

Optimized UAV waypoints selection for maximum area coverage

Mark Bastourous¹,David Strubel ^{1;2},Olivier Morel¹,David Fofi¹

Abstract—Area coverage is a very crucial application in many domains. It requires time, precision, and sometimes repetition which prevails the important use of robots. Over many years in research, several robotics platforms on the ground, in aerial, or underwater have been studied, developed and tested. These robots can reach, navigate and execute tasks that humans are not capable of or can be tedious or harmful.

Coverage path planning (CPP) is the problem of finding the most suitable path with least cost in terms of time, power, and dynamics that can cover a given area. In this work the CPP of unmanned aerial vehicles (UAV) problem is partitioned into optimally selecting the poses that will guarantee highest area coverage, then plan the path traversing these selected poses. Path planning is done in two stages consisting of; global and local planners. The global planner is responsible for generating the path with minimal length passing by the predefined waypoints. The local planner's role is to find the clear way in between these waypoints that will be used to build the robot's trajectory.

The problem is approached from an optimization point of view. Genetic algorithm (GA) and particle swarm optimization (PSO) are tested to solve the problem of choosing the coverage waypoints. Then GA is re-used again to solve the global planner challenge. The robot poses from the coverage are formulated by the well-known computer science problem traveling salesman problem (TSP). Then several methods are tested to solve the local planner challenge like linear, spline piecewise, artificial potential field. After generating the path, in the phase of executing the UAV trajectory both in simulation and on the practical platform.

I. INTRODUCTION

Aerial robots have grown great attention in the last decades due to its capabilities in solving many problems in many domains. They are still under study, investigation and development because of the several constraints and challenges that are in software and hardware of its construction on many levels and layers.

Some of the software challenges are state estimation, control, decision making, mapping, and path planning. Some of the hardware challenges are the weight/load ratio, power source, sensors, etc.

There are various applications that practically make use of unmanned aerial vehicles (UAV) and much more are still under study and development in the research labs and institutes. These applications are covering many fields of interest in both civilian and military purposes. Some of these practical applications are search and rescue, inspections, surveillance, photography, agricultural terrain mapping, mineral exploration, etc. Some prospective applications like

medical cargo delivery because it will not rely on the normal road maps if they exist, or traffic constraints.

There are many types of UAVs categorized based on the geometry and designs like fixed wing, flapping wing, and rotor crafts, mentioned in more details in [13]. From cheap and small toys that you can be bought anywhere as the RC planes, toy quadcopter, to big military projects such as the Global Hawk.

UAVs have recently reached a decline in their cost especially the quadcopters. In this paper during the practical implementation part, quadcopters as one type of the rotor crafts will be used. The quadcopter used is Ar.drone 2.0 from the french company Parrot. It is off shelf drone that can be found on the market with comparable cheap price in range of 300 euros depending on the extras. It has been used several times in research labs and studied like in [18],etc.

There are many advantages that make quadcopter as a specific type of UAVs, suitable for both indoor and outdoor applications. It takes off vertically, do not need a runway, hover in its place, comparably light weight, and small in size.

For simulation V-REP with a model of quadcopter available was used. Some modification in this model was introduced to cope with the problem being solved and will be discussed later in more details. In both the practical work and simulation, ROS packages were used, tuned and implemented to control the quadcopter.

Some of the previously mentioned applications require area coverage of outdoor or indoor mapping. Coverage path planning is an active research topic as the sub division of the general path planning problem that is studied by robotics domain for several decades till our day. It has been applied on many platforms in many areas where these platforms work. Normally the area to be covered is not a regular one. Most of the literature review that comes to the awareness to the author of this thesis are concerned with uniform areas and prior map with static or dynamic obstacles. Platforms here means the mobile robots like autonomous underwater vehicles(AUV), unmanned aerial vehicle(UAV), or ground vehicles.

Prior information about the environment is assumed to be given in the form of a rough map for the area required to be covered. For this work, we model the set of coverage problems as arc routing problems. Although these routing problems are generally NP-hard, our approach aims for optimal solutions through the use of low-complexity algorithms in a branch-and-bound framework when time permits and approximations when time restrictions apply.

The final objective of this paper research is to design a global optimization scheme allowing a cameras network to

1 LE2I UMR6306, CNRS, ENSAM, Univ. Bourgogne Franche-Comte

2 CISIR, Universiti Teknologi Petronas

Mark Bastourous is doing Masters of computer vision, Universite De Bourgogne, France mark.nabil.guc@hotmail.com

be self organized or to plan single trajectory of a flying robot equipped with a camera, according to fixed priority and constraints, in order to ensure a full coverage of a given scene. Applicable solution for both indoor and outdoor with ensuring coverage of the terrain while minimizing path repetition. Then building a mosaicking of the area covered and compare it with the original scene.

II. RELATED WORK

A. Waypoint Selection

Finding the waypoints to have the best coverage of the area is close to the problem of positioning cameras or sensors to cover an area efficiently. Sensor positioning problem has been investigated since a few decades, mainly for video surveillance [1]. Without any additional constraint, this problem is NP-Hard as stated in [1]–[5] for the Watchman Route Problem (which is very similar to the optimal positioning waypoint for UAV path). Two non-optimal solutions have been proposed. The first one is based on Art Gallery Problem (AGP) [2], [3] and the second one is based on the Wireless Sensors Networks [6]–[9] trying to find the best position to design an efficient network which can collect data with any kind of sensors.

However, the solution proposed to the problem addressed the coverage problem but linked with additional and specific constraints, which are out of our scope.

One of the algorithms used is the Particle Swarm Optimization (PSO) as detailed in [10], [11]. Zhou *et al.* [10], some experimental results are provided and one solution running in real time is proposed. However, the scene used in these experiments is rather small and many cameras are employed to fully cover it. On the other hand, [11] uses a cost function but the cost function is not only focused on the position for surveillance and coverage, but also handling resolution and lighting, which affect the final solution by not covering the under illuminated areas. Reddy *et al.* [11] also introduced the concept of an acceptable response, allowing non-optimal/sub-optimal solutions. If the coverage score is higher than a given threshold, the solution is accepted and not locked by the research of an optimal solution.

B. Coverage Path Planning

There are various ways to obtain and optimize the path planning. CPP problem is a sub-field of path planning and well studied for ground vehicles like cases in [14], [15].

In operations research, the CPP problem represents the environment as a graph. The problem can be represented as the TSP or postman problems to generate optimal solutions. In the graph representation, locations in the environment is represented as nodes in the graph and the paths between the locations are the edges. Each edge has a cost assigned to it. The cost can represent measurements such as distance(Euclidean,Mahalanobis,etc) between locations, terrain traversability, travel time or a combination of several metrics. These edges can be constrained or unconstrained with directions. More precisely undirected , directed graphs.

Voronoi diagram is also another possible solution for decomposing the desired area and find the feasible solution from the starting point to the goal point through two-step path planning algorithm, but it doesn't take into consideration the repetition rate constraint or full area coverage. For these reasons considering problem representation as arc routing problem is most beneficial. Solving these problems can be achieved by using bio-inspired algorithms like neural networks or evolutionary algorithms.

TSP is considered one problem of a large class of problems known as combinatorial problems. It is shown in UAV path planning for several purposes like refueling depots in [16] and many other cases. This is a non-deterministic polynomial-time hard (NP-hard) problem, that is sub-optimally solvable by many approaches as found in various research fields. Evolutionary approaches specifically will be considered in this paper.

Evolutionary algorithms: Evolutionary Algorithms(EA) as a sub branch of meta-heuristic optimization algorithms, imitates the biological process of evolution in nature. There are various algorithms that are branched from it like Ant colony optimization (ACO), particle swarm optimization (PSO),Genetic Algorithm GA and much more which can be studied from [17]. GA uses techniques of inheritances, mutations, selections and crossovers of chromosomes over several generations of possible solutions to find convergence to the most optimized solution. Explanation in the next chart is the general abstract view of GA, more details will be explained in the methodology chapters.

Coverage path planning can be categorized into sampling based algorithms, node based algorithms, mathematic model based algorithms, bio-inspired algorithms. Then comes the category emerging lately in the next subsection.

III. METHODOLOGY

A. Waypoints Selection

The main purpose of our work is to estimate the position of n camera waypoints for surveying a given area in order to maximize the visual coverage. Each camera provides a top view of the area similar to UAV views. The coverage area of each camera is defined by the projection of the visual field onto the ground. This way, the mosaic composed by the captured images should be very close to a complete top view of the area. In order to find the best coverage many experiments have been done to compare PSO and also GA. PSO is easier to implement and runs faster but GA is more flexible and generic thanks to the many tunable parameters. The following subsections will give an overview our method, which is based on GA, and provide a comparison between PSO and GA that demonstrates the overall advantage of the latter on the former.

B. Cost function

Since the goal is to maximize the visual coverage of the camera network, a cost function has been chosen to quantify

it, as follows:

$$\sum_{i=1}^n = \frac{\text{cover}(i)}{\text{size}(\text{grid})}_{1 \leq i \leq n}, \quad (1)$$

where n is the number of waypoints; grid represents the discretization of the ground plane (floor); $\text{cover}(\dots)$ is a function which computes the area on the ground which is covered by at least one camera ; $\text{size}(\dots)$ is the dimension of the full area which must be $\text{covered}(\text{grid})$.

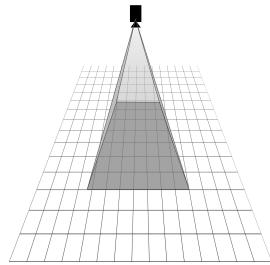


Fig. 1. Projection of the camera on the ground.

Camera projection model is not explicitly taken into account, but the ground-projected visual field instead, as described in Fig.1.

C. Genetic algorithm

Motivated by Darwin's theory of evolution and the concept of survival of the fittest, GAs use processes analogous to genetic recombination and mutation to promote the evolution of a population that best satisfies a predefined goal [12]. Such kind of algorithms require the definition of a genetic representation of the problem and of a cost function used to evaluate the solution. The candidate solution is represented by a data structure named chromosome, defined by Eq.(2) with x, y and z the cartesian coordinates and θ the rotation of the camera with respect to the optical axis: only two possible angles are allowed, 0° or 90° (portrait or landscape). To pass from an iteration (or generation) to the other a few steps are necessary (see Fig.2).

$$A = \begin{bmatrix} X_i \\ Y_i \\ Z_i \\ \theta_i \end{bmatrix}_{1 \leq i \leq n} \quad (2)$$

In our experiments, we empirically fixed the number of chromosomes to be 90, the mutation rate to be 0.001 and the crossover rate to be 0.919.

D. Context of experimentation

In order to compare the two algorithms and evaluate their performances, we tested them on different scenarios depicted in Fig.3, with areas of different sizes and shapes, where:

- z is the height of the camera between (within the range $[1/z; z]$).
- Figure 3(a) is an area of size 120×80 (named Room).
- Figure 3(c) is an area of size 240×160 (named Big room).

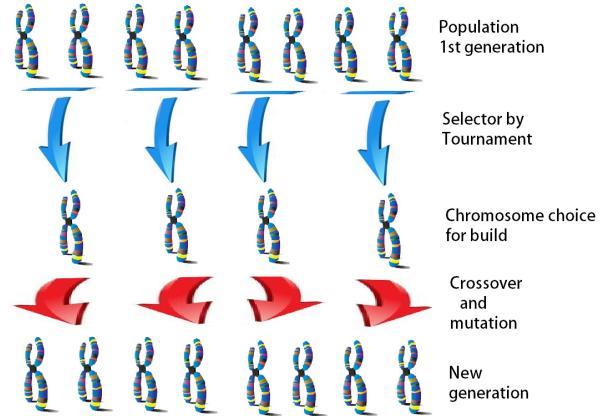


Fig. 2. GA explanation, from one generation to the other.

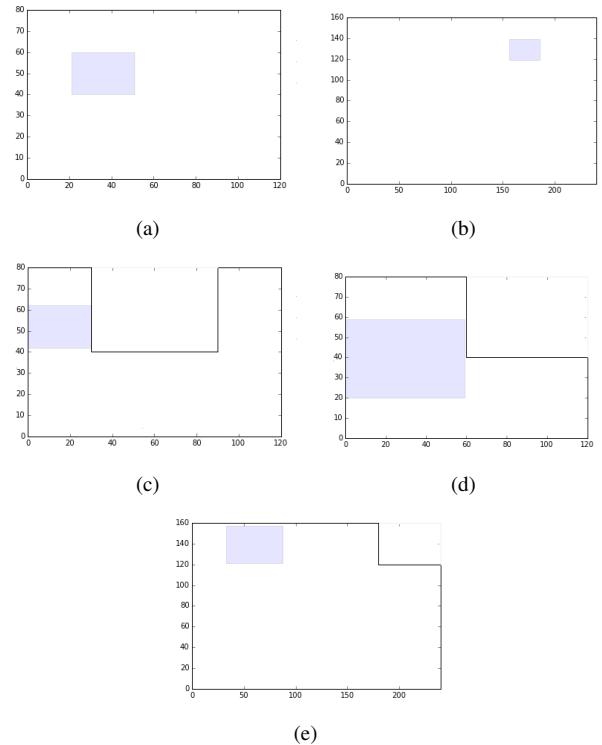


Fig. 3. Scenarios used for the experiments: (a), (b), (c) are with $z=1$ and (d), (e) with $z=2$. The gray rectangle represents the field of view of one camera projected onto the ground.

- Figure 3(b) is an area of size 120×80 (named Room U)
- Figure 3(d) is an area of size 120×80 (named Room L)
- Figure 3(e) is an area of size 240×80 (named Big room L)

The design of experiments in Table I has been set up to identify the most efficient algorithm for the positioning of a set of waypoints with the maximum of coverage.

The Ground Truth (GT) is the minimum number of waypoints required to fully cover a given area. The size of the area has been selected so that the GT can be easily estimated.

z=1		GA		PSO	
		GT	NW	GT	NW
Room	120x80	16	20	16	20
	240x160	64	70	64	70
Room U	120x80	12	20	12	20
	z=2	GA		PSO	
Room	120x80	4	10	4	10
	240x160	16	20	16	20
Room L	120x80	3	10	3	10
	240x160	15	20	15	20

TABLE I

DESIGN OF EXPERIMENT FOR COMPARE THE EFFICIENCY OF PSO AND GA IN DIFFERENT CONDITION. (GT IS GROUND TRUTH AND NW IS NUMBER OF WAYPOINTS).

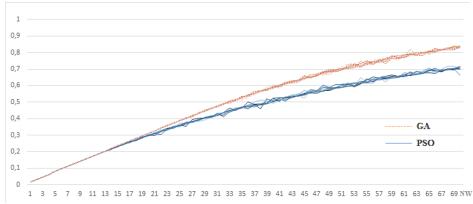


Fig. 4. Comparison of eight solution given by GA, eight solution given by PSO algorithms with a Z equal to 1, in the big room 240x160 and ground truth equal to 64.

NW is the maximum number of waypoints (or camera views) used for the experiments. At each experiment a solution is computed for a number of waypoints from 1 to NW. In order to compare the different algorithms in similar conditions, only 10000 calls of the cost function is allowed for each set of waypoints.

E. Analysis of the result

After performing the design of experiments (see Table I) it appears that GA and PSO algorithms are close in performance. In some cases GA is much more efficient (see in Fig.4) particularly in the case where the search space is large (big room and big number of cameras) as example in Fig.4). Instead PSO is more effective to optimize small areas (see in Fig. 5). This efficiency can be explained by the small variation of the solution introduced by the PSO.

However, this small variation is not enough to find an optimized solution in a big search space which happen when a lot of cameras are required or when the local minima is deeper. Although the variety of solutions introduced by the GA allow to escape from local minima, it can affect negatively the accuracy of the solution, which may require a further optimization step to refine.

Following the comparison of the 2 algorithms, the GA seems more suited to find UAV waypoints especially if it navigates in a large room or outdoor scene. Furthermore, our comparative study demonstrated that the GA is less dependent on the shape of the area to cover.

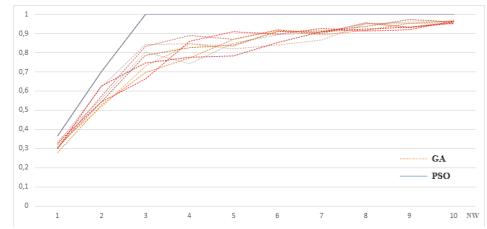


Fig. 5. Comparison of eight solution given by GA, eight solution given by PSO algorithms with a Z between [1/2; 2], in the room with L shape 120x80 and ground truth equal to 15.

F. Path Planning

There are several ways to globally solve and find the robot path within a map. Some operations research methods, such as traveling salesman problem (TSP), Chinese postman problem and rural postman problem can be considered.

1) *Global Planner*: The robot traversing the waypoints can be formulated as traveling sales man problem(TSP). The TSP can be shortly explained as a salesman has to visit several cities (or road junctions). The goal is to find the salesmans route of minimum length with the constrain of passing by all the cities only once. Mathematically modeling the problem as a complete graph with n vertices, the salesman will make a tour or hamiltonian cycle [9]. Sorting the path can be addressed as an optimization problem. Every node which is a point in space (3D position) is represented as a city and the euclidean distances between the cities are calculated and used as the optimization cost function. The path is organized based on the minimum length of traversing over all the waypoints. To find an optimized solution GA is used. The privilege of TSP problem formulation and solving it using GA over the other shortest path algorithms like Dijkstra, is that it provides global complete solution traversing all the waypoints not finding a path from a starting node to a goal node. The GA approach for multiple waypoint path planning is more clarified and discussed by Trevor et al. in [10]. GAs generally consist of three operators: selection, crossover, and mutation. The evaluation function for the N cities two-dimensional Euclidean TSP is the sum of Euclidean distances between every pair of cities in the tour.

2) *Local Planner*: After succeeding in getting the main waypoints sorted in a way to grantee shortest path length. Forthwith comes the issue of generating the mid waypoints that the robot should traverse to generate the trajectory.

Linear Piecewise: Where the line segment between points will be the line between every waypoint and the consecutive one.

Spline Piecewise: The goal of the spline interpolation is to find the shortest smooth path.

Artificial Potential Field: The goal position to be reached is an attractive pole for the robot and obstacles are repulsive surfaces.

IV. EXPERIMENTS AND RESULTS

In our experiments, V-REP is used to simulate the hardware of the UAV and all its mounted sensors like camera

which is the core sensor. It was also used to build the room as explained in more details afterwards. In order to ease the deployment of the algorithms on a real platform, we chose ROS as the implementation framework to command the simulated UAV.

Results generated by using 18 waypoints, providing 79% of area coverage.

Parameter	Corresponding Values	
Area Coverage	79%	90.68%
Number of waypoints	18	22
	486	511
Distance in meters	463.47	
	463	547
	474	

TABLE II
DIFFERENT RESULTS OF THE PATH GENERATED BY GA

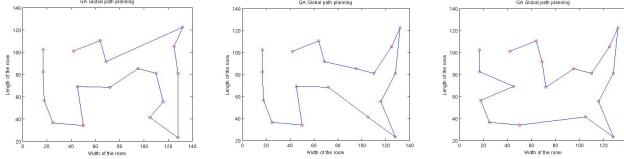


Fig. 6. GA path planning followed by linear piecewise of 18 waypoints to cover 79% of an area

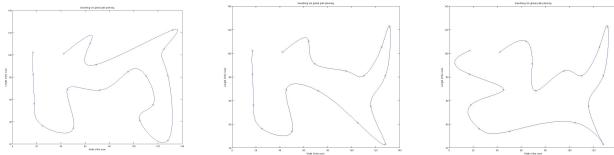


Fig. 7. Smoothing GA path planning of 18 waypoints to cover 79% of an area

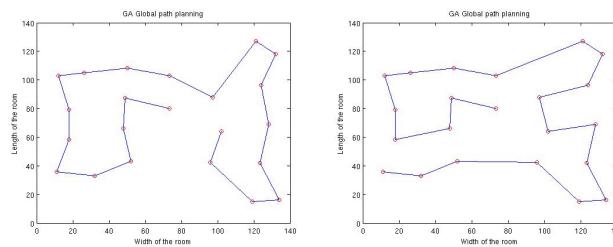


Fig. 8. GA path planning followed by linear piecewise of 22 waypoints to cover 90.68% of an area

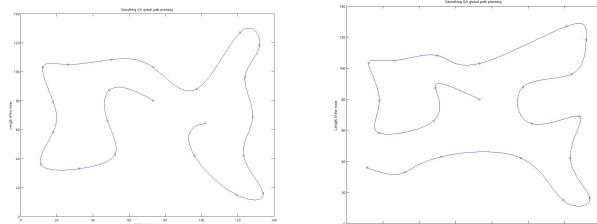
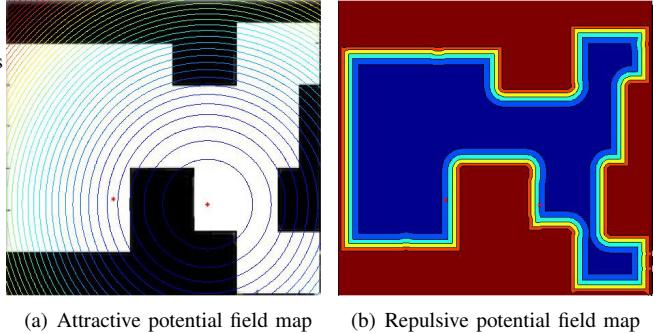
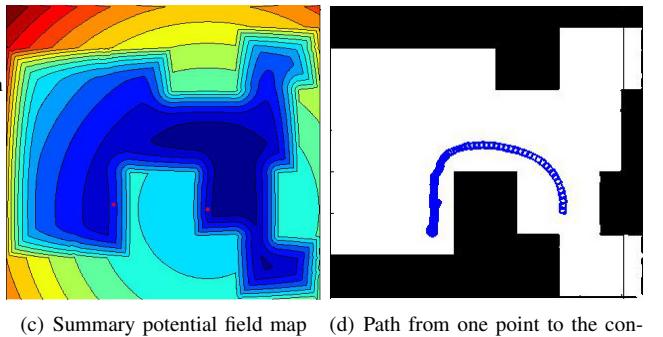


Fig. 9. Smoothing GA path planning of 22 waypoints to cover 90.68% of an area

Artificial Potential Field(APF) results can be exemplified in the following figure.



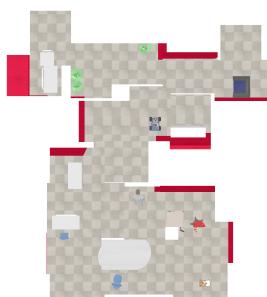
(a) Attractive potential field map (b) Repulsive potential field map



(c) Summary potential field map (d) Path from one point to the consecutive

Fig. 10. Potential field map

A. Final Mosaick



(a) Room mosaicing



Fig. 11. Room Coverage

The robot used in the practical context is Ar.Drone 2.0. It was inddor localized using visual SLAM tum_ardrone

package that was running on ROS indigo.

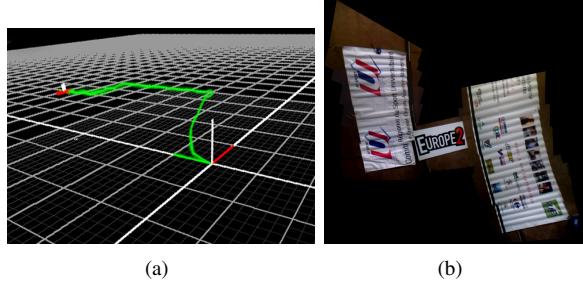


Fig. 12. Ar.Drone real experiment Path Planning and mosaick

A video showing the robot navigation, path execution, frontal camera scene and mosaicking generation; can be found in this link [19].

V. CONCLUSIONS AND FUTURE WORKS

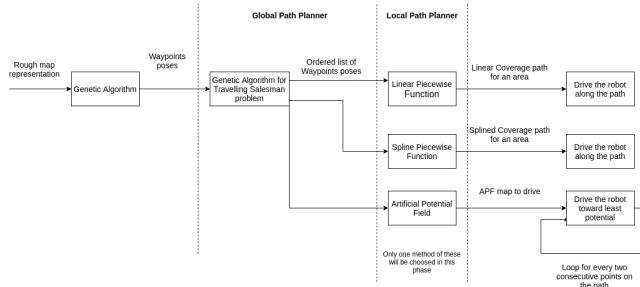


Fig. 13. Pipeline of the methodology

A. Conclusions

In this paper, the coverage path planning is addressed with a new approach. This approach is dealing with area coverage problem as two different challenges. The first challenge is the optimized choice of poses that guarantee maximum area coverage. The second challenge is path planning of these chosen poses.

This thesis is considering nonregular areas. Evolutionary algorithms specifically genetic algorithm (GA) is used and compared with other methods like particle swarm algorithm to solve the first problem of area coverage. GA approach efficiently cover 90% of a given area.

Several path planning approaches were tested. The design of having the multi layer of path planning is taken into account. Three algorithms were implemented, tested and compared results were presented. In all the three algorithms, there are two layers of path planning. The first layer is formulating the robot poses as cities and connect them to form a graph which resembles the TSP. GA is used to solve TSP and generate a list of poses of the cities that will insure least length of tour.

Then the second layer is different in the three algorithms. The first algorithm, takes the list of ranked poses and generate linear piecewise function linking all the poses. The second algorithm is using spline piecewise function

instead of linear which generate smoother paths. Last but not least, the third approach, uses APF as the second layer of map representation and path planning. It is used mainly to avoid obstacles that appear on the map. Static obstacles are considered in this paper. Efficiently traversing the map without the known falling in the trap of local minima.

One of the drawbacks of APF is the vast amount of parameter tuning needed before having the efficient results. This tuning is dependent on many factors like; a scaling factor of both the attractive and repulsive potentials, the current heading of the robot. It is also dependent on the shape of the map. The initial and final goal location being traversed are influencing the potential field too.

B. Future Works

- Impose dynamic obstacles in the map to validate the artificial potential field.
- Re-planning algorithms in real time can be tested.
- RRT can be a good alternative to being tried instead of the artificial potential field.
- The down camera of AR.Drone 2.0 is of low resolution. So thinking of attaching a camera to the drone and testing it will be of great importance for better results.

REFERENCES

- [1] Chin, W. Ntafos, S.: Optimum watchman routes. *Inform. Process. Lett.* (1988)
- [2] Moeini, M., Krller, A., Schmidt, C. Une Nouvelle Approche Pour la Resolution du Probleme de la Galerie d'Art.
- [3] Erdem, U. M., & Sclaroff, S. (2006). Automated camera layout to satisfy task-specific and floor plan-specific coverage requirements. *Computer Vision and Image Understanding*, 103(3), 156-169.
- [4] Packer, E. (2008). Computing multiple watchman routes. In *Experimental Algorithms* (pp. 114-128). Springer Berlin Heidelberg.
- [5] Zhao, J., Cheung, S. C., & Nguyen, T. (2008). Optimal camera network configurations for visual tagging. *Selected Topics in Signal Processing, IEEE Journal of*, 2(4), 464-479.
- [6] Song, B., Soto, C., Roy-Chowdhury, A. K., & Farrell, J. (2008, September). Decentralized camera network control using game theory. In *Distributed Smart Cameras, 2008. ICDSC 2008. Second ACM/IEEE International Conference on* (pp. 1-8). IEEE.
- [7] Liu, L., Zhang, X., & Ma, H. (2010). Optimal node selection for target localization in wireless camera sensor networks. *Vehicular Technology, IEEE Transactions on*, 59(7), 3562-3576.
- [8] Ma, H., Yang, M., Li, D., Hong, Y., & Chen, W. (2012, March). Minimum camera barrier coverage in wireless camera sensor networks. In *INFOCOM, 2012 Proceedings IEEE* (pp. 217-225). IEEE.
- [9] Wang, Q., Wu, J., & Long, C. (2013, October). On-line configuration of large scale surveillance networks using mobile smart camera. In *Distributed Smart Cameras (ICDSC), 2013 Seventh International Conference on* (pp. 1-6). IEEE. *Transactions on*, 2004, vol. 52, no 3, p. 771-779.
- [10] Zhou, P., & Long, C. (2011, October). Optimal coverage of camera networks using PSO algorithm. In *Image and Signal Processing (CISP), 2011 4th International Congress on* (Vol. 4, pp. 2084-2088). IEEE.
- [11] Reddy, K. K., & Conci, N. (2012, October). Camera positioning for global and local coverage optimization. In *Distributed Smart Cameras (ICDSC), 2012 Sixth International Conference on* (pp. 1-6). IEEE.
- [12] Boeringer, Daniel W. et Werner, Douglas H. Particle swarm optimization versus genetic algorithms for phased array synthesis. *Antennas and Propagation, IEEE*
- [13] Piegl LA, Valavanis K, OhP. *Unmanned aircraft systems*. Springer, New York, 2008.
- [14] Howie Choset. Coverage for roboticsa survey of recent results. *annals of mathematics and artificial intelligence* 31.1-4. pages 113–126, (2001).

- [15] Marc Carreras Galceran Enric. A survey on coverage path planning for robotics. *Robotics and autonomous systems* 61.12. pages 1258–1276, 2013.
- [16] Kaarthik Sundar and Sivakumar Rathinam. Algorithms for routing an unmanned aerial vehicle in the presence of refueling depots. *Automation Science and Engineering, IEEE Transactions on*, 11(1):287–294, 2014.
- [17] Dan Simon. *Evolutionary optimization algorithms*. John Wiley & Sons, 2013.
- [18] Cooper Bills, Joyce Chen, and Ashutosh Saxena. Autonomous mav flight in indoor environments using single image perspective cues. In *Robotics and automation (ICRA), 2011 IEEE international conference on*, pages 5776–5783. IEEE, 2011.
- [19] Mark Bastourous video of the practical experiment. <https://onedrive.live.com/redir?resid=7D510DC6427EBCFD!2442&authkey=!ADaFBcw-AiQErOI&ihtint=folder%2cwmv>, 2016. Online; accessed 29-May-2016.