Optimal Area Covering using Genetic Algorithms

Paulo A. Jimenez, Bijan Shirinzadeh, Ann Nicholson and Gursel Alici

Abstract— **Path planning problems involve computing or finding a collision free path between two positions. A special kind of path planning is complete coverage path planning, where a robot sweeps all area of free space in an environment. There are different methods to cover the complete area; however, they are not designed to optimize the process. This paper proposes a novel method of complete coverage path planning based on genetic algorithms. In order to check the viability of this approach the optimal path is tested in a virtual environment. The simulation results confirm the feasibility of this method.**

I. INTRODUCTION

CONVENTIONAL goal-oriented and map-based path planning methods do not address the problem of complete coverage path planning, in which a path is found to ensure that every point in a given workspace is covered at least once. Complete coverage is needed for a variety of commercial and governmental applications such as vacuum cleaners robots, painter robots, landmine detection, mapping, harvesters, and lawn mowers.

In general, there are two ways of covering an area: exhaustive and random coverage. Exhaustive coverage is best used when the robot's niche is limited (indoors); because of time and power restrictions, it is not suitable for covering large environments completely. Random coverage, on the other hand, does not guarantee complete coverage, but it does not necessarily require costly localization sensors or computational power.

II. RELATED WORK

Various approaches to complete coverage path planning have been developed, e.g. Artificial Potential Field (APF), cellular decomposition, template based, sensor-based, neural networks and fuzzy logic. APF, for instance, determines the positions to which the robot should move by controlling the forces that move the robot. Ratering and Gini [1] navigate in a known environment using a hybrid APF that combines two different types of APF. Hussein and Elnagar [2] propose the use of Maxwell's equation to eliminate local minima problem in APF. The concept behind cellular decomposition is to decompose the environment into a number of non-overlapping cells. Wong and MacDonald approach [3] uses natural landmarks in the environment to construct subregions. Choset [4] uses Boustrophedon, back and forth ox-like motions, to cover cells. Using a template based method, the complete trajectory is planned as a sequence of pre-defined trajectories or templates. The template based method introduced by Caravalho et al. [5] is able to deal with newly appearing obstacles. Slack's planner [6], which combines APF and Template Based approaches, responds to changes in the environment. Sensory based approaches use incoming sensory data to search a path that passes through all parts. Acar and Choset's method [7] finds and cover all critical points in an unknown map, thus covering the whole area. Lui et al. [8] provide sensor information to motion templates; then the robot uses random search to cover the area. Neural Network approach uses biologically inspired networks to produce path for total coverage; Luo et al. [9] were able to build a local map dynamically and avoid obstacles. Probabilistic methods utilises a probability density map to sweep an area passing over most of the critical points (e.g. landmines). Acar's robot [10] recovered landmines in an unstructured indoor environment, where the robot has a probability map of the landmines. Although, these methods cover the complete area, they are not designed to optimize the process.

In this paper, a genetic optimization is proposed for an area covering problem for a relatively structured environment (office building or factories). The environment is divided in sub-regions as in cellular decomposition method [11]. Then a path for each region is created. Since finding a solution for several sub-regions is time consuming and computationally costly, a genetic optimization algorithm is used to provide the most efficient coverage path planning.

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III. PROPOSED ALGORITHM

Consider a planar region R, which describes an indoor environment, populated with polygonal obstacles. In general, R may be divided into a series of polygonal sub-regions hole-free as shown in Figure 1. The idea behind this decomposition is to discriminate between geometric areas, or cells that are free and areas that are occupied by objects.

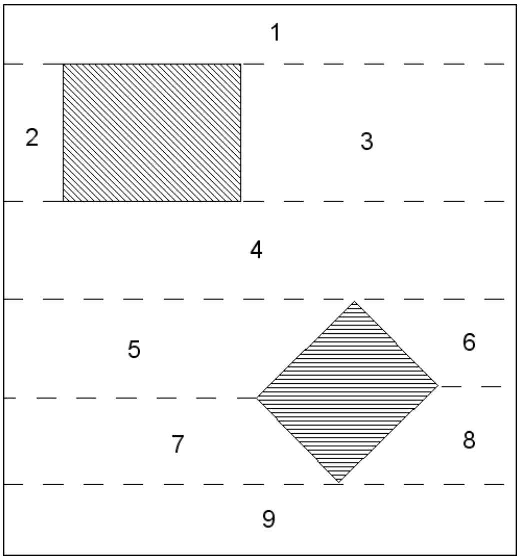

Figure 1: Horizontal decomposition

Using Horizontal decomposition it is possible to obtain a global undirected graph (Figure 2) $G = \{S, L\}$ where S and L represent the sub-regions, and connections respectively.

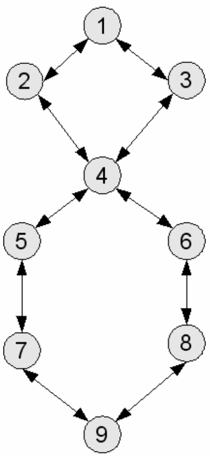

Figure 2: Graph of the Global region.

The Decomposition Algorithm performs two main operations: it divides R into simple, connected sub-regions S; and it determines which clear cells are adjacent and constructs a Global Graph.

Each sub-region can be represented as a completed weighted graph $S = \{V, L, W\}$

where:

$V = \{v_1, v_2, ..., v_n\}(n \geq 3)$ is the vertex set

$E = \{e_{ij} \mid v_i, v_j \in V\}$ is the edge set

$W = \{w_{ij} \mid w_{ij} > 0 \wedge w_{ii} = 0, \forall i, j \in N(n)\}$ is the cost set

v_i is the i^{th} vertex

e_{ij} is the edge connecting the vertices v_i and v_j

w_{ij} is the cost corresponding to edge e_{ij}

$N(n)$ is the subset $\{1, 2, ..., n\}$ of the natural number set

Testing every possibility for N nodes in a solution would be $N!$ which is time and resource consuming. Hence, a genetic algorithm will be employed to optimize the process.

A. *Genetic Path Planner*

Genetic Algorithms (GA) utilize an interactive approach, inspired by evolution via natural selection, to solve optimization problems. In a GA, the solutions (genome or chromosome) are initialized randomly. These populations are evaluated based on fitness functions; higher fitness values will have more chance of passing to following generations [12]. In order to maintain a constant number of chromosomes, new populations of candidate solutions replace existing chromosomes; they are generated by applying operators inspired by biologic genetic variation. The most popular operators are selection, crossover (also called recombination), and mutation. The strength of GA lies in their ability to implicitly identify the favorable proprieties associated with potential solutions. The genetic process is shown in Figure 3. To illustrate this more concretely, the processes applied to the area covering problem is described as follows.

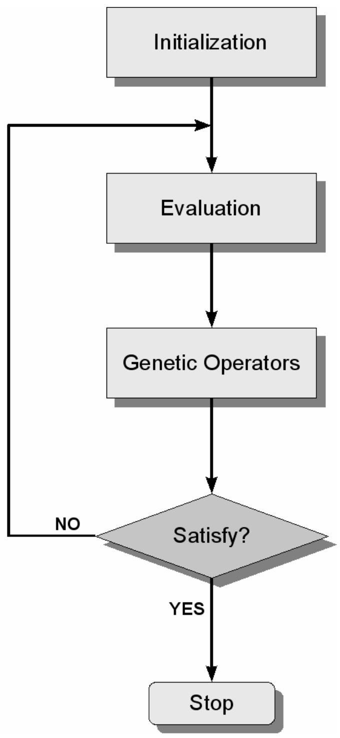

Figure 3: Genetic Process

1) Encoding:

One of the first decisions to be made before building a GA is the selection of the encoding scheme. Encoding the chromosome cannot be simply the list of nodes in the order visited; therefore, more complex encoding methods are required.

In this study, the genome is made of two parts: head and body. The head contains the order of the sub-regions as well as starting and finishing points. The body holds the solution for each sub-region; each solution is represented by the link between two nodes. The genome or Chromosome is shown in Figure 4.

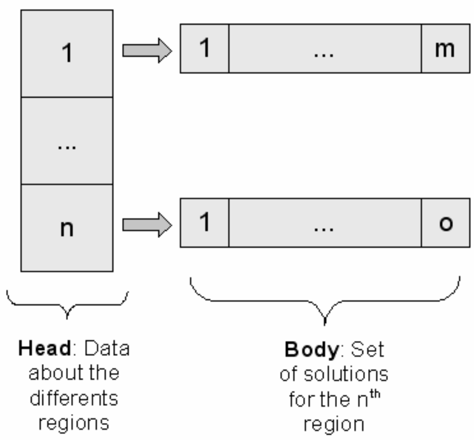

Figure 4: Chromosome Encoding

2) Generation of initial solutions:

Firstly a random order is given to each sub-region; the only rule here is to choose a neighboring area if possible. As a result, random chromosomes are generated for each region based on two common templates, *zigzag* and *windowing*. Variations in directions provide a diversity of templates (Figure 5). In this case, solutions have to pass over all of the nodes of the graph.

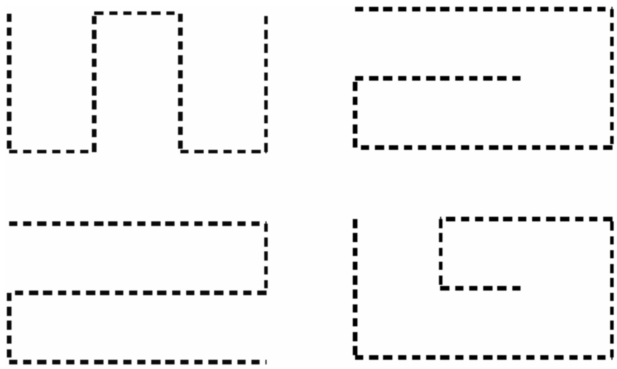
Figure 5: Motion Templates

3) Fitness Function:

The evaluation function serves as the major link between the problem and the algorithm. The fitness function rates individuals in the population: the fitter the individuals, the better their chances of survival and reproduction. Two parameters are reasonable to evaluate the fitness of individual chromosomes: total distance traveled and time. The time varies according to number of turns as shown in [13, 14]. An appropriate fitness function is constructed as:

$$F_i = w_{dist} \sum dist + w_{time} \sum time ,$$

where w_{dist} and w_{time} represent (%) weighs for distance and time respectively, in this study time was converted to distance in order to add these physical values.

4) Genetic operators:

Two different genetic operators were developed to improve the fitness. Crossover and Mutation are related to the corresponding strategies of evolution and adapted for similar operations.

Crossover is the processes of exchanging information between chromosomes by mixing attributes. For simplicity, a random crossover point is adopted here. Any crossover offspring must meet the following requisites. The first node is always at starting location. Each node must be covered at least once. To reduce time and distance each node should be cover only once, however it is possible to find some solutions where it is necessary to pass through nodes already covered.

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Mutation is any change in the chromosome; its principal objective is to introduce variation into the population. For the purposes of this algorithm, mutation is based on a random operation. Two nodes are randomly selected from the population, then swapped; in this way the solution will be valid.

IV. Simulation Results

The goal was to generate a feasible moving path, which is required to start from the origin and cover the area. Firstly, the algorithm divided the area into sub-regions. Next, a large number of possible solutions were provided using directional variations in two moment templates, zigzag and windowing. The optimization criteria were length and time, where time is depends on the number of turns. These criteria were evaluated and an optimal solution obtained. The path provided by the genetic planner is shown in Figure 6.

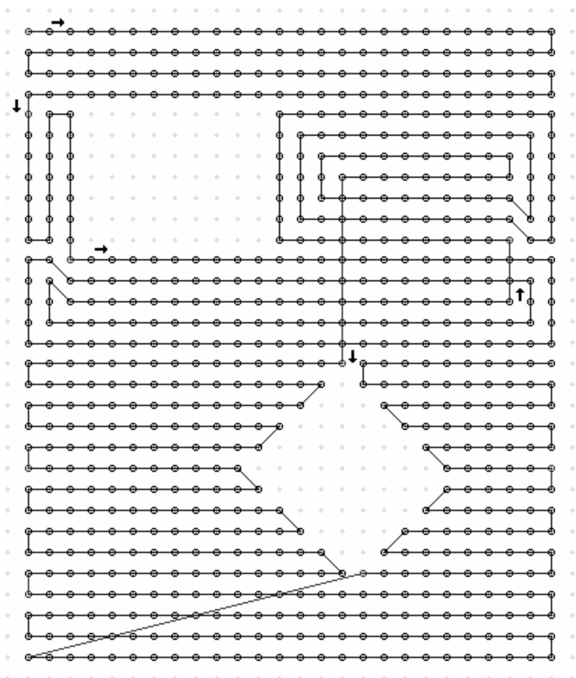

Figure 6: Optimal Area Covering Path

This method has two programs: the first one is a genetic path planner which produces a series of nodes (path) for the robot to cover an area. The other is a virtual environment where the robot follows the path generated by the path planner. The simulation allows to verify the robots trajectory according to the genetic path planner. Thus, the robot performance can be seen whenever it encounters a known obstacle. However if an unexpected obstacle comes across, the robot finds its way back and process to the next node. The virtual environment is composed of boxes and robots. The virtual robot possessed IR sensors to avoid collision. Figure 7 show the robot moving around the room. In addition to IR sensors, the virtual robot has contact sensors for narrow paths. Whenever the robot could not reach a node, it found its way back and proceeded to the next node.

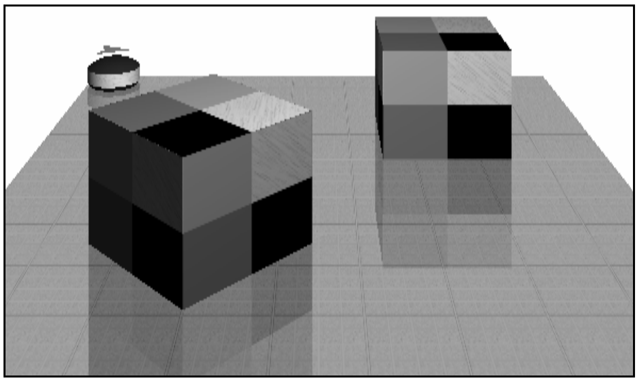

Figure 7: Robot Simulation

V. Conclusion

A novel solution for the optimal covering problem, based on a genetic algorithm has been successfully developed here. By means of cellular decomposition the whole region was divided into sub-areas, which subsequently were split into nodes. Subsequently, a genetic algorithm found the best path for the robot to follow combining two templates. The best solution is based on the minimum value of the fitness function. Simulation results showed the feasibility of the proposed planner. In addition, the genetic operations such as crossover and mutation could be applied to similar optimization problems.

Acknowledgment

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