Multi-Goal Trajectory Planning with Motion Primitives for Hexapod Walking Robot

Petr Vaněk, Jan Faigl, Diar Masri
Department of Computer Science, Czech Technical University in Prague, Technická 2, 166 27 Prague, Czech Republic
{*vanekpe5, faiglj, masridia*}*@fel.cvut.cz*

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Abstract: This paper presents our early results on multi-goal trajectory planning with motion primitives for a hexapod walking robot. We propose to use an on-line unsupervised learning method to simultaneously find a solution of the underlying traveling salesman problem together with particular trajectories between the goals. Using this technique, we avoid pre-computation of all possible trajectories between the goals for a graph based heuristic solvers for the traveling salesman problem. The proposed approach utilizes principles of self-organizing map to steer the randomized sampling of configuration space in promising areas regarding the multi-goal trajectory. The presented results indicate the proposed steering mechanism provides a feasible multi-goal trajectory in a less number of samples than an approach based on a priori known sequence of the goals visits.

1 Introduction

Walking robots provides a great flexibility to operate in complex unstructured environments. On the other hand, motion planning for such a vehicle is challenging because of its high-dimensional configuration space $\mathcal{C}$. In this paper, we address a more challenging problem, where several optimal trajectories have to be determined for a hexapod walking robot to repeatedly visit a given set of locations with a specified precision. The problem is called the multi-goal motion planning (MGMP) and it combines challenges of the motion planning together with challenges of the combinatorial optimization as it is necessary to determine an optimal sequence of the goals visits together with the cheapest trajectory connecting the goals.

The optimal sequence can be found as a solution of the traveling salesman problem (TSP), which is known to be NP-hard and efficient heuristics have been proposed in operational research (Applegate et al., 2007). However, the main computational difficulty lies in the determination of the particular trajectories between the goals, which is a challenging problem itself, e.g., PSPACE-hard (Reif, 1979) for a polyhedral problem representation. For n goals, up to n^2 goal–goal trajectories can be needed for a standard graph-based TSP solver. Moreover, this bound does not hold for kinodymamic or non-holonomic constraints, where it can be desirable to find a cost efficient trajectory for a sequence of the goals.

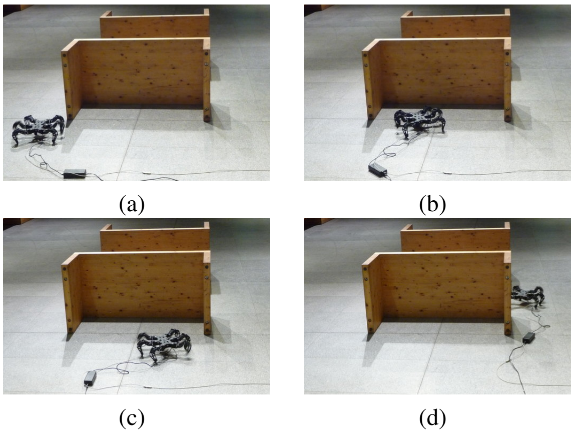


Figure 1: Hexapod performing found multi-goal trajectory

A trajectory between two goals can be found by randomized sampling based motion planner, e.g., Rapidly-exploring Random Tree (RRT) and Rapidly-exploring Random Graphs (RRG) (Karaman and Frazzoli, 2011). However, a complex robotic platform has a large set of possible control inputs, which does not allow to efficiently use randomized planners with all possible control inputs. Therefore, a set of motion planning primitives can be considered for walking and complex platforms (Bevly et al., 2000; Pivtoraiko and Kelly, 2005). Motion primitives efficiently provide only local motion, but they can be used in randomized planners, such as the RRT (Vonásek et al., 2013), to find a global trajectory between two configurations.

We propose to leverage on motion primitives and steer the randomized sampling in the RRG to directly find a solution of the multi-goal trajectory problem for a hexapod walking robot without prior determination of the (optimal) sequence of the goals visits. The idea is based on an on-line unsupervised learning on top of the growing motion planning roadmap to consider promising areas of $\mathcal{C}$ regarding the solution of the sequencing part of the MGMP. Our early results indicate the steering reduces the required number of roadmap expansions to find an admissible multi-goal trajectory and thus demonstrate feasibility of the proposed approach for multi-goal trajectory planning.

The paper is organized as follows. The problem is introduced in Section 2 together with description of the considered robotic platform. A reference algorithm for the MGMP problem for a given sequence of the goals visits is presented in Section 3. The proposed unsupervised learning based MGMP algorithm is described in Section 4 and its validation in selected case studies is presented in Section 5. The concluding remarks and future work are summarized in Section 6.

2 Problem Statement

The MGMP problem is studied in a 3D environment $\mathcal{W} \subset \mathbb{R}^3$ represented by a set of triangles forming a set of obstacles O. The trajectory planning can be formulated using the notion of the configuration space $\mathcal{C}$. Following (Karaman and Frazzoli, 2011), the simple start–goal trajectory from a configuration q_{init} to the desired goal configuration q_{goal} can be found as a motion query asking for a feasible path $\kappa : [0,1] \to \mathcal{C}_{free}$ such that $\kappa(0) = q_{init}$ and $d(\kappa(1), q_{goal}) < \varepsilon$, where $\mathcal{C}_{free}$ denotes the obstacle free part of $\mathcal{C}$ as $\mathcal{C}_{free} = \mathrm{cl}(\mathcal{C} \setminus \mathcal{C}_{obs})$, ε is an admissible distance of the trajectory end-point to the desired goal, cl() is the closure of a set, and $d(,)$ is a distance between two configurations.

Our motivational scenario is a visual inspection planning problem to cover n given areas of interest from particular locations $\mathcal{G} = \{g_1, g_2, \ldots, g_n\}$. We assume each location is described by a 6D vector $\mathbb{R}^3 \times SO(3)$ consisting of a position (x,y,z) in $\mathcal{W}$ accompanied by a desired orientation of the camera pointing to the requested goal area denoted as (α, β, γ) for roll, pitch, and yaw, respectively. We assume it is sufficient the trajectory is within ε distance to the goal location and provides a coverage of the area, i.e., a camera orientation is within particular angular limits. For simplicity, we assume the camera is attached at the center of the robot's coordinate system and the robot position is a 6D pose in $\mathcal{W}$.

Similarly to a simple trajectory a multi-goal trajectory visiting a set of goals $\mathcal{G}$ can be defined as follows. Let the sequence of the goals visits be $(v_1, v_2, \ldots, v_n)$ for which $v_i \in \mathcal{G}$ and $\bigcup_{1<i\leq n} v_i = \mathcal{G}$. Then, we can define the feasible and admissible multi-goal trajectory as a closed trajectory $\tau : [0,1] \to \mathcal{C}_{free}$ such that $\tau(0) = \tau(1) = q_{start}$ and for which there exists n points on τ such that $0 \leq t_1 \leq t_2 \leq \ldots \leq t_n$ and $d(\tau(t_i), v_i) < \varepsilon$. In other words, there exists n points from which the robot will cover the objects of interest.

Having these preliminaries, the MGMP problem can be formulated as follows: *for the given set of goals $\mathcal{G}$, configuration space $\mathcal{C}$, admissible distance ε, and monotonic, bounded, and strictly positive cost function c: find a feasible and admissible (according to ε) trajectory τ^* such that* $c(\tau^*) = \min\{c(\tau) \mid$ *τ is feasible admissible multi-goal trajectory*$\}$.

The proposed approach is based on the RRG algorithm used for an incremental construction of the graph $\mathbf{G}_{RRG}$=$(\mathbf{V}_{RRG}, \mathbf{E}_{RRG})$, which represents the motion planning roadmap constructed by the RRG algorithm. The set of vertices $\mathbf{V}_{RRG}$ represents particular configurations of the robot $q \in \mathcal{C}_{free}$ and an edge $e \in \mathbf{E}_{RRG}$ describes a feasible motion between two configurations $v_i, v_j \in \mathbf{V}_{RRG}, i \neq j$. The graph is a result of the graph expansion from the nearest vertex of the graph towards a random sample by applying a particular control command from a considered set of possible commands / motion primitives. The assumptions and specifications of the RRG for the considered hexapod walking robot are described in the following section.

2.1 RRG for Hexapod Walking Robot

The robotic platform considered in this study is 18 degrees of freedom (DoF) hexapod walking robot (PhantomX), see Fig. 1. The body of the robot has dimensions about 26 cm × 20 cm and its dimensions with fully deployed legs are about 75 cm × 70 cm. Motion planning for an 18 DoF platform can be computationally demanding, and therefore, we consider a set of motion primitives that significantly reduces computational burden in randomized sampling based motion planners for complex robots. The proposed online-learning and steering of the randomized sampling is general and does not assume a particular motion; however, we consider simple motion primitives in this initial study because they allow more convenient deployment and verification.

The used motion primitives allow crawling in forward/backward, left/right, and diagonal direction and crawling along a part of the circle with the defined radius. The primitives are designed in such a way that they can be interchangeably shifted after finishing one step, which allows a spread variety of combination of motion patterns. Each primitive is parametrized by a number of steps to be performed. The diagonal crawling is parametrized by a direction angle from the current state to the desired position, and curvature of the circle for circular crawling. Thus, these primitives allow the robot to perform 14 possible actions that means 28 different motions.

For construction of the roadmap $\mathbf{G}_{RRG}$ by the RRG only a single parameter for each primitive is used and the number of steps is set to 1. The length of the particular motion step slightly differs and it is around 10 ± 1 cm. Notice, the motion primitives restrict ability to reach an arbitrary configuration in few RRG expansions. However, it provides a smooth trajectory to reach vicinity of the desired goal locations.

In this study, we further simplify the problem by considering robot motion on a plane. Besides, the collision checking is computed using a bounding box of the platform. These simplifications do not affect the principle of the proposed steering but reduce the computational burden. An additional speed improvement is gained using goal bias and goal zooming techniques (Lavalle and Kuffner, 2001) in sampling $\mathcal{C}_{free}$ during expansion of the RRG.

3 Reference MGMP Algorithm

A simple multi-goal trajectory planner for a given sequence of goals visits is considered for a comparison with the proposed direct solution of the MGMP. The planner represents a straightforward deployment of the RRG algorithm for finding a multi-goal trajectory. The required sequence of the goals visits can be determined as a solution of the TSP, e.g., using the CONCORDE solver (Applegate et al., 2003), with approximation of the goal–goal distances. The reference planner follows the approach proposed in (Saha et al., 2006) and Euclidean distances between the locations are used for finding the sequence.

The reference algorithm is directly based on an incremental construction of the roadmap $\mathbf{G}_{RRG}$ by the RRG. A robot starts at the position of the first goal g_1, which also initializes the roadmap. The goals from the given sequence of locations $(g_1, \ldots, g_n)$ are iteratively alternating to be the temporal goal q_t of the goal bias. After k_s expansions with the same temporal goal, the new one is altered. This is repeated until k total expansions of the RRG. Then, for each goal $g_i \in \mathcal{G}$ the closest configuration $q_i = \arg\min_{v \in \mathbf{V}_{RRG}} d(v, g_i)$ is found. If the distance $d(q_i, g_i) > \varepsilon$ the algorithm fails; otherwise, the trajectory between q_{i-1} and q_i is found and connected to the final trajectory τ. Finally, the trajectory is enclosed connecting q_n to q_i. This algorithm can provide a first admissible trajectory in nk_s RRG expansions and the trajectory can be then further improved during the total of k expansions.

4 Proposed MGMP Algorithm

The proposed multi-goal trajectory planner is based on adaptation rules of the self-organizing map (SOM) for the TSP (Faigl et al., 2011), which is a two layered neural network accompanied by an unsupervised learning procedure. SOM provides a non-linear approximation of a high-dimensional input space into a one dimensional output space that represents the requested tour as a sequence of the output units. The first layer is the input layer for presenting goals to be visited and towards which the network is adapted. The output layer consists of m units $\mathcal{N} = \{\nu_1, \ldots, \nu_m\}$ representing neurons weights.

The unsupervised learning of SOM for the TSP is performed in a series of learning epochs. At each epoch, all goals to be visited are presented to the network in a random order and for each goal the units compete to be a winner using its distance to the presented goal. The winner node is then adapted to the goal together with its neighbouring nodes. This learning procedure is repeated until each goal has a distinct winner sufficiently close (e.g., in a distance less than a given threshold δ).

The adaptation of neuron weights can be imagined as a movement of the node closer towards the goal, which may provide an intuitive insight to the learning process. In our case, the neuron weights are particular configurations in $\mathcal{C}$ and to ensure they are in $\mathcal{C}_{free}$, the evolution of SOM is considered on a motion roadmap $\mathbf{G}_{RRG}$ constructed by the RRG. Thus, the weights are restricted to be at the graph edges or vertices and the adaptation can be imagined as movements of neurons along the graph edges (Yamakawa et al., 2006). Once the network is stabilized, the sequence of the goals visits can be retrieved by traversing the output layer and selecting associated goals to the winning units, i.e., the closest unit to a graph vertex representing the desired goal location $v_g \in \mathbf{V}_{RRG}$.

The fundamental issue of using SOM in MGMP is that the selection of the winner node to a presented goal g is based on computing a distance between node ν and g. Such a distance corresponds to the length of the trajectory from ν to g, which is obviously not known due to a sparse coverage of $\mathcal{C}$ by $\mathbf{G}_{RRG}$. This issue is addressed by new proposed approximation of the distance, which together with the proposed adaptation turns out to a steering strategy for randomized sampling in the RRG planner.

The approximation combines the Euclidean distance (e.g., as in (Englot and Hover, 2011)) with the current knowledge about $\mathcal{C}$ stored in the incrementally built roadmap $\mathbf{G}_{RRG}$. The current roadmap should be used as much as possible, because it provides a realistic estimation about the expected distance $d(\nu, g)$. Therefore, a part of $d(\nu, g)$ is based on a trajectory in $\mathbf{G}_{RRG}$ from ν towards the vertex $v_{\nu,g}$ that is found as

$$v_{\nu,g} = \arg\min_{v \in \mathbf{V}_{RRG}} (c(\kappa_{\nu,v}) + |(v,g)|), \qquad (1)$$

where $c(\kappa_{\nu,v})$ is the cost of the trajectory κ from ν to v. A path $P(\nu, g)$ from ν to g consists of a trajectory $\kappa_{\nu,v_{\nu,g}}$ in $\mathbf{G}_{RRG}$ and a straight line segment $(v_{\nu,g}, g)$ from $v_{\nu,g}$ to g as

$$P(\nu, g) = \kappa_{\nu,v_{\nu,g}} \oplus (v_{\nu,g}, g). \qquad (2)$$

On the other hand, the Euclidean distance between two configurations would be always shorter or equal to the length of the trajectory in G_{RRG}, and therefore, $d(\nu, v)$ has to respect the current knowledge of $\mathcal{C}$ and the influence of the usually shorter Euclidean distance should be suppressed. Therefore, we propose to compute $d(\nu, g)$ for winner selection as

$$d(\nu, g) = |P(\nu, g)| = c(\kappa_{\nu,v_{\nu,g}}) + |(v_{\nu,g}, g)|^2. \qquad (3)$$

The adaptation modifies the neuron weights to get a neuron closer to the goal. Thus, new weights ν' of the neuron after its adaptation represents a point on the path $P(\nu, g)$ at the distance from ν defined by the learning rules. The power of adaptation of winner and its neighbors is controlled by the fractional learning rate μ and neighbouring function that has form $exp(-l^2/\sigma^2)$, where l is a distance of the node from the winner and σ is called learning gain, which is decreased after each learning epoch. Therefore, the expected "traveled" distance of ν towards g is

$$|P(\nu, g)| - |P(\nu', g)| = |P(\nu, g)|\mu e^{-l^2/\sigma^2}. \qquad (4)$$

Such a new location can be out of the current roadmap $\mathbf{G}_{RRG}$; however, we can consider the expected location ν' as a temporal goal for expanding $\mathbf{G}_{RRG}$ in k_a iterations. Hence, ν' is used to steer the randomized sampling in the RRG. After the expectation of $\mathbf{G}_{RRG}$, ν' is restricted to be on an edge or vertex of $\mathbf{G}_{RRG}$ to guarantee the neurons weights always represent feasible and reachable configurations.

An intuitive insight to the learning procedure and the final trajectory determination may arise from the analyzing the situation at the final learning epochs. The winners are closed to the goals, and therefore, a trajectory from a neighbouring node to the goal will likely go over the edge (or vertex) where the winner node is located after the adaptation. Hence, the roadmap graph $\mathbf{G}_{RRG}$ is expanded to support determination of the final multi-goal trajectory by preferring direction for expansion steered by the SOM evolution.

Completeness – Notice, the proposed procedure does not affect the probabilistic completeness of the RRG. It can be considered as a meta-heuristic strategy to steer the randomized sampling towards the goals. The unsupervised learning can be terminated at any time and a regular RRG can be used to grow the roadmap and find optimal trajectories between each consecutive goals in the found sequence. Notice, the learning gain is decreased after each learning epoch, which means the effective adaptation is terminated in a finite number of learning epochs. Thus, the main purpose of the unsupervised learning is to force sampling to quickly find a feasible solution and also to determine the sequence of the goals visits. These expectations are verified for the robot motion model introduced in Section 2.1 and our early results are presented in the following section.

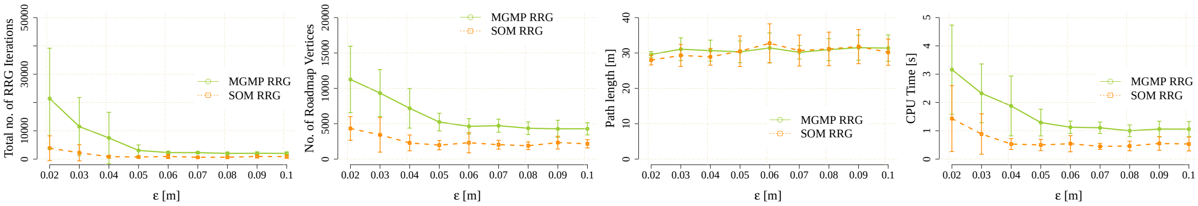
5 Case Study

A validation of the proposed SOM based multi-goal trajectory planner has been performed in two scenarios to verify if the proposed steering strategy provides a feasible multi-goal trajectory in less RRG expansion steps than the reference method (denoted as MGMP RRG) for the given sequence of goals. In the both scenarios, the studied indicators of the planner performance are the total number of RRG expansions n_{RRG}, the number of vertices and edges of the build roadmap $\mathbf{G}_{RRG}$, and the required computational time for the first feasible admissible multi-goal trajectory that is closer than the selected ε to all goals. All the presented results have been computed using a single core of the iCore7 processor running at 3.4 GHz.

The used number of expansions k_a in the SOM RRG is 15 iterations for the winner and 10 iterations are used for neighbouring nodes.

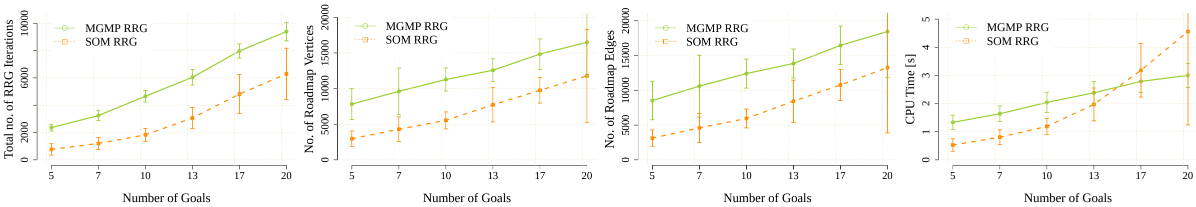
5.1 Influence of the admissible distance

The first evaluation is performed for a simple environment, where the optimal sequence to visit 5 goals can be determined using Euclidean distance. The environment is depicted in Fig. 4 where selected found first feasible paths are visualized. Both algorithms RRG and SOM are randomized, and therefore, 50 trials have been performed for each planner and the admissible distance ε from the range $0.02 \leq \varepsilon \leq 0.1$.



(a) no.of RRG expansions (b) no. of $\mathbf{G}_{RGG}$ vertices (c) trajectory length (d) computational time

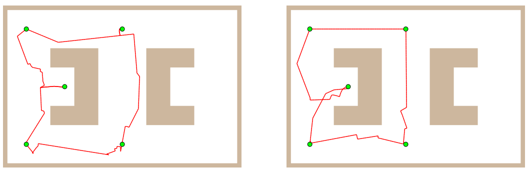
Figure 2: Average values of the studied indicators in simple MGMP problem with 5 goals and admissible distance ε



(a) no. of RRG expansions (b) no. of $\mathbf{G}_{RGG}$ vertices (c) no. of $\mathbf{G}_{RGG}$ edges (d) computational time

Figure 3: Average values of the studied indicators for the first feasible trajectory in *potholes* environment and number of goals

Notice, the reference planner uses the given sequence of the goals visits, while the SOM RRG approach also determines the sequence. Because of this, it may happened that not the same sequence of the goals visits as for the reference algorithms is determined. Therefore, only SOM MGMP solutions with the identical sequence to the reference are considered. The reference algorithms utilize $k_s = 200$ RRG expansions for particular sampling towards the temporal goal. In all cases, a feasible trajectory is found within the given maximal number of RRG expansions, which is set to 20 000.



(a) RRG, n_{RRG}=2000 (b) SOM, n_{RRG}=715

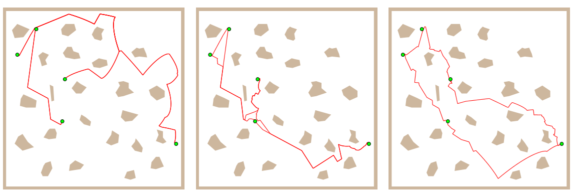
Figure 4: Found feasible solutions of the MGMP with 5 goals projected to a ground plan of the environment

The average values of the studied indicators are depicted in Fig. 2. Regarding the required n_{RRG} to find the first feasible multi-goal trajectory, the proposed SOM based steering of the randomized sampling requires the lowest number of the RRG expansions. The main differences are for small ε, which makes the problem more difficult for the randomized planners with motion primitives.

A feasibility of the found multi-goal trajectories has been experimentally verified for a real traversability by the hexapod walking robot using the considered motion primitives. Although the robot was controlled in the open loop it was able to follow the planned trajectory and reach all the desired goal locations. Snapshots form the deployment are depicted in Fig. 1.

5.2 Influence of the number of goals

In the second scenario, we study performance indicators for increasing complexity of the underlying TSP with the number of goals $n \in \{5, 7, 10, 13, 17, 20\}$. For each n, 20 random instances have been created in the environment called *potholes* that gives 120 problems in total. A single value of $\varepsilon = 0.1$ m has been selected and the number of RRG expansions was increased to k_t=500 and the total number of expansions to k =50 000 for the MGMP RRG algorithm. Each problem is solved 20 times, which gives 2400 trials for both MGMP RRG and SOM RRG algorithms. Here, SOM may provide different sequence of goals visits more frequently, and therefore, we include all sequences in the computation of the average values of the studied performance indicators. The average values over all trials for the first found admissible trajectories are shown in Fig. 3.



(a) n_{RRG}=1 045 (b) n_{RRG}=10 570 (c) n_{RRG}=41 500

Figure 5: Found feasible solutions for 5 goals in *potholes* environment: (**a**) the first feasible solution found by SOM RRG; (**b**) evolved feasible SOM RRG solution; (**c**) refined solution by the MGMP RRG.

Also in this case, SOM RRG requires less number of RRG expansions to find a feasible solution. Such a solution can be then improved by the RRG expansions in a similar way as the reference algorithm works, which is demonstrated in Fig. 5.

5.3 Discussion

Despite of the relatively simple problems considered, the presented early results validate a feasibility of the proposed approach for steering the randomized sampling in the RRG. The results indicate SOM for the TSP can be applied directly in $\mathcal{C}$ and thus a construction of the motion planning roadmap prior sequencing part of the MGMP can be avoided. The SOM RRG provides first feasible solutions of the MGMP in fewer expansions steps albeit the quality of such a solution is worse than for reference algorithm utilizing the known sequence of the goals.

The SOM based approach seems to be faster than the reference algorithm in finding the first feasible solution; however, we found out that the selection of the winner node is computationally more demanding with increasing learning epoch and the number of goals, see Fig. 3(d). It is because the graph $\mathbf{G}_{RRG}$ becomes denser, which increases computational burden of the determination of the vertex $v_{\nu,g}$ by (1). This issue may be addressed by removing non-perspective roadmap's vertices or by building an additional structure to support path queries in the roadmap.

6 Conclusion

In this paper, we address multi-goal trajectory planning with motion primitives and we introduce a new steering strategy for randomized sampling in RRG to improve its performance for a hexapod walking robot. The proposed approach is based on principles of unsupervised learning of self-organizing maps that allow to simultaneously solve the sequencing part of the MGMP together with determination of the particular trajectories. The presented early results of the proposed idea in simple case studies provide a ground work for a further research. Despite of the simple problems considered, a straightforward MGMP planner based on a priori known sequence of goals visits and the standard RRG algorithm requires more expansion steps to find a feasible solution than the proposed approach. This indicates that the proposed steering of the randomized sampling in the RRG can improve the performance of the planner significantly.

The encouraging results motives us to evaluate the proposed idea in more complex problems and to compare the performance regarding the solution quality of the final multi-goal trajectory provided by other approaches based on postponed distance evaluation techniques.

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