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Approaches to complete coverage path planning using neural network and grid division

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Abstract. Since the goal of using complete coverage path planning is to generate a continuous and uninterrupted path that covers an area of interest while avoiding obstacles, its use could be extremely vital in today's field of robotics. Not only could it help our daily lives like lawnmowers, window cleaners, and painter robots, but it could also solve some dangerous or complex but vital problems for human beings; For example, mine detection, vacuum cleaning, and photogrammetry. This paper proposes two paths of successful approaches to Complete Coverage Path Planning: Neural Network and Grid division. After detailed data comparisons, both proved to have been efficient and successful, respectively. In addition, both plans' field applications would be placed at the end.

Keywords: Complete Coverage Path Planning, Neural Network, Grid Division, Spanning Tree.

1. Introduction

Since the goal of using complete coverage path planning is to generate a continuous and uninterrupted path that covers an area of interest while avoiding obstacles, its use could be extremely vital in today's field of robotics [1]. Not only could it help our daily lives like lawnmowers, window cleaners, and painter robots, but it could also solve some dangerous or complex but vital problems for human beings; For example, mine detection, vacuum cleaning, photogrammetry and underwater projects [2].

Abundant research is addressed upon CPP. Wassim Khiati, Younes Moumen, and their Morocco team have developed a grid-clustering algorithm to help solve air surveillance problems with uncrewed aerial vehicles(UAV), which were remarkably unlike the Point Gathering Approach(PGA), which was used before [3]. They first cut each area into several smaller ones to solve the performance restrictions of the UAV, then after modelling each environment using points that indicate the related longitude and altitude. Then, after applying the grid-clustering algorithm to separate the zone in such a way, they could successfully get the results that, considering the time consumption, GPA could perform much better than PGA. Furthermore, Mario Arzamendia, Daniel Gutierrez Reina, and their team have discovered a graphical way to help Autonomous Surface Vehicles (ASV) monitor environmental tasks like finding the percentage of pollution within a lake [4]. By placing beacons at the shore of lakes, they could transfer coverage problems into data. Then, by modelling it using Eulerian circuits and a Genetic Algorithm, the results were compared to those using a lawnmower and found that it drastically improved to nearly doubling.

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Within this paper, two different paths of successful approaches to Complete Coverage Path Planning will be proposed, which are Novel Neural Network and Grid division. Neural networks, also known as artificial neural networks or simulated neural networks, are a subset of machine learning and are at the heart of deep learning algorithms [5]. Their name and structure are inspired by the human brain, mimicking how biological neurons signal to one another. The Novel Neural Network way is mainly based on an originated neural network in a 2-D Cartesian workspace. A shunting equation by Hodgkin and Huxley's membrane model allows the cleaning robots to cover every spot, and the whole environment is constructed using the dynamic activity landscape in the neural network. The entire model can respond to sudden environmental change in a CCP with the ability to avoid an unstructured environment. This is the first time a well-developed CCP could be approached using a non-learning-based neural network. Grid division, on the other hand, could be conducted in many areas. This paper mainly focuses on uncrewed underwater vehicles(UUV) [6]. To successfully approach its goal, grid division has to combine with a spanning tree- a subset of Graph G, which has all the vertices covered with the minimum possible number of edges.

After attaching a value to every grid cell, the cells would be re-partitioned into four cells to form a mega-cell, so the original small cell is called a sub-cell. Therefore, by applying the Internal spiral coverage (ISC) algorithm to such a grid, the UUV could then function in the work of detecting naval mines. In addition, both plans' field applications would be placed at the end. After detailed data comparisons, both proved to have been efficient and successful, respectively.

In this specific paper, the followings are the sections respectfully. In section II, the path of neural networks will be discussed in the case of a cleaning robot. While in section III, the process of Grid Division is introduced with the help of a spanning tree in the circumstances of uncrewed underwater vehicles. In addition, section IV would be to give a comparison between the two approaches using a graph. Finally, to sum up, section V will cover the conclusion with an instruction on the further development of the field of CCP.

2. The approach by using neural network

Simon. X Yang and Chaomin Luo proposed the Neural Network technique, which uses a robot to use conventional real-time planning methods to let the robot manipulate easily in a non-stationary, unstructured, and complicated environment.

Building up such an environment would be beneficial and significant for spreading the 2-D Cartesian workspace into equal squares, with the wide radius of the robot equal to the diagonal length of the discrete area. Therefore, every square could be added to a discrete point representing that the robot has moved. As long as the robot covers that discrete area, the path would be a CPP in such a workplace.

After successfully monitoring the whole environment, they imputed an algorithm to let the robot successfully avoid obstacles and to let the robot move to the following location. The whole algorithm will be presented as the following.

To let the robot move more efficiently and less time-consumingly, the robot would be moving in a shorter and easier path with some turns of directions as well. Different from other models, this proposed model would be generated from both the dynamic activity landscape and an early robot location to change the navigation directions successfully. Subsequently, when a robot is currently in space S, designated by, the following robot location is denoted as and is obtained as

$$p_n \leftarrow x_{p_n} = max\{x_j + cy_j, j = 1,2,\cdots,k\} \quad (1)$$

which c is a positive constant, and k is how many neighboring neurons are present within the neuron. It is the neural activity of the neuron while a monotonic function increases. Variable is classified as the function of the fore location, the actual location, and the following available location; e.g.

$$y_j = 1 - \frac{\Delta\theta_j}{\pi} \quad (2)$$

where $\Delta\theta_j \in [0, \pi]$ represents the change of the absolute angle of the present and next directions.

Therefore, $\Delta\theta_j$ can be stated as $\Delta\theta_j = |\theta_j - \theta_c| = \left| a\sin 2\left(y_{p_j} - y_{p_c}, x_{p_j} - x_{p_c}\right) - a\tan 2\left(y_{p_c} - y_{p_p}, x_{p_c} - x_{p_p}\right)\right|$. By the time the robot reaches the subsequent location, the following location would automatically change by its varying environment.

3. Solving by Grid Division

In the process of Grid Division, they came up with a successful project in which each drone could maximize its ability to scan through an area by choosing the shortest routine. So they used CPP to find the most efficient mission plan for the UAV to cover the zone of interest.

In the whole process, the path would be generated using a spanning tree in a grid map which the robot constructs thanks to its onboard sensors, which allows the robot to cover all the grid cells once and accomplish a successful travel a CCP. To generate a proper spanning tree, every grid cell is correlated to a specific value which tells whether an obstacle is there or is clear and able to pass. An example is Fig 1 of grid division, where dark cells stand for obstacles.

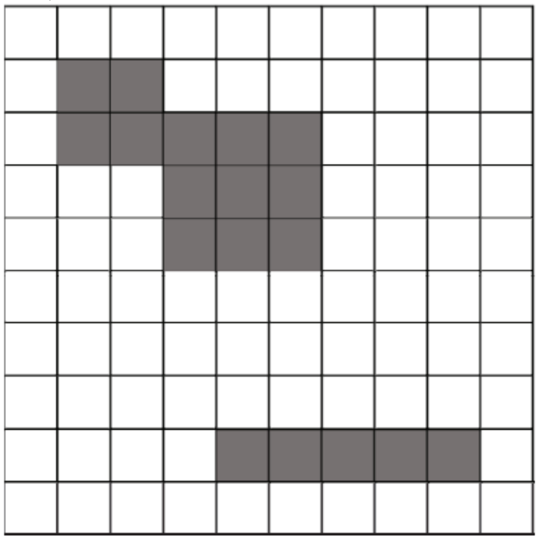
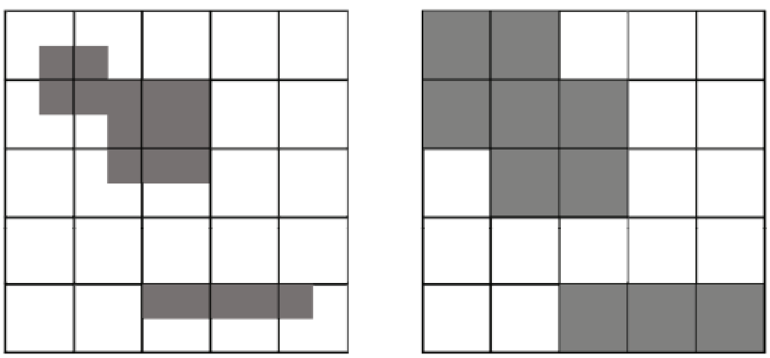


Figure 1. An example of grid division [4].

In addition, it is assumed that each cleaning robot is equipped with a contact sensor range of at least three cells. Therefore, grid division could be re-partitioned into a mega-cell which consists of a group of 4 connected cells, and the original cell is called a sub-cell, as seen in Fig 2.



(a) Result of grouping 4 cells into a macro cell. (b) Result of obstacle marking

Figure 2. Repartition of grid in Figure1 [4].

According to the mega cells introduced above, a spanning tree could be conducted using the Kruskal algorithm, mainly used to find the minimum spanning tree in a non-weighted graph [7]. The Kruskal algorithm's main aim is to find the subset of the edges using which we can traverse every vertex of the graph [8]. It follows the greedy approach that finds an optimum solution at every stage instead of focusing on a global optimum.

After the spanning tree is built, to successfully let the graph function in real life, the next task would be to model the cells with the exact size as the detection range of UUV, discussed above. Also, some pre-processions should be made to modify the whole function to process in real-world conditions. To begin with, they rearranged the provided environment created before. Then, elicited from the mega cells, they constructed a spanning tree and kept it in the memory. Moreover, connect every cell respectively in each mega cell if the spanning tree does not disrupt it, or connect two mega cells to every cell if there exists an edge of the spanning tree. Finally, starting from each nearest free cell located in the free mega cell F, the free cells located in the mega cells are considered obstacles using the depth-first search, which is mainly used to search for a tree data or graph structure [9]. It would first explore from the top of the node and reach as far as it could down to the branch, then return and try to find a newly unexplored path [10]. In the end, if the path is considered as not a circuit, it would just return to F. Furthermore, the whole function would be that the UUV starts from the sub-cell S, moves straightly along the routine constructed above, and ultimately ends as soon as the UUV reaches the sub-cell S again.

4. Results

The models proposed above for the neural network approach were then successfully used in a CCP case in which there is an unstructured that is in an arbitrary shape in the environment(see Fig. 3)

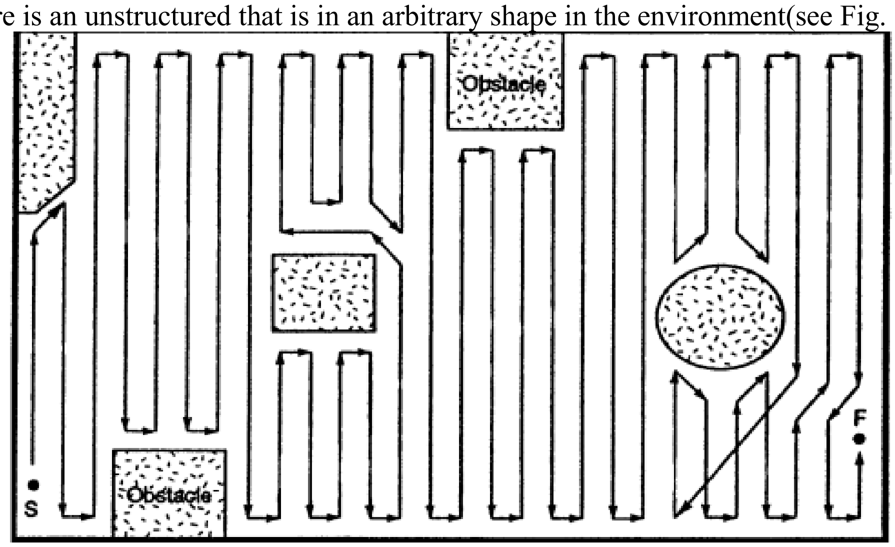


Figure 3. Complete coverage path planning in an unstructured environment [3].

In this particularly discrete workspace, areas that are already occupied by an obstacle would be considered an obstacle areas. Compared to the previous cases, elements such as neurons, no initial neural activities, and equal model parameters have not appeared in previous articles. The new neural network in Fig. 4 shows that their cleaning robot could successfully and automatically sweep from left to right across the entire environment and can avoid obstacles.

In addition, the grid-based approach improved the UUV to scan static and known environments to process even in unknown workplaces. So, therefore, UUV would be controlled online. Thus, UUV could automatically sense the obstacles and find the path, with the spanning tree constructed on its thanks to their assumption of the obstacle's sensibility.

To begin with, they first store several different observations in the memory, which are "visited" for the starting point S, "unvisited" or "unvisitable" depending on the reports sent back from the sensors, and lastly, "unvisitable" when a sub-cell is kept in a mega cell. Also, to be mentioned, mega cells and

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sub-cells are both marked the same. Later, by placing and scanning the surroundings of a mega cell M, they can decide the surroundings conditions according to the above 3kinds. For that sake, when finding that it is "unvisited," UUV would build an edge of a spanning tree from the middle of M to its neighbor. If the finding were "unvisitable," every single free sub-cell would be moved back to the sub-cell using DFS and backtrack.

Furthermore, if every neighbor is "unvisitable," UUV would shift to the nearest mega cell with an unvisited sub-cell within range. Otherwise, the whole algorithm would be called an end. Finally, each step from the above would be revised until the task stack is empty.

5. Conclusion

To sum up, both ways of CCPP are proven qualified and accessible, even though problems still seem to have not been solved, like the number of model parameters being too few, it is not sensitive enough, and so on. Nevertheless, these are still plausible and quite efficient in the world today.

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