2018 Latin American Robotic Symposium, 2018 Brazilian Symposium on Robotics (SBR) and 2018 Workshop on Robotics in Education (WRE)

An Energy-Aware Real-Time Search Approach for Cooperative Patrolling Missions with Multi-UAVs

Tauã M. Cabreira, Kristofer Kappel, Lisane B. de Brisolara, and Paulo R. Ferreira Jr.

***Abstract*— This paper proposes a novel energy-aware approach to solve the patrolling problem using multi-UAVs (Unmanned Aerial Vehicles), called NC-Drone, which extends the Node Counting method aiming to reduce the number of turns in order to save energy. We present two versions of NC-Drone: a Centralized version and a Decentralized one. The Centralized version collects/spreads the information, reading/writing pheromones in the scenario and it is compared to the real-time search methods. Our results point out that the Centralized NC-Drone overcomes all real-time search methods in most of the performance metrics, presenting better results in Quadratic Mean of the Intervals and drastically reducing the Number of 90° Turning Maneuvers, and thus impacting positively on energy consumption. The Decentralized NC-Drone version uses individual pheromone matrices to guide the vehicles, replacing the centralized scheme of pheromones disposed in the scenario. When a vehicle is close to another, they send its matrices to each other, simulating the use of a short-range communication technology. Additional experiments compare variations of the Decentralized NC-Drone to analyze the impact of the adopted information merge scheme on coverage. The Decentralized version emerges as a promising solution to support real-world applications using low-cost aerial vehicles.**

I. INTRODUCTION

The Unmanned Aerial Vehicles (UAVs) have increasingly been employed in several application domains, such as patrolling [1], search and rescue missions [2], crop field monitoring [3], forest fire surveillance [4], ice management information gathering [5], landmines detection [6], and photovoltaic plant planning and monitoring [7]. These vehicles consist of aircrafts with no pilots on-board, usually controlled remotely by a pilot on the ground, or offline programmed with a flight plan, or yet controlled by intelligent systems.

The patrolling problem is a specific domain of the coverage path planning problem, usually employed for surveillance and inspection activities, where the agent should visit and revisit areas at regular intervals in order to supervise it. The quality of the patrolling can be measured by metrics as, i.e., number of visits in each part of the scenario or time between those visits. Land exploration techniques can be extended and applied in UAVs to solve these problems. However, several aspects must be considered when dealing with aerial vehicles, such as vehicle's physical characteristics, endurance, maneuverability limitations, restricted payload, environmental external conditions, among others.

Real-time search methods (RTSM) interleave planning and plan execution, allowing fine-grained control over how much planning to perform between plan executions. As RTSM present a low computational cost, these have been proposed to solve patrolling problems with land vehicles, since computational power represents a hard constraint to any autonomous vehicle [8]. However, most of the previous studies are limited only to simulations [8], [9] and just a few methods have addressed contexts with aerial vehicles in real-world scenarios [10], [11].

The RTSM use a digital pheromone scheme representing the number of visits on each scenario's location to perform the patrolling. The scheme simulates the real pheromones left by insects in the nature. A Ground Control Station (GCS) has a global map of the area and marks all visits performed by the vehicles, leading them to the less explored places through a communication protocol. However, this centralized model demands extensively communication between the vehicles and the base and is not robust to failures, once all vehicles depend on the base to move around the scenario and need to constantly update the base about their current positions.

Flight patterns based on simple geometric shapes, as back-and-forth or spiral, have been employed for coverage tasks [2]. But these patterns are predictable and can not be used for patrolling missions and military surveillance. Once the movement is known, for instance, the UAV can be avoided by an intelligent object of interest by moving in an opposite direction or keeping in a certain place for a while. In this case, RTSM may be applied in patrolling missions, since its behavior is unpredictable for an external observer. However, this unpredictability comes from the massive number of turns and constant changes in the movement direction of the vehicles, which increases the energy consumption to perform a coverage mission. Therefore, in real-world scenarios, aerial vehicles should minimize the number of turning maneuvers to save energy and prolong the mission execution time.

This paper aims to propose a novel energy-aware decentralized RTSM for patrolling missions with multi-UAVs, which maintains the unpredictable behavior, while minimizes the number of turns in order to save energy. The main contributions of the paper can be summarized as follows: (i) an extension of the Node Counting aiming to reduce the number of maneuvers during the algorithm search phase; (ii) a decentralized version of the proposed extension that uses internal matrices and synchronization schemes allowing vehicles to merge or combine information related to visited

The work of K. Kappel, L. B. de Brisolara, and P. R. Ferreira Jr. was financed in part by FAPERGS/CNPq under Grant 16/2551-0000/472-2. The work of P. R. Ferreira Jr. was also supported in part by CNPq under Grant 308487/2017-6.

Programa de Pós-Graduação em Computação (PPGC), Centro de Desenvolvimento Tecnológico (CDTec), Universidade Federal de Pelotas (UFPel), Pelotas, RS, Brazil (e-mail: {tmcabreira, kskappel, lisane, paulo}@inf.ufpel.edu.br

978-1-5386-7761-2/18/$31.00 ©2018 IEEE
DOI 10.1109/LARS/SBR/WRE.2018.00054

places to replace the centralized decision-making process and support real-world applications.

This paper is organized as follows: in Section II, we discuss the related work. Section III revises the real-time search methods. Section IV explains the proposed energy-aware approach and explores variations of implementation to obtain a decentralized approach. Section V presents the performed experiments and discusses achieved results. Finally, Section VI draws conclusions and future work.

II. Related Work

A simulated study to coordinate ant-robots teams to perform land coverage is presented in [8], considering the following heuristics: Node Counting (NC), Learning Real-Time A* (LRTA*), Thrun's Value-Update Rule (TVUR) and Wagner's Value-Update Rule (WVUR). Experiments include robot's fail simulation, pheromone's marks elimination and robot's position change. Despite being one of the most relevant works on RTSM, the simulations are restricted to land robots.

More recently, four heuristics for coverage task, including NC, LRTA*, Edge Counting and PatrolGRAPH*, have been evaluated in [10]. The authors implement the NC in a real system with a quadcopter and a hexacopter. An offboard control implemented in Robot Operating System (ROS) guides the vehicles sending target positions and periodically receiving vehicle's localization information. However, the system is less robust to failures because the vehicles depend on the communication with the GCS to perform their tasks. We are interested in a distributed system with communication among vehicles to exchange map information and enhance coverage performance, while reducing energy consumption. Even in a scenario with no communication, all vehicles must be able to individually cover the area with only its own information.

In another effort, an algorithm based on cellular automata is applied to coordinate robots in land coverage tasks, using partially a pheromone-based strategy [9]. The robot's behavior is determined by a set of rules. The authors employ this strategy to control two quadcopters in exploration and monitoring tasks [11]. Despite being considered as an adaptive decentralized system by the authors, vehicles share a global memory using the GCS and does not make the decisions alone. Finally, in [12] the authors explore the strategy to react to the loss of communication, simulating degradation on virtual marks in the environment. However, the degradation drops the algorithm's efficiency and causes a lot of collisions between vehicles.

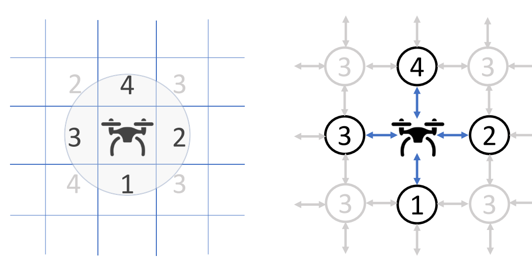
Ant Colony Optimization (ACO) algorithm is adapted to coverage with multi-UAVs in [13]. The UAVs share a virtual pheromone map indicating recently visited areas through high rates of pheromone. These pheromones are repulsive and guide the vehicles to unexplored areas. Based on this study, the Chaotic ACO to Coverage (CACOC) is proposed in [14], combining an ACO approach with a chaotic dynamical system for surveillance missions. The deterministic system allows the GCS operator to forecast the UAVs paths, keeping it unpredictable to the enemies. Despite there is no need of communication among vehicles and the base to track the vehicle's position, the swarm of vehicles still shares a virtual pheromone map through a centralized process.

The combination of digital pheromones and evolutionary strategies is employed to coordinate vehicles in cooperative area coverage [15]. The environment is decomposed into rectangular subareas associated with each vehicle using Genetic Algorithm (GA) and digital pheromones are used to convey information about search area. The authors use two pheromone flavors: search pheromone and path pheromone. The UAVs should find such path that maximizes the expected change of search pheromones and minimizes the strength of path pheromones to place vehicles along the intended path. Differently of [15], we do not intend to split the environment and our vehicles are free to move all around the scenario.

Most of heuristics have a short range perception about the environment. Usually, the strategies can sense the immediately neighbor cells and communicate indirectly by reading and writing information in the surrounding areas. These strategies are called 1-range strategies. In [16], a technique is proposed to convert 1-range strategies into 0-range strategies. In this case, each cell stores data from the neighbor cells and the vehicle decides the next cell to visit only sensing its current cell. Each vehicle keeps in its memory a similar data structure and synchronizes it with others cells during future visits. The authors employ two metrics in experiments: Quadratic Mean of Intervals (QMI) and Standard Deviation of Frequencies (SDF). Despite the sensing reduction, the vehicle still needs to read/write from/to the environment cells.

III. Real-Time Search

Real-time search methods [8] typically employ local search restricted to the nearest neighborhood area. The scenario is divided into small cells and the field of view is a square composed of nine small other squares, as shown in Fig. 1a. The von Neumann neighborhood is adopted for search and displacement in the connected graph at each simulation step, as illustrated by Fig. 1b.



(a) Field of view (b) Connected graph

Fig. 1: Environment representation

In general, RTSM work with an associated value for each cell of the environment, named *u-value*, which indicates how many times a cell was visited by the vehicles. This value represents the pheromone marks left by the movement of the vehicles in the scenario - an analogy to the natural behavior of ants, leaving traces of pheromone on the ground. Pheromones are used by vehicles as an indirect communication channel provided by the scenario, assisting in the next destiny decision-making.

Vehicles use the *u-value* to select the neighbor cell to be visited in next step, always choosing the cell with the lowest value, once the goal is to move through unexplored or less frequently visited regions. Before making the correspondent move, the vehicle must update the *u-value* of the current cell by adding a certain amount. What distinguishes each different RTSM is basically the adopted update rule.

Node Counting approach uses a simple rule to update the *u-value*, adding one unit to the current value. The algorithm checks in the neighborhood which is the cell with the lowest associated *u-value* - initially, all the cells have zero value. When determined and saved the selected cell, the vehicle updates the current cell and moves to the next one. This procedure is repeated until it reaches at a stop predefined criterion, such as number of simulation cycles or number of complete coverages.

In the LRTA*, instead of using the value of the current cell itself, the value of the next cell to be visited by the vehicle added by one is used. In the TVUR, after choosing the next neighbor to be visited, the update rule changes the *u-value* of the current cell by comparing it to that of its successor cell. The highest value is taken and increased by one unit, replacing the *u-value* of the current cell. In the WVUR, the update rule is conditional. The value of the current cell is updated only if it is not larger than the value of the selected neighbor cell. In this case, it is increased by one unit. If the condition is not met, the value of the current cell remains the same.

IV. NC-Drone

In this section, we present the NC-Drone, a novel energy-aware RTSM, proposed to save energy through the reduction of the number of turns in cooperative patrolling missions. First, we introduce the Centralized NC-Drone, which explores the reading and writing pheromone scheme. Second, we propose the Decentralized NC-Drone, where the vehicles use an internal matrix to store the information about the visited places. The main goal of this method is to become the energy-aware approach feasible in real-world scenarios, replacing the centralized decision-making process employed in the studies found in the literature. Finally, we present a few variations of the Decentralized NC-Drone that uses a synchronization method to merge or combine the individual information stored in the vehicles.

A. Centralized NC-Drone

The RTSM always sense the neighbor cells, choosing the one with the lowest value to be visited at each step. However, when a tie between two or more cells happens, the vehicle randomly chooses one of the cells to move. At the beginning of the coverage, all cells are marked with zero and several ties are computed, leading the vehicle to repeatedly change its orientation due to the random process. As changes in direction have a negative impact on energy consumption, this completely random decision is not satisfactory.

The Centralized NC-Drone is able to sense and share the information through the environment and always chooses the least visited cell as the original NC. However, in a case of a tie, our proposed approach verifies all the tied cells. If one of them is in front of the vehicle, this one is chosen to be the next cell. Otherwise, the next cell is randomly chosen. This aims to reduce the number of random decisions and keeps the vehicle in the same direction, avoiding unnecessary turns and consequently saving energy.

Although NC-Drone may be applied in a centralized way as the previous methods, our approach can also be adopted without the reading/writing pheromone scheme. Thus, we also propose here variations of the NC-Drone, which do not require the environment's shared information. In these variations, UAVs have their own information about the visited places and can decide autonomously their next movements. Some of these variations use a communication model to share information about the environment in order to provide a completely decentralized solution. These variations are discussed in Sec. IV-B.

B. Decentralized NC-Drone

In the proposed Decentralized NC-Drone, each vehicle keeps an internal map of the environment in matrix-form and uses an internal variable to store the current position of the vehicle (line and column of the matrix). Each position of the matrix represents a cell of the environment and stores the number of times the vehicle passed over the location, i.e, each vehicle keeps its own visited cells in the internal matrix. Following this decentralized approach, the vehicle decides the next cell to be visited based on its matrix, instead of reading in the environment as in the centralized approach. The algorithm verifies the neighbor positions in the matrix and chooses the smallest value, respecting the tie rule implemented to maintain the vehicle in the same direction. This first implementation of NC-Drone is named as Decentralized NC-Drone without communication. However, a same cell is visited by different vehicles in distinct times and this approach without communication cannot deal with that, since each vehicle stores only its own visits and consequently, its decision does not consider visits by other UAVs.

A synchronization process can be used to share the information stored in the matrices of the vehicles, and thus, build an updated coverage status. Here, we propose a matrix-based communication model to support this synchronization. While in the simulation the UAVs use a simple function to check the presence of other vehicles in the neighborhood at a certain radius, in real-world scenarios, the vehicles can use XBee devices to communicate with each other over the air, sending and receiving wireless messages, every time they are close enough. The XBee can also communicate with intelligent devices via the serial interface to merge the information of the vehicle's matrices.

We evaluated three different methods of information merge to update the matrices during the synchronization: MAX, AVG, and RESET. The NC-Drone MAX compares every position in both matrices and chooses the highest value. The NC-Drone AVG calculates the mean between the original values in each position of both matrices and round the result to the nearest integer number. The NC-Drone RESET also compares values and selects the highest ones to update the matrices, but if, after the synchronization, the vehicle detects that its own matrix does not have an unvisited cell -complete coverage- it fills the matrix with zeros.

Another idea is combining the information stored in multiple matrices in order to make a decision without merging the values into a single matrix. In this case, the vehicles copy the matrices of other vehicles when they are at the synchronization range, keeping to itself the information. These matrices are individually updated every time the vehicles pass by each other. When a vehicle needs to move, it sums the values of each neighbor of its current position considering all the matrices stored in its own memory and chooses the smallest one to move to. After that, only its own matrix is updated with the recent move. This method is called NC-Drone MULTI.

V. Experiments

The experiments were performed in a multi-agent systems development platform, the NetLogo. The platform allowed us to use agents as UAVs to navigate and interact with the scenario, while reading and writing information in the cells. The patrolling task were executed in a 50 x 50 grid with four UAVs launched from the same starting position at the lower left corner of the scenario. Thirty simulations with 10.000, 15.000 and 20.000 cycles were executed for each approach, where only one vehicle was able to move from one cell to another per cycle.

A. Performance Metrics

The performance metrics employed were Quadratic Mean of the Intervals (QMI), Standard Deviation of the Frequencies (SDF), Number of 90° Turning Maneuvers (NTM) and Number of Complete Coverages (NCC). The QMI metric fulfills an application requirement related to the frequency-regularity equilibrium. It has the property of reflecting a combination of the frequency of visits and the evenness of the intervals between visits. QMI presents a balance between the average value, maximum value and standard deviation of intervals [17]. Equation (1) illustrates the QMI metric:

$$QMI = \left[\frac{1}{N_{intervals}} \sum_{x \in cells} \left(\sum_{j=1}^{visits(x)+1} (i_j^x)^2 \right) \right]^{1/2} \quad (1)$$

where i_j^x represents the intervals between the visits j to the cells x and $N_{intervals}$ represents the total number of intervals.

The SDF metric fulfills an application requirement related to uniform visitation - i.e., measures how equally the visits are distributed among the cells. The zero value represents the ideal situation where all cells are visited exactly with the same frequency. QMI and SDF are independent of one another and has potential applications individually. Equation (2) presents the SDF metric:

$$SDF = \left[\frac{1}{|cells|} \sum_{x \in cells} (\ freq(x) - F_{avg})^2 \right]^{1/2} \quad (2)$$

where $freq(x)$ represents the frequency of visits of each cell x, F_{avg} represents the average of the frequencies of all cells and $cells$ is the total number of cells in the scenario.

The NTM metric fulfills an application requirement related to the energy consumption. In order to perform turning maneuvers, the vehicles must decelerate, rotate and accelerate again, which may increase the time and energy consumption of a mission [18]. Equation (3) presents the NTM metric:

$$NTM = \sum_{u \in uavs} \left(\sum_{k=1}^{turns(u)} t_k^u \right) \quad (3)$$

where t_k^u represents the number of turns for each UAV u.

Finally, the NCC metric fulfills an application requirement related to the continuous patrolling, where all the cells must be visited several times to perform repeatedly coverage. While QMI, SDF and NTM should be minimized, the NCC metric should be maximized.

B. Results

1) Centralized NC-Drone versus RTSM: The Centralized NC-Drone is compared with NC, LRTA*, TVUR, and WVUR. The approaches share the information through the environment, while reading and writing in the cells. The centralized process coordinates the vehicles sensing the neighbor cells and moving them through the scenario. Table I and Table II present the average/mean (M) and standard deviation (SD) results achieved by the approaches regarding QMI and SDF metrics, respectively. The best approaches are highlighted in bold for each metric.

TABLE I: QMI for Centralized NC-Drone and RTSM

Approaches	10K		15K		20K	
	M	SD	M	SD	M	SD
C. NC-Drone	**768.55**	**28.29**	**770.34**	**16.24**	**773.48**	**9.26**
NC	806.62	9.07	826.70	8.29	829.54	6.47
LRTA*	805.73	8.23	820.97	7.94	828.07	5.87
TVUR	791.89	7.29	808.93	7.38	813.12	6.24
WVUR	816.55	9.28	831.88	8.84	840.48	6.82

The Centralized NC-Drone proves to be the best approach among the evaluated RTSM regarding QMI metric, overcoming all approaches with a difference that is considered to be extremely statistically significant with 95% of confidence. In 20K cycles, the NC-Drone improves the QMI metric around 5% compared to the TVUR approach, which is the second best approach in this metric, and 7% compared to the original NC. The SDF results point out that NC-Drone overcomes NC, LRTA* and TVUR in 10K and 20K cycles, while presents results equivalent to the ones achieved by WVUR. In 15K cycles, the C. NC-Drone is superior than NC and TVUR - around 11% compared to both approaches, and is similar to the WVUR and LRTA* approaches.

TABLE II: SDF for Centralized NC-Drone and RTSM

Approaches	10K		15K		20K	
	M	SD	M	SD	M	SD
C. NC-Drone	**0.73**	**0.08**	**0.75**	**0.09**	**0.76**	**0.09**
NC	0.84	0.13	0.84	0.10	0.83	0.10
LRTA*	0.83	0.08	**0.78**	**0.08**	0.84	0.09
TVUR	0.87	0.10	0.84	0.10	0.84	0.09
WVUR	**0.77**	**0.08**	**0.76**	**0.08**	**0.76**	**0.09**

The NTM metric results are presented in Table III. The NC-Drone overcomes all approaches in all simulations with values three or four times smaller than the other methods. The rule of choosing the frontal cell in case of a tie between the lowest values drastically reduced the number of turns, which implies in decreasing the energy consumption during the coverage.

TABLE III: NTM for Centralized NC-Drone and RTSM

Approaches	10K		15K		20K	
	M	SD	M	SD	M	SD
C. NC-Drone	**5.8k**	**587.36**	**9.9k**	**653.55**	**14.5k**	**621.11**
NC	23.7k	78.87	35.6k	111.88	47.5k	150.01
LRTA*	24.2k	120.08	36.3k	141.23	48.4k	151.23
TVUR	24.0k	111.59	36.0k	108.93	48.1k	160.95
WVUR	23.8k	86.54	35.7k	110.46	47.6k	147.78

Results achieved by the approaches regarding the NCC metric are presented in Table IV. Despite the similar NCC values reached by the approaches, NC-Drone statistically overcomes NC, LRTA* and WVUR. The TVUR approach presents the best results in this criteria and overcomes NC-Drone. However, NC-Drone defeats the TVUR approach in the other three metrics, which is a valid trade off in patrolling missions, considering the energy saving and the uniform distribution of the visits.

TABLE IV: NCC for Centralized NC-Drone and RTSM

Approaches	10K		15K		20K	
	M	SD	M	SD	M	SD
C. NC-Drone	13.90	0.40	21.93	0.25	29.93	0.25
NC	13.47	0.68	21.43	0.50	29.37	0.67
LRTA*	13.47	0.51	21.37	0.61	29.37	0.49
TVUR	**15.23**	**0.68**	**24.47**	**0.57**	**33.47**	**0.57**
WVUR	12.07	0.37	19.40	0.56	26.63	0.49

2) Decentralized NC-Drone variations: The five decentralized variations NC-Drone without communication (D. W.C.), NC-Drone MULTI, NC-Drone MAX, NC-Drone AVG, and NC-Drone RESET are compared with the adopted metrics. In most cases, the centralized version overcomes all decentralized variations once it has unlimited access to all information available in the environment. Thus, we added the centralized results as an upper bound reference in gray color. The best decentralized-approach are highlighted in black and bold for each metric.

TABLE V: QMI results for the NC-Drone variations

Approaches	10K		15K		20K	
	M	SD	M	SD	M	SD
C. NC-Drone	772.33	33.24	773.79	18.31	779.47	19.66
D. MULTI	849.80	16.24	884.63	11.21	895.21	10.82
D. MAX	**797.58**	**10.97**	**816.81**	**8.54**	**825.43**	**6.86**
D. AVG	**795.57**	**9.60**	**813.00**	**5.80**	**823.67**	**7.36**
D. RESET	810.66	21.05	827.20	14.64	839.65	13.96
D. WC.	842.36	27.18	849.01	21.07	855.36	19.52

Among the decentralized versions, the D. MAX and the D. AVG present the best results in the QMI metric merging the information of the matrices every time the vehicles pass by each other. The D. MULTI presents the worse results only combining the information to make a decision every time, instead of merging the matrices. Ranking the methods according to this metric, we obtain C. NC-Drone, D. AVG, D. MAX, D. RESET, D. WC, and D. MULTI. Table V summarizes the QMI metric results.

TABLE VI: SDF results for the NC-Drone variations

Approaches	10K		15K		20K	
	M	SD	M	SD	M	SD
C. NC-Drone	0.72	0.07	0.73	0.07	0.78	0.09
D. MULTI	**1.14**	**0.13**	**1.14**	**0.11**	**1.16**	**0.15**
D. MAX	2.10	0.15	2.50	0.21	2.92	0.17
D. AVG	2.21	0.11	2.77	0.11	3.14	0.15
D. RESET	5.20	0.77	7.68	1.00	10.12	1.34
D. WC.	1.86	0.29	1.70	0.19	1.66	0.18

In the SDF results presented in Table VI, D. MULTI presents the best results and achieves the most uniform visitation among the decentralized variations. The information merging techniques were not able to equally distributed the visits between the cells. Even the D. WC overcomes the synchronization methods, D. MAX and D. AVG, using only its own matrix information to navigate through the scenario. The D. RESET was designed in an attempt to avoid distortions in the information caused by the merging techniques along the time but presents the worse results in this metric. Ranking the methods according to this metric, we obtain C. NC-Drone, D. MULTI, D. WC., D. MAX, D. AVG, and D. RESET.

Table VII summarizes the NTM results achieved by the compared approaches. In this comparison, the D. WC. presents the best results in 10K and 15K cycles, while the D. RESET presents improvements compared to D. WC in 20K. This can be explained by the lack of complete information on both approaches. While the D. RESET approach erases the

TABLE VII: NTM results for the NC-Drone variations

Approaches	10K		15K		20K	
	M	SD	M	SD	M	SD
C. NC-Drone	5.7k	523.18	9.9k	716.76	14.2k	671.15
D. MULTI	7.9k	521.24	13.8k	634.17	20.0k	674.05
D. MAX	6.5k	282.11	11.1k	294.72	15.5k	316.20
D. AVG	6.4k	266.83	10.8k	415.43	15.8k	396.71
D. RESET	3.2k	268.76	5.0k	383.06	**6.8k**	**456.54**
D. WC.	**2.5k**	**185.92**	**4.7k**	**353.94**	7.5k	547.07

entire matrix when it is completed, the D. WC. does not exchange information with other vehicles during the coverage. As the vehicles share information about the visits they face fewer ties in the search, which may increase the number of turns. Thus, the decentralized versions with communication do not take advantage of the main characteristic of the NC-Drone, which is to keep the same movement direction during ties and what, consequently, leads to the worse results in this metric. Ranking the methods according to this metric, we obtain D. WC., D. RESET, C. NC-Drone and D. MAX/AVG, and D. MULTI.

TABLE VIII: NCC results for the NC-Drone variations

Approaches	10K		15K		20K	
	M	SD	M	SD	M	SD
C. NC-Drone	13.97	0.18	21.77	0.43	29.97	0.18
D. MULTI	**12.67**	**0.55**	**20.67**	**0.55**	**28.63**	**0.49**
D. MAX	10.70	0.53	17.33	0.66	23.73	0.83
D. AVG	10.13	0.51	16.37	0.61	22.90	0.80
D. RESET	7.30	0.95	12.07	1.36	17.57	1.59
D. WC.	11.53	0.68	19.27	0.69	27.40	0.67

The D. MULTI presents interesting results in the NCC metric, overcoming all the decentralized variations and almost reaching similar values to the centralized one. Once more, the D. WC. overcomes both synchronization methods, D. MAX and D. AVG, while D. RESET has the worse results in all simulations. Ranking the methods according to this metric, we obtain C. NC-Drone, D. MULTI, D. WC., D. MAX, D. AVG, and D. RESET. Table VIII presents the comparison results of the NC-Drone variations regarding the NCC metric.

VI. Conclusion

This paper presented a novel energy-aware RTSM called NC-Drone for the patrolling problem using multi-UAVs. A centralized version using the reading and writing pheromone scheme is compared with the RTSM and drastically reduces the number of turns and, hence, decreases the energy consumption. However, the centralized approach is not feasible in real-world scenarios due to the constant communication necessary between the vehicles and a base. Thus, we presented a decentralized approach using internal matrices to store the visited cells in vehicle's memory. In this approach, UAVs are able to merge and combine their information through different synchronization schemes. The decentralized NC-Drone versions emerge as promising solutions to be applicable in coverage tasks, once fulfill all the metrics related to patrolling missions.

As a future work, we intend to improve the coverage performance considering the entire matrix in the search phase, instead of only the immediate neighbors. We also intend to implement the Decentralized NC-Drone in real flights performed with multirotors.

References

[1] B. Hefferan, O. M. Cliff, and R. Fitch, "Adversarial patrolling with reactive point processes."

[2] H. L. Andersen, "Path planning for search and rescue mission using multicopters," Master's thesis, Norway, 2014.

[3] A. Barrientos, J. Colorado, J. del Cerro, A. Martinez, C. Rossi, D. Sanz, and J. Valente, "Aerial remote sensing in agriculture: A practical approach to area coverage and path planning for fleets of mini aerial robots," *J. Field Robot.*, vol. 28, no. 5, pp. 667–689, 2011.

[4] D. W. Casbeer, D. B. Kingston, R. W. Beard, and T. W. McLain, "Cooperative forest fire surveillance using a team of small unmanned air vehicles," *Int. J. Systems Science*, vol. 37, no. 6, pp. 351–360, 2006.

[5] A. Stalmakou, "Uav/uas path planning for ice management information gathering," Master's thesis, Norway, 2011.

[6] C. Castiblanco, J. Rodriguez, I. Mondragon, C. Parra, and J. Colorado, "Air drones for explosive landmines detection," in *ROBOT2013: First Iberian Robotics Conference: Advances in Robotics, Vol.2*. Springer International Publishing, 2014, pp. 107–114.

[7] M. Aghaei, P. Bellezza Quater, F. Grimaccia, S. Leva, E. Ogliari, and M. Mussetta, "Pv plant planning and performance monitoring by means of unmanned aerial systems (uas)," in *8th AIGE (Italian Association of Energy Management) National Conference*, Jun 2014.

[8] S. Koenig and Y. Liu, "Terrain coverage with ant robots: A simulation study," in *Proceedings of the Fifth International Conference on Autonomous Agents*, 2001, pp. 600–607.

[9] J. Zelenka and T. Kasanickỳ, "Insect pheromone strategy for the robots coordination," *Applied Mechanics and Materials*, vol. 613, pp. 163–171, 2014.

[10] C. Nattero, C. T. Recchiuto, A. Sgorbissa, and F. Wanderlingh, "Coverage algorithms for search and rescue with uav drones," in *Artificial Intelligence, Workshop of the XIII AI*IA Symposium on*, Dec 2014.

[11] J. Zelenka and T. Kasanickỳ, "Outdoor uav control and coordination system supported by biological inspired method," in *Robotics in Alpe-Adria-Danube Region (RAAD), 2014 23rd International Conference on*, Sep 2014, pp. 1–7.

[12] J. Zelenka and T. Kasanickỳ, "Insect pheromone strategy for the robots coordination - reaction on loss communication," in *Computational Intelligence and Informatics (CINTI), 2014 IEEE 15th International Symposium on*. IEEE, 2014, pp. 79–83.

[13] E. Kuiper and S. Nadjm-Tehrani, "Mobility models for uav group reconnaissance applications," in *2006 International Conference on Wireless and Mobile Communications (ICWMC'06)*. IEEE, 2006, pp. 33–33.

[14] M. Rosalie, G. Danoy, S. Chaumette, and P. Bouvry, "From random process to chaotic behavior in swarms of uavs," in *6th ACM Symposium on Development and Analysis of Intelligent Vehicular Networks and Applications*, 2016.

[15] M. Paradzik *et al.*, "Multi-agent search strategy based on digital pheromones for uavs," in *Signal Processing and Communication Application Conference (SIU), 2016 24th*. IEEE, 2016, pp. 233–236.

[16] P. Sampaio, R. Sousa, and A. Rocha, "New patrolling strategies with short-range perception," in *Proceedings of the 2016 XIII Latin American Robotics Symposium and IV Brazilian Robotics Symposium*, 2016.

[17] P. A. Sampaio, "Patrulha temporal: taxonomia, métricas e novas soluções." Ph.D. dissertation, Universidade Federal de Pernambuco, 2013.

[18] C. Di Franco and G. Buttazzo, "Coverage path planning for uavs photogrammetry with energy and resolution constraints," *Journal of Intelligent & Robotic Systems*, pp. 1–18, 2016.