerating and flying at a constant speed. Thus, it is possible to evaluate the path and estimate the total energy (and time) using the Equation (2) as follows:

$$\Gamma_E = \sum_{i=1}^{m} \Big(\int_0^{v_i} P_{acc}\,\mathrm{d}v + P_{v_i} \Delta T_i + \int_{v_i}^{0} P_{dec}\,\mathrm{d}v \Big) + \sum_{i=1}^{m} E_{turn}(\gamma^{\{i\}}) \tag{2}$$

where the first summation computes the energy consumed during a set of straight lines i by splitting it into three phases (acceleration, deceleration, and constant speed), and the second summation considers all the rotations of the path. P_{acc}, P_{dec}, and P_v define the power consumed when accelerating, decelerating, and flying at a constant speed. $E_{turn}(\gamma^{\{i\}})$ is the energy to rotate an angle γ at the i-th waypoint (computed as the power consumed when turning P_{turn} multiplied by the duration of the rotation). ΔT_i is the time when flying the portion of the path at a constant speed, and it is computed considering the total distance and constant acceleration and deceleration. The terms in Equation (2) are polynomial functions obtained through real measurements and allow reaching high accuracy in the energy prediction of a given trajectory [11].

The algorithm proposed by Valente et al. [23] presents a high computational time due to the complexity of the area. In this way, we also include two pruning techniques to reduce the computational time and save even more energy. The original approach computes the entire cost of all possible paths at the end of the algorithm, including those paths whose costs are much higher than the minimum value. Thus, we modified the algorithm to store the minimum-cost and the path associated with it. We then check if the current path's cost is higher than the minimum-cost path at each iteration. By adopting this technique, it is possible to drastically reduce unnecessary recursive calls, pruning a vast number of partial paths. It is necessary to compute a path's cost during the search phase, i.e., while nodes are being explored. There is no need to compute the cost of the path from the starting cell to the current one at each iteration, but only the additional cost introduced by choosing the next neighbor. The current cost is passed as a parameter of the function and added to the additional cost. The two proposed pruning techniques can be applied to the algorithm using the original and the energy-aware cost function. The techniques drastically reduce the algorithm's computational time, making it time-affordable for real-world applications.

4.3 NC-Drone

Pheromone-based methods are suitable for missions where UAVs contain incomplete information about a partially known environment. These methods comprise algorithms based on colonies of insects, specifically ants, as their natural behavior consists of leaving traces of pheromones while exploring areas outside the anthill. While moving around the area of interest, UAVs leave virtual marks in the grid-discretized scenario's visited cells. This information helps other vehicles in the next destiny decision-making. UAVs should move to unvisited or less frequently visited locations to obtain full coverage, which means exploring cells (von Neumann neighborhood) with the least amount of pheromone.

NC-Drone is an extension of the Node Counting (NC) for patrolling missions, a specific domain of the CPP problem dealing with area surveillance. A cooperative fleet must visit areas at regular intervals to supervise it. During the coverage, NC chooses the next locations with the least amount of pheromone. When there is more than one cell with the same minimum-value, NC randomly chooses among them. Our NC-Drone adopts a simplified version of the energy model to consider energy as a decision factor. It can identify when there is a tie between two or more cells, verifying if one of these cells is aligned with the UAV's sweeping direction. In this case, the correspondent cell is selected, keeping the UAV in the same direction and avoiding unnecessary turns. In this way, we can prolong the straight segments of the path and minimize the number of turning maneuvers to reduce energy consumption.

Furthermore, we develop decentralized variations of the NC-Drone, where UAVs do not need to read and write in the grid as a centralized way. Instead, each UAV stores the visited places in a matrix-form internal map of the area. They select the next destinations based on the number of visits stored in the neighbor positions of its current position in the matrix. A matrix-based communication model is employed to share and synchronize individual information stored in the UAVs' internal matrices. We propose three types of synchronization when UAVs are within a range: MAX, AVG, and MULTI. MAX compares every position in both matrices and chooses the highest value. AVG calculates the mean between the original values of both matrices and round the result to the nearest integer. Both methods update the original matrix. MULTI combines multiple matrices from all vehicles to decide where to move. UAVs copy the information from each other when they are within the synchronization perimeter. When performing a move, the UAV superposes the stored content, summing its current position's neighbor values. Then, it chooses the least visited location as the next place to be covered. UAV updates only its matrix during coverage. Other matrices internally stored are individually updated when there is a new synchronization.

We also propose cooperative strategies, further exploring relevant aspects of the patrolling problem, such as time, uncertainty, and communication. First, we introduce the Watershed Strategy (WS), a technique used to represent matrices as topographic relief. In this relief, the lower elevations correspond to the minor values in the matrix, i.e., less frequently explored cells. The UAVs are attracted to clusters of cells formed in these areas. Second, we present the Time-based Strategy (TS), an approach exploring not only the number of visits but also the time when the last visit occurs to guide the UAVs during coverage. Both strategies can be combined. Then, we propose the Evaporation Strategy (ES) to model uncertainty due to the absence of visits in certain places during patrolling. We also explore the concept of full-range communication with Communication-Frequency Strategy (CFS), where UAVs reduce communication, exchanging matrix-information from time to time. Finally, we combine all strategies into a single solution for the patrolling problem.

5 Experiments and Results

The E-Spiral is compared to the energy-aware back-and-forth (E-BF) [11], performing a wide range of simulations on MATLAB®. We explore a set of polygonal areas with different characteristics, such as vertices, irregularity, and size. The number of vertices varies from 6 to 10. The level of irregularity varies from 0 to 1. The average diameter varies from 200 to 600 meters. We generated fifty different areas with all possible configurations, totalizing 3750 tested areas.

We set the optimal speeds that minimize energy for every straight segment of the path using Equation (1). Then, we used the improved energy model to compute the energy spent by each approach. The higher the number of vertices, the better is the performance of the E-Spiral. The improvement reaches 16.1% in areas containing ten vertices. Considering the irregularity, E-Spiral presents a percentage of improvement of around 13%. Finally, the performance of E-Spiral decreases as the area increases, but still overcomes the E-BF around 10%.

Table 1. Energy consumption and mission time in simulation and real flight (RF) with the E-Spiral and the E-BF in Polygonal (P) and Rectangular (R) Areas.

	Energy Consumption			**Mission Time**		
Path/Area	**Simulation**	**RF**	**Accuracy**	**Simulation**	**RF**	**Accuracy**
E-Spiral (P)	$79158J$	$79228J$	99.91%	$379.35s$	$377.20s$	99.43%
E-BF (P)	$87945J$	$85837J$	97.54%	$420.60s$	$414.40s$	98.50%
E-Spiral (R)	$46681J$	$47329J$	98.63%	$223.91s$	$231.00s$	96.93%
E-BF (R)	$48182J$	$47401J$	98.35%	$230.81s$	$229.60s$	99.47%

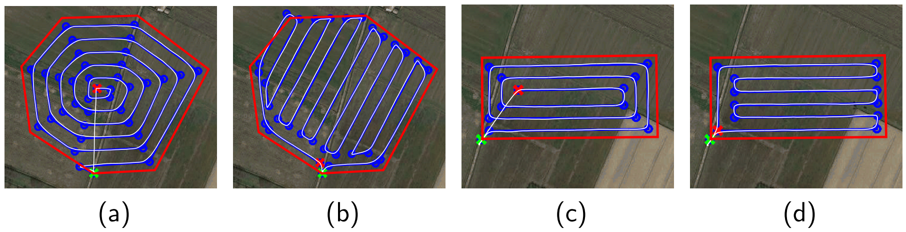

Fig. 3. Real flight paths: (a) E-Spiral in polygonal area, (b) E-BF in polygonal area, (c) E-Spiral in rectangular area, and (d) E-BF in rectangular area.

Real flights were also performed in two different areas: a polygon and a rectangle. Table 1 presents the results and Fig. 3 illustrates the areas of interest (red), the planned path (blue), the performed path (white), the starting (green "x"), and the final position (red "x"). E-Spiral algorithm overcomes E-BF in both areas of interest. It reduces the mission execution time around 9%, and the energy consumption around 7.7% compared to E-BF.

Next, the EG-CPP algorithm is compared to the original grid-based [23]. The area of interest consists of a concave polygon with an internal no-fly zone containing 47 valid cells. Cells outside of the area or within the NFZ are not included. We ran both algorithms to generate 47 paths considering every valid cell as a potential starting position. The minimum-cost path generated by the energy-aware cost function (EF) starts at the cell (4,2), while the one generated by the original cost function (OF) starts at the cell (6,1).

Table 2. Energy consumption in simulation (OF and EF) and real flights.

Path	**OF**	**EF**	**Real Flight**	**Accuracy**
Cell (6,1) OF	1890º	$7.7053 \times 10^4 J$	$7.3583 \times 10^4 J$	95.49%
Cell (4,2) OF	2205º	$7.3593 \times 10^4 J$	$7.1655 \times 10^4 J$	97.36%
Cell (6,1) EF	1980º	$6.8607 \times 10^4 J$	$6.7354 \times 10^4 J$	98.17%
Cell (4,2) EF	2025º	$6.6165 \times 10^4 J$	$6.2710 \times 10^4 J$	94.77%

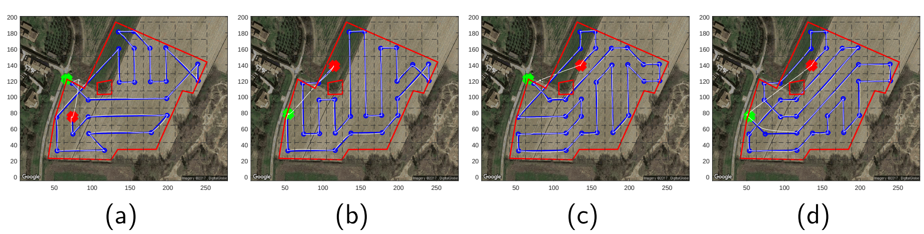

Fig. 4. Four real flights: (a) EF minimum-cost starting at cell (4,2), (b) EF starting at cell (6,1), (c) OF starting at cell (4,2), (d) OF minimum-cost starting at cell (6,1).

Four real flights were performed to evaluate energy consumption, as shown by Table 2 and Fig. 4. EF obtains the best results with an energy saving of 17%. The EF path starting at the cell (4,2) consumes $6.2710 \times 10^4 J$, overcoming OF path starting at the cell (6,1), which consumes $7.3583 \times 10^4 J$. EF with cell

(6,1) also overcomes the original approach (OF with cell (4,2)), with an energy consumption of $6.7354 \times 10^4 J$ VS $7.1655 \times 10^4 J$. The ideal path pointed out by OF is unreliable, consuming more energy than an ordinary path: $7.3583 \times 10^4 J$ VS $7.1655 \times 10^4 J$.

The NC-Drone is evaluated on NetLogo with three metrics: Quadratic Mean of the Intervals (QMI), Standard Deviation of the Frequencies (SDF), and Number of Turning Maneuvers (NTM) [16]. These metrics highlight different application requirements, such as the spatial/temporal distribution of visits and energy. We ran 30 simulations with 10k, 15k, and 20k cycles with 4 UAVs in a 50x50 grid, analyzing the results with Student's T-Test. Fig. 5 presents the QMI results.

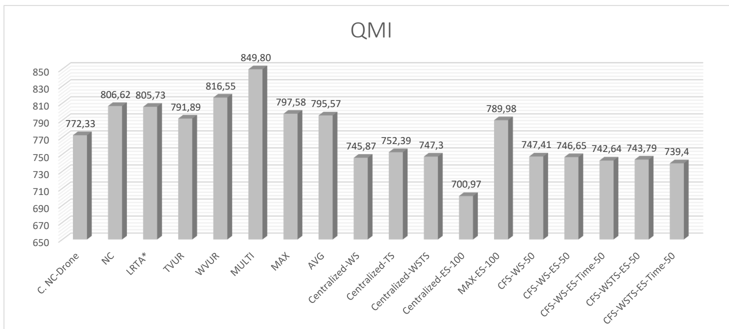

Fig. 5. QMI results for NC-Drone strategies.

First, we compared NC-Drone with four heuristics [12]: Node Counting (NC), Learning Real-Time A* (LRTA*), Thrun's Value-Update Rule (TVUR), and Wagner's Value-Update Rule (WVUR). All approaches allow UAVs to write pheromones in the visited places that can be read by vehicles. NC-Drone overcomes all heuristics in QMI and reduces the NTM three to four times. NC-Drone also overcomes NC, LRTA*, and TVUR in SDF, and presents similar results to WVUR. Next, we compared decentralized variations of NC-Drone, which adopt a matrix-based communication protocol. MAX and AVG present the best results in QMI and NTM, while MULTI overcomes the two approaches in SDF.

We also ran experiments adding different strategies, such as Watershed (WS), Time-based (TS), Evaporation (ES), and Communication-Frequency (CFS). WS, TS, and WSTS outperform the original NC-Drone, improving QMI and drastically reducing the standard deviation (SD) from 76% to 88%. MULTI, MAX, and AVG present no improvements by adopting the strategies. We ran four ES experiments with intervals of 100, 250, 500, and 1k cycles between each evaporation with a factor of 0.1, which means that pheromone drops 0.1 at x intervals. ES overcomes NC-Drone in all intervals regarding QMI, and ES-100 presents the best result with a significant improvement (10%). ES also improved MULTI in all runs and MAX in the interval of 100. Exploring the CFS, we ran five experiments with intervals of 50, 100, 250, 500, and 1k cycles between every synchronization. CFS-50 presents the best results in QMI, obtaining an outcome equivalent to the one presented by NC-Drone, even sharing the matrices only at every 50 cycles.

QMI improvements impact negatively on SDF and NTM in all approaches. One can observe a trade-off and correlation between the QMI and NTM metrics. Finally, we present a few combinations and a final algorithm composed of all strategies. Results are slightly improved as more combinations are adopted, with the best solution being CFS-WS-ES-Time-50. One can download all algorithms and the complete set of results on GitHub [1]. Full thesis is on Google Drive[2].

6 Conclusion

This work proposed energy-aware coverage path planning algorithms for unmanned aerial vehicles. All approaches explored an improved version of an energy model to generate energy-efficient coverage trajectories. Our solutions include a flight pattern (E-Spiral), a complete algorithm (EG-CPP), and a pheromone-based heuristic (NC-Drone), able to deal with regular and irregular-shaped areas containing full and partial information. We compared the proposed algorithms with state-of-the-art strategies through simulations on MATLAB® and real flights using an IRIS quadcopter.

As future work, we intend to explore a generic energy model for any UAV based on parameters and characteristics, such as propellers, rotors, and payload. One can consider using the closed-form energy model to generate energy-efficient coverage planning strategies for different types of UAVs.

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