Abstract—This paper presents a deep-learning based CPP algorithm, called Coverage Path Planning Network (CPPNet). CPPNet is built using a convolutional neural network (CNN) whose input is a graph-based representation of the occupancy grid map while its output is an edge probability heat graph, where the value of each edge is the probability of belonging to the optimal TSP tour. Finally, a greedy search is used to select the final optimized tour. CPPNet is trained and comparatively evaluated against the TSP tour. It is shown that CPPNet provides near-optimal solutions while requiring significantly less computational time, thus enabling real-time coverage path planning in partially unknown and dynamic environments.

Index Terms—Coverage path planning, deep neural network, real-time planning, complex environments.

I. INTRODUCTION

Coverage Path Planning (CPP) aims to find a trajectory for an autonomous vehicle that enables it to pass over all points in the search area while avoiding obstacles [1], [2]. Its applications for autonomous underwater vehicles (AUVs) include seabed mapping [3]–[11], structural inspection [12]–[15], oil spill cleaning [16], [17], mine hunting [18], and other underwater tasks [19], [20]. A variety of methods have been developed to solve the coverage path planning problem; a review of existing coverage methods is presented in [21]. In general, coverage path planning methods can be categorized into a priori known and a priori unknown environments. While methods for covering unknown environments compute the paths in situ, and are thus adaptive to the environment, methods for known environments attempt to generate the solution that optimizes a specific cost function, e.g., trajectory length, number of turns, and energy.

CPP in known environments is an application of the traveling salesman problem (TSP), in that the optimal CPP trajectory is also an optimal TSP tour. Finding the optimal solution, however, is NP-Hard. While many heuristics exist, these methods are either: i) sub-optimal, or ii) not suitable for online computation [22]. Many AUV missions are dynamic in nature, requiring fast online coverage path replanning when changes in the environment or mission occur. As such, it is of critical importance to develop a coverage path planner that can quickly find near-optimal tours under dynamic conditions [23].

Many algorithms have been developed for the CPP problem in a priori known environments. Zelinsky et. al. [24] proposed a grid-based method where a distance field is constructed given specific start and goal cells. The coverage path is then generated along the steepest ascent from the start to the goal. Acar et al. [25] developed an offline method which identifies the critical points on the boundaries of obstacles for dividing the area into subregions and creating an adjacency graph. Then, the sequence that visits each node exactly once is computed by the depth-first-search method, while the coverage is achieved via back-and-forth motion in each cell. These methods can achieve complete coverage, however, the resulting coverage path may not be globally optimal.

Huang et al. [26] utilized dynamic programming to minimize the total number of turns by allowing different sweep directions in each subregion. Xie et al. [27] proposed a similar approach to cover multiple disjoint obstacle-free subregions for Unmanned Aerial Vehicles (UAVs). The search space is divided into a set of subregions. Each subregion has four potential back-and-forth coverage paths with starting point in different corners. Then, a Generalized Travelling Salesman Problem (GTSP) is formulated to find the optimal subregion traversal sequence and the associated coverage paths using dynamic programming. This problem is computationally expensive, thus it is not real-time implementable in arbitrary environments; limiting real-world applications.

Recently, many methods have been developed to utilize machine learning techniques to solve the related motion planning problems in high-dimensional spaces [28], [29]. These methods can find near-optimal solutions in complex scenarios much faster than the traditional approaches. Therefore, we developed a deep learning-based algorithm, called Coverage Path Planning Network (CPPNet), which can quickly find the near-optimal coverage path in complex environments.

CPPNet is built using a convolutional neural network (CNN), whose input is a graph-based representation of the occupancy grid map, and whose output is an edge probability heat graph, where the value of each edge is the probability of belonging to the optimal TSP tour. A greedy search can then be performed over this heat graph to rapidly produce a near-optimal TSP tour in an environment of arbitrary complexity. CPPNet can be invoked on-demand to generate a near-optimal coverage path for the environment with the most up-to-date information. The advantages of CPPNet are as follows: i) produces near-optimal coverage trajectories, ii) efficiently works in environments with complex shapes, and iii) is computationally efficient for real-time implementation.

The rest of the paper is organized as follows. Section II formulates the CPP problem. Next, the CPPNet algorithm is described in Section III. The results including the generated coverage paths for some scenarios are shown and discussed in Section IV. Finally, Section V concludes the paper and provides recommendations for future work.
II. PROBLEM STATEMENT

Let \( A \subset \mathbb{R}^2 \) be the search area which is bounded either by a hard boundary (e.g., seamount) or by a soft boundary (e.g., sub-space of a large area). A number of obstacles are populated inside \( A \). First, we construct a tiling on \( A \) as follows.

**Definition 1** (Tiling). A set \( \mathcal{T} = \{\tau_i \subset \mathbb{R}^2, i = 1, \ldots, |\mathcal{T}|\} \) is called a tiling of \( A \) if its elements: i) have mutually exclusive interiors, i.e., \( \tau_i^0 \cap \tau_j^0 = \emptyset, \forall i \neq j \), where \( i, j \in \{1, \ldots, |\mathcal{T}|\} \), and superscript \( 0 \) denotes the interior, and ii) form a cover of \( A \), i.e., \( A \subseteq \bigcup_{i=1}^{|\mathcal{T}|} \tau_i \).

The tiling \( \mathcal{T} \) is separated into obstacle \( (\mathcal{T}^o) \) and allowed \( (\mathcal{T}^a) \) regions. While the obstacle cells are occupied by obstacles, the allowed cells are desired to be covered. Let \( \mathcal{A} (\mathcal{T}^a) \) denote the total area of the allowed cells in \( \mathcal{T}^a \subseteq \mathcal{T} \). First, we define the feasible trajectory for complete coverage.

**Definition 2** (Feasible Trajectory). Given start point \( \tau_s \) of the vehicle, a sequence of cells \( \pi = (\pi_1, \ldots, \pi_{|\pi|}) \) visited by the autonomous vehicle is called a feasible trajectory if:

- \( \pi_1 = \tau_s \).
- \( \pi_n \in \mathcal{T}^o, \forall n \in \{1, \ldots, |\pi|\} \).
- \( \pi \) forms a cover of \( \mathcal{A}(\mathcal{T}^a) \), i.e., \( \mathcal{A}(\mathcal{T}^a) \subseteq \bigcup_{n=1}^{|\pi|} \pi_n \).

Let the set of all feasible trajectories in a given environment be denoted as \( \Pi = \{\pi^1, \pi^2, \ldots, \pi^{||\Pi||}\} \). The optimal coverage path planning problem is to find the optimal and feasible solution \( \pi^* \in \Pi \) that has the minimum length, i.e.,

\[
\pi^* = \min_{\pi \in \Pi} L(\pi) \tag{1}
\]

where \( L(\pi) \) indicates the length of \( \pi \).

III. CPPNET ALGORITHM

This section presents the proposed deep learning based CPP algorithm, called CPPNet. The architecture of the approach is shown in Fig. 1. CPPNet is a deep learning based planner built using a convolutional neural network (CNN) [30] comprised of three parts: 1) creating the dataset of 2D obstacle environments for the training and testing of CPPNet, 2) offline training of CPPNet, and 3) online testing of CPPNet.

A. Dataset Description

The data set for training and testing of CPPNet was created by: 1) generating a set of random 2D scenarios with various obstacle densities, 2) selecting a collision-free coverage start point, and 3) generating the optimal TSP tours. In particular, we created a total of 1384 \( 10m \times 10m \) scenarios with a random obstacle density ranging from 0% to 50%. Then, the scenarios were partitioned into a \( 10 \times 10 \) tiling structure consisting of \( 1m \times 1m \) cells. Each tiled map has up to 100 obstacle-free cells that need to be visited depending on the obstacles. The start point was selected as the top-left corner of the map. Finally, the optimal TSP tour was found using the 2-opt algorithm [31]. Of the 1384 scenarios, 1024 were used for training CPPNet, 200 for validation, and 160 for testing.

B. Offline Training

CPPNet consists of three components to solve the CPP problem. The first component is the input layer which encodes the nodes and edges of the adjacency graph representation of the tiled scenario, where each node represents an obstacle-free cell and each edge indicates the connectivity between the local neighboring cells, as seen in Fig. 1. The second component is a sequence of Graph Convolution Layers which extracts abstract feature vectors by applying non-linear transformations to the outputs of the preceding layer. The last component is a Multi-layer Perceptron (MLP) which is used to compute the probability of an edge belonging to the optimal TSP tour. We present a summary of each of these components below; for more information, we refer the reader to [30].

1) Input layer: The inputs to CPPNet are: 1) the 2D center location of each node \( i \), denoted as \( x_i \in \mathbb{R}^2 \), and 2) a \( 100 \times 100 \) adjacency matrix \( E \) derived from the tiled map, which contains the distance between all node pairs \( i \) and \( j \), denoted as \( e_{ij} \). Specifically, \( e_{ij} = ||x_i - x_j|| \) if \( i \) is adjacent to \( j \) and both \( i \) and \( j \)
(a) Scene 1: obstacle density is 10%; trajectory length is 90.82 m; computational time is 5.288 s.
(b) Scene 2: obstacle density is 22%; trajectory length is 80.48 m; computational time is 4.636 s.
(c) Scene 3: obstacle density is 41%; trajectory length is 63.41 m; computational time is 2.999 s.

Fig. 2. Coverage trajectories generated by the 2-opt algorithm.

(a) Scene 1: obstacle density is 10%; trajectory length is 92.65 m; computational time is 0.229 s.
(b) Scene 2: obstacle density is 22%; trajectory length is 82.07 m; computational time is 0.176 s.
(c) Scene 3: obstacle density is 41%; trajectory length is 63.83 m; computational time is 0.162 s.

Fig. 3. Coverage trajectories generated by the CPPNet.

and $j$ are obstacle-free, and $e_{ij} = 0$ otherwise. The input layer aims to make high-dimensional feature vectors before feeding them to the Graph Convolutional Layers. The feature vector of node $i$ is

$$x_i^0 = W_1^0 x_i + b_0^0$$

(2)

where $W_1^0 \in \mathbb{R}^{h \times 2}$ is a set of weights, $b_1^0 \in \mathbb{R}^h$ is a set of biases, $h$ is a user-defined hidden parameter, and $0$ refers to the input layer. We also define an indicator function $\delta_{ij}$ that has a value of 1 if nodes $i$ and $j$ are obstacle-free and adjacent, 2 for self-connections, and 0 otherwise. The embedding of the edge connecting node $i$ to node $j$ is:

$$e_{ij}^0 = (W_2^0 e_{ij} + b_2^0) \| W_3^0 \delta_{ij}$$

(3)

where $W_2^0, W_3^0 \in \mathbb{R}^{\frac{h}{2} \times 1}$ are weights, $b_2^0 \in \mathbb{R}^{\frac{h}{2}}$ are biases, and $\| \cdot \|$ is the vertical concatenation operator. Note that $x_i^0, e_{ij}^0 \in \mathbb{R}^{h \times 1}$.

2) Graph convolution layer: $x_i^\ell$ and $e_{ij}^\ell$ are the node and edge feature vectors corresponding to node $i$ and edge $ij$, respectively, at layer $\ell$. The feature vectors at the next layer are [30]:

$$x_i^{\ell+1} = x_i^\ell + ReLU \left\{ BN \left( W_1^\ell x_i^\ell + \sum_{j \sim i} \eta_{ij}^\ell \circ W_2^\ell x_j^\ell \right) \right\}$$

(4)

$$\eta_{ij}^\ell = \frac{\sigma(e_{ij}^\ell)}{\sum_{j' \sim i} \sigma(e_{ij'}^\ell)}$$

(5)

$$e_{ij}^{\ell+1} = e_{ij}^\ell + ReLU \left\{ BN \left( W_3^\ell e_{ij}^\ell + W_4^\ell x_i^\ell + W_5^\ell x_j^\ell \right) \right\}$$

(6)

where $W_1^\ell, W_2^\ell, W_3^\ell, W_4^\ell, W_5^\ell \in \mathbb{R}^{h \times h}$ are weight matrices, $\sigma$ is the sigmoid function, ReLU is the rectified linear unit, and $BN$ is batch renormalization.

3) Multi-layer Perceptron (MLP): Each edge feature vector $e_{ij}^L$ from the last Graph Convolutional Layer $L$ is used by MLP to calculate the probability that edge $ij$ belongs to the optimal TSP tour [30]:

$$p_{ij}^{TSP} = MLP(e_{ij}^L)$$

(7)

After computing $p_{ij}^{TSP}$ for each edge $ij$, the probabilistic heat map over the adjacency matrix of connections between nodes...
Graph Convolutional Layers and Multi-Layer Perceptron Layers. The hidden parameter $h$ is 50. The initial learning rate was set to 0.001 while the mini-batch size was 20. The training converged within 6 epochs in about 16 minutes.

Fig. 2 and Fig. 3 show the coverage trajectories of the 2-opt algorithm and CPPNet in three different scenarios, representing a low obstacle density (0-10%), medium obstacle density (20-30%), and high obstacle density (40-50%), respectively. The starting point is the top-left corner of each map, and the trajectory is marked by the red color. The trajectory lengths of CPPNet are 92.65m, 82.07m, and 63.83m in the three scenarios, respectively. On the other hand, the trajectory lengths of the 2-opt algorithm are 90.82m, 80.48m, and 63.41m, respectively. Similar to the 2-opt trajectories, CPPNet trajectories have minimal overlap and provide high-quality solutions. The online inference times of CPPNet in these scenarios are 0.229s, 0.176s, and 0.162s, respectively, while the inference times of the 2-opt algorithm are 5.288s, 4.636s, and 2.999s, respectively. Thus, CPPNet generated near-optimal solutions in all three scenarios while requiring significantly less computational time as compared to the 2-opt algorithm.

Fig. 4 presents the box plots of the trajectory lengths (left) and online inference times (right) of the 2-opt and CPPNet solutions over all testing scenarios. In general, CPPNet is able to generate trajectories that are within 5-27% of the 2-opt solution; however, CPPNet requires several orders of magnitude less computation time.

Overall, CPPNet is able to produce near-optimal trajectories comparable to the 2-opt algorithm in real-time, thus making it suitable for online coverage path planning in dynamic or partially unknown environments.

V. CONCLUSIONS AND FUTURE WORK

This paper presents a Deep Neural Network-based Coverage Path Planning algorithm, called Coverage Path Planning Network (CPPNet). CPPNet is built on a convolutional neural network (CNN) which takes the adjacency graph representation of an occupancy grid map as the input and outputs an edge probability heat graph, where the value of each edge is the probability of it belonging to the optimal TSP tour. A greedy search is then applied over the heat graph to produce the final TSP tour. The process concludes with $A^*$ being applied to the

\[ P_{TSP} \] is obtained. Thus, the output is a $100 \times 100$ edge probability heat graph $P_{TSP}$ with probabilities $p_{ij}$, where a high probability means edge $ij$ has a high chance of belonging to the optimal solution, and a low probability means this edge likely does not belong to the optimal solution. During training, these output probabilistic heat graphs are compared against the ground truth 2-opt TSP solution, where $p_{ij} = 1$ means edge $ij$ belongs to the optimal solution, and 0 otherwise. The loss is then computed, and the weights of CPPNet are updated accordingly.

4) Loss Function: The edge probability heat map over the adjacency graph $P_{TSP}$ is compared against the adjacency graph of the ground-truth 2-opt TSP solution $P_{TSP}$. The weighted binary cross-entropy loss is computed and minimized using the Adam optimizer.

C. Online Coverage Path Planning

The online phase exploits the neural models from the offline training phase to perform coverage path planning in obstacle-rich environments. The overall flow of online coverage path planning is shown in Fig. 1. Specifically, an adjacency graph representation is generated based on a binary occupancy grid map. Then, the graph is given as the input to the trained CPPNet, which outputs a probabilistic heat graph over the adjacency matrix of tour connection. The value of each edge in the heat graph is the probability of belonging to the optimal TSP tour. A greedy search is then used to find the final tour by selecting the next node in the local neighborhood possessing the highest probability. Note that if there is not an unvisited node in the local neighborhood, we expand the size of local neighborhood incrementally until an unvisited node is found. After the optimal TSP tour is obtained, the $A^*$ algorithm is used to construct the final path along this tour.

IV. RESULTS AND DISCUSSION

In this section, the coverage paths produced by CPPNet and the 2-opt algorithm are shown and compared. CPPNet was trained on a Windows 10 computer with an Intel Core i5 processor with 8GB RAM using PyTorch. There are a total of 3 Graph Convolutional Layers and 2 MLP layers. The hidden

Fig. 4. Monte Carlo simulation results.
TSP tour to create the final coverage path. CPPNet is trained on and comparatively evaluated against the 2-opt algorithm. It is shown that CPPNet provides near-optimal solutions requiring significantly less computational time, thus enabling online coverage path planning in dynamic environments.

In order to improve CPPNet, we first plan to create a larger and more diverse data set in order to ensure CPPNet is robust and reliable in various complex obstacle-rich environments. We will also improve the solution quality of CPPNet by including the node visitation sequence information of the near-optimal TSP solutions during training. Finally, we will develop new and scalable transfer learning approaches in order to simplify and speed up the training of CPPNet.

REFERENCES

[1] J. Song and S. Gupta, “⋆: An online coverage path planning algorithm,” IEEE Transactions on Robotics, vol. 34, pp. 526–533, 2018.

[2] J. Song and S. Gupta, “Care: Cooperative autonomy for resiliency and efficiency of robot teams for complete coverage of unknown environments under robot failures,” Autonomous Robots, vol. 44, pp. 647–671, 2020.

[3] E. Galceran, R. Campos, N. Palomeras, D. Ribus, M. Carreras, and P. Ridao, “Coverage path planning with real-time replanning and surface reconstruction for inspection of three-dimensional underwater structures using autonomous underwater vehicles,” Journal of Field Robotics, vol. 32, no. 7, pp. 952–983, 2015.

[4] Z. Shen, J. Song, K. Mittal, and S. Gupta, “An autonomous integrated system for 3-D underwater terrain map reconstruction,” in OCEANS 2016 MTS/IEEE Monterey, pp. 1–6, IEEE, 2016.

[5] Z. Shen, J. Song, K. Mittal, and S. Gupta, “Autonomous 3-D mapping and safe-path planning for underwater terrain reconstruction using multi-level coverage trees,” in OCEANS 2017-Anchorage, pp. 1–6, IEEE, 2017.

[6] N. Palomeras, N. Hurtós, M. Carreras, and P. Ridao, “Autonomous mapping of underwater 3-D structures: From view planning to execution,” IEEE Robotics and Automation Letters, vol. 3, no. 3, pp. 1965–1971, 2018.

[7] L. Paull, M. Seto, J. J. Leonard, and H. Li, “Probabilistic cooperative mobile robot area coverage and its application to autonomous seabed mapping,” The International Journal of Robotics Research, vol. 37, no. 1, pp. 21–45, 2018.

[8] Z. Shen, J. P. Wilson, and S. Gupta, “An online coverage path planning algorithm for curvature-constrained AUVs,” in OCEANS 2019 MTS/IEEE SEATTLE, pp. 1–5, IEEE, 2019.

[9] Z. Shen, J. P. Wilson, and S. Gupta, “⋆: An online coverage path planning algorithm for energy-constrained autonomous vehicles,” in Global Oceans 2020: Singapore – U.S. Gulf Coast, pp. 1–6, 2020.

[10] Z. Shen, J. Song, K. Mittal, and S. Gupta, “CT-CPP: 3D coverage path planning for unknown terrain reconstruction using coverage trees,” arXiv preprint arXiv:2010.09231, 2020.

[11] V. Yordanova and B. Gips, “Coverage path planning with track spacing adaptation for autonomous underwater vehicles,” IEEE Robotics and Automation Letters, vol. 5, no. 3, pp. 4774–4780, 2020.

[12] B. Englert and F. S. Hover, “Three-dimensional coverage planning for an underwater inspection robot,” The International Journal of Robotics Research, vol. 32, no. 9-10, pp. 1048–1073, 2013.

[13] E. Vidal, J. D. Hernández, K. Istenič, and M. Carreras, “Online view planning for inspecting unexplored underwater structures,” IEEE Robotics and Automation Letters, vol. 2, no. 3, pp. 1436–1443, 2017.

[14] A. Bircher, M. Kamel, K. Alexi, H. Oleynikova, and R. Siegwart, “Receding horizon path planning for 3D exploration and surface inspection,” Autonomous Robots, vol. 42, no. 2, pp. 291–306, 2018.

[15] S. Song, D. Kim, and S. Jo, “Online coverage and inspection planning for 3D modeling,” Auton. Robots, vol. 44, no. 8, pp. 1431–1450, 2020.

[16] J. Song, S. Gupta, J. Hare, and S. Zhou, “Adaptive cleaning of oil spills by autonomous vehicles under partial information,” in 2013 OCEANS-San Diego, pp. 1–5, IEEE, 2013.

[17] J. Song and S. Gupta, “SLAM based shape adaptive coverage control using autonomous vehicles,” in 10th System of Systems Engineering Conference (SoSE), pp. 268–273, IEEE, 2015.

[18] K. Mukherjee, S. Gupta, A. Ray, and S. Phoha, “Symbolic analysis of sonar data for underwater target detection,” IEEE Journal of Oceanic Engineering, vol. 36, no. 2, pp. 219–230, 2011.

[19] J. Song, S. Gupta, and T. A. Wettergren, “⋆: Time-optimal risk-aware motion planning for curvature-constrained vehicles,” IEEE Robotics and Automation Letters, vol. 4, pp. 33–40, Jan 2019.

[20] J. P. Wilson, Z. Shen, S. Gupta, and T. A. Wettergren, “T*: A fast time-risk optimal motion planning algorithm for multi-speed autonomous vehicles,” in Global Oceans 2020: Singapore – U.S. Gulf Coast, pp. 1–6, 2020.

[21] E. Galceran and M. Carreras, “A survey on coverage path planning for robotics,” Autonomous and Autonomous Systems, vol. 61, no. 12, pp. 1258–1276, 2013.

[22] G. Laporte, “The traveling salesman problem: An overview of exact and approximate algorithms,” European Journal of Operational Research, vol. 59, no. 2, pp. 231–247, 1992.

[23] Z. Zeng, L. Lian, K. Sammut, F. He, Y. Tang, and A. Lammas, “A survey on path planning for persistent autonomy of autonomous underwater vehicles,” Ocean Engineering, vol. 110, pp. 303–313, 2015.

[24] A. Zeimsky, R. A. Jarvis, J. Byrne, and S. Yuta, “Planning paths of complete coverage of an unstructured environment by a mobile robot,” in Proceedings of International Conference on Advanced Robotics, vol. 13, pp. 533–538, 1993.

[25] E. U. Acar, H. Choset, A. A. Rizzi, P. N. Atkar, and D. Hull, “Morse decompositions for coverage tasks,” The International Journal of Robotics Research, vol. 21, no. 4, pp. 331–344, 2002.

[26] W. Huang, “Optimal line-sweep-based decompositions for coverage algorithms,” in Proceedings of IEEE International Conference on Robotics and Automation (ICRA), vol. 1, pp. 27–32 vol.1, 2001.

[27] J. Xie, L. R. G. Carrillo, and L. Jin, “Path planning for UAV to cover multiple separated convex polygonal regions,” IEEE Access, vol. 8, pp. 51770–51785, 2020.

[28] A. H. Qureshi, Y. Miao, A. Simeonov, and M. C. Yip, “Motion planning networks: Bridging the gap between learning-based and classical motion planners,” IEEE Transactions on Robotics, 2020.

[29] J. Wang, W. Chi, C. Li, C. Wang, and M. Q.-H. Meng, “Neural RRT*: Learning-based optimal path planning,” IEEE Transactions on Automation Science and Engineering, vol. 17, no. 4, pp. 1748–1758, 2020.

[30] C. K. Joshi, T. Laurent, and X. Bresson, “An efficient graph convolutional neural network technique for the travelling salesman problem,” arXiv preprint arXiv:1906.01227, 2019.

[31] E. Aarts, E. H. Aarts, and J. K. Lenstra, Local search in combinatorial optimization. Princeton University Press, 2003.

[32] P. E. Hart, N. J. Nilsson, and B. Raphael, “A formal basis for the heuristic determination of minimum cost paths,” IEEE transactions on Systems Science and Cybernetics, vol. 4, no. 2, pp. 100–107, 1968.