On Unsupervised Learning in Multi-Goal Motion Planning Problem

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***Abstract*— The multi-goal motion planning is a problem to determine a cost efficient path to visit a given set of goals that combines a problem of optimal motion planning with combinatorial optimization to determine an optimal sequence of the goals visit. We address this challenging problem by unsupervised learning technique that is utilized to simultaneously learn the topology of the robot configuration space and based on this acquired knowledge, the learning procedure is also used to steer construction of the motion planning roadmap towards promising areas regarding the expected solution of the problem. The proposed approach is based on a combination of the optimal motion planner with unsupervised learning procedure of the self-organizing map for the traveling salesman problem. Our early results of the proposed approach indicate this combination provides solutions of the multi-goal motion planning problem with similar or better quality than conventional techniques based on a priory known sequence of the goals visit.**

I. SUMMARY

Multi-goal motion planning (MGMP) is a problem that can be find in various robotic scenarios, e.g., inspection, surveillance and patrolling missions, where a robot is requested to visit a predefined set of goal locations. The MGMP problem combines challenges of motion planning together with challenges of combinatorial optimization as it is necessary to determine optimal sequence of the goals visit together with cost efficient trajectories connecting the goals in the sequence. The problem can by formulated as follows: *Let $\mathcal{C}$ be a configuration space of the robot, then for a given set of goals $\mathcal{G} \subset \mathcal{C}_{free}$, and an admissible distance ε, the problem is to find a trajectory τ^* such that: $\tau^* = \arg\min_{\tau \in T} c(\tau)$, where T is a set of all admissible multi-goal trajectories connecting the goals $\mathcal{G}$ and $c(.)$ is a strictly positive cost function.* A trajectory τ is called admissible regarding $\mathcal{G}$ and ε, if for each goal $g \in \mathcal{G}$ there exists a point p_g on τ, such that $p_g \in \tau$ and $|(p, g)| \leq \varepsilon$, i.e., τ is closer to all goals of $\mathcal{G}$ than the selected ε.

The sequencing part of the MGMP problem can be formulated as the traveling salesman problem (TSP). The TSP stands to find a shortest tour visiting a given set of cities (goals) and it is known to be NP-hard, unless P=NP. Having a graph representation of all possible connections between the goals with the associated goal–goal travel costs, the problem can be solve by heuristic algorithms from the operational researchers [1], e.g., using CONCORDE solver [2].

However, connections between the goals represent a path between the goals and each such a path is a solution of the motion planning problem, which is a challenging problem itself and can be PSPACE-hard[3] for polyhedral obstacles and considering uncertainties. For n goals, up to n^2 trajectories need to be determined, which can be computationally very demanding. Therefore, approaches to avoid computation of all trajectories are studied. For example, Saha et al. propose a lazy evaluation algorithm [4] that is based on initial approximation of the distances by Euclidean distance and an iterative refinement of the goal–goal distances combined with a solution of the TSP based on the minimum spanning tree approach. Authors reported a significant reduction of motion planning queries for selected robotic scenarios but they also mentioned the approach determines all goal to goal trajectories in the worst case.

Another approach is proposed in [5], where authors construct a motion planning roadmap that is then used as a graph input to find a solution of the TSP. Instead of combinatorial heuristic, a solution is based on the self-organizing map (SOM) for the TSP on a graph [6]. Our approach is based on this unsupervised learning technique of SOM for the TSP; however, we rather consider a simultaneous construction of the roadmap and its direct utilization during the planning, which avoid a prior construction of the roadmap.

In [7], we propose to steer a roadmap expansion in the asymptotically optimal motion planner (the Rapidly-exploring Random Graph (RRG) [8]) by the adaptation mechanism of the SOM. The proposed solution is based on two ideas. First, the two layered neural network of SOM is adapted towards the desired goals while the neuron weights are restricted to be only on the roadmap, which represents the exploring configuration space $\mathcal{C}$ and thus the output layer of the network represents a feasible trajectory in $\mathcal{C}$. The second idea is to use the adaptation of neurons to steer the roadmap expansion towards goals that in the end, provides a roadmap connecting the goals $\mathcal{G}$ and a solution of the MGMP problem.

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