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Self-organizing map for determination of goal candidates in mobile robot exploration

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Abstract. This paper addresses a problem of determining goal candidates in the frontier-based mobile robot exploration. The proposed solution is based on self-organizing map for the traveling salesman problem with neighborhoods and it allows to study the exploration formulated as a problem of repeated coverage of the current frontiers where the minimal number of goal candidates is determined simultaneously together with the expected cost to visit the candidates. The early results enabled by the proposed self-organizing map-based solution indicate exploration improvement for the proposed problem formulation. The presented work demonstrates how neural network approach can provide interesting insights and ground for studying optimizations problems arising in robotics.

1 Introduction

A problem of collecting information about an unknown environment can be considered as a robotic exploration problem in which a mobile robot is requested to create a map of the environment. A fundamental approach to the robotic exploration is Yamauchi's frontier-based approach proposed in late nineties [1]. In this event-based exploration, a mobile robot is navigated towards a selected goal location at the frontier that represents an area between already known and unknown parts of the environment. After reaching the location, the robot takes a new sensor measurement, information about the environment is updated, and the next robot goal is determined until the whole reachable space is covered by the robot sensor, see an example of exploration steps depicted in Fig. 1.

Frontiers represent a huge set of possibilities from which the most suitable one has to be selected in order to explore the whole environment as quickly as possible. Yamauchi's simple selection of the closest frontier provides a feasible solution of the problem; however it does not lead to the fastest exploration possible. Therefore, various approaches combining expected information gain of the goal candidate together with its distance from the robot in a utility function have been proposed [2, 3, 4]. Even though these approaches provide a better performance than using only a pure distance cost, they consider only an immediate benefit of visiting the next best goal without planning for a longer horizon.

Authors of [5] proposed to consider visitation of selected frontier locations (representatives) only from which all frontiers can be covered and formulated the problem of determination of the next robot goal as the problem to find a

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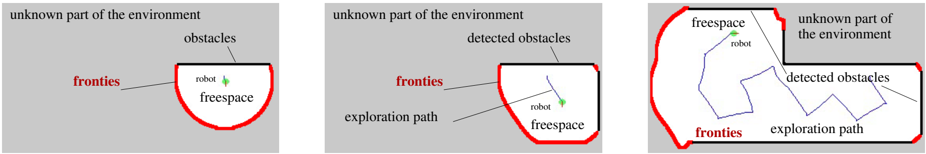

Fig. 1: Exploration process using a grid map of the environment being explored.

shortest multi-goal path visiting all such representatives. The multi-goal path planning problem is solved as the traveling salesman problem (TSP), e.g., by Concorde [6], where an additional *virtual* goal is used to find a shortest open path starting from the robot position and visiting all goal candidates. The next robot goal is then selected as the first goal of the found multi-goal path.

Representatives of the frontiers improve exploration performance and also reduce the number of goal candidates in the TSP and thus decrease the computational burden. However, despite significantly better performance of the approach [5] than a simple navigation to the closest frontier, the representatives are determined by k-means algorithm, which does not explicitly consider any expected coverage from the frontiers nor the distance to the robot. The representatives are determined more like in an *ad-hoc* manner, and therefore, the approach does not provide insights to the relation of the exploration performance and the way how the goal candidates are determined.

In this paper, we formulate the problem of determination of the next robot goal as the traveling salesman problem with neighborhoods (TSPN) and propose self-organizing map (SOM) to determine the goal candidates explicitly considering both aspects, the expected coverage of the frontiers and the distance of a tour connecting the candidates. The proposed SOM is based on our prior work on SOM for the watchman route problem [7] and traveling salesman problem with neighborhoods [8], which is here extended to the robotic exploration context.

Regarding SOM-based approaches to robotic exploration, to the best of the authors knowledge, the proposed approach is the first SOM based solution that is directly employed in the robot exploration task with limited visibility. Although Peano curve provided by SOM has been considered as an exploration path in [9], the paper lack any guarantee the whole environment would be explored using a sensor with a limited range. In addition, the authors consider only an environment without obstacles and their approach needs several parameters. On the other hand, the herein presented approach provides guaranteed exploration using sensing range ρ and does not need specific parameter tuning. Moreover, it is also compared with other robotic exploration approaches and thus it makes a benefit of the SOM approach more evident.

2 Problem Definition

The environment being explored is represented by a probabilistic occupancy grid (Occ), where integration of new sensor measurements is performed using Bayes rule [10]. The next robot goal is determined within a grid map of the environ-

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ment $\mathcal{M}$ that is created from the occupancy grid as a result of the thresholding the probability a grid cell is occupied. Cells of $\mathcal{M}$ are one of three possible values: *empty*, *occupied*, and *unexplored*. The exploration procedure can be summarized as follows:

1. Initialize the occupancy grid *Occ* and integrate the first sensor measurement of the omnidirectional laser scanner with the sensing range ρ.
2. Create the map $\mathcal{M}$ from the occupancy grid.
3. Detect all frontier cells: $\boldsymbol{F} \leftarrow$ detect_frontiers($\mathcal{M}$).
4. Determine goal candidates $\boldsymbol{G}$: $\boldsymbol{G} \leftarrow$ get_goal_candidates($\boldsymbol{F}$).
5. `If` $|\boldsymbol{G}| > 0$
   (a) Select the next robot goal $g \in \boldsymbol{G}$ using the TSP distance cost [5].
   (b) Navigate the robot towards g.
   (c) Collect new measurement with the range ρ and integrate it to *Occ*.
   (d) Go to Step 2.
6. `Terminate` – the whole environment has been explored as there is no reachable goal (frontier).

The problem addressed in this paper is to determine new goal candidates at Step 4. The optimization criterion is the time needed to explore the whole environment that is measured as the distance traveled by the robot until all reachable frontiers are covered. This length is denoted as L.

Even though L is not directly optimized at Step 4, the proposed approach is based on the idea that a shorter TSP tour determined in Step 5a will provide overall improved performance of the exploration as it has been presented in [5].

3 Self-Organizing Map for Determining Goal Candidates

The proposed SOM is designed to determine goal candidates that are positioned on a shortest closed path connecting them and from which all frontiers are covered. The idea behind the procedure design is motivated by the fact that it is not necessary to visit a frontier to explore new area surrounding it. Therefore, goal candidates are found as points located at the distance $\rho' < \rho$ from frontier cells. Each frontier cell is represented as a set of possible grid cells from which the frontier can be covered; hence, the problem is formulated as a variant of the TSPN to find a shortest tour visiting the sets that guarantees complete coverage of all frontiers. Therefore, we consider the self-adjusting adaptation schema [8] in which we avoid adaptation to already covered frontiers similarly to [7].

The used SOM is a two-layered competitive neural network where the input layer is two dimensional vector for presenting frontiers to the network and the output layer is a uni-dimensional array of neurons. Neuron weights and the input frontiers are coordinates in the grid $\mathcal{M}$ and the array of neurons weights represents a path in $\mathcal{M}$. The path is called ring and it is determined as a sequence of shortest paths between the consecutive neuron weights, e.g., using [11]. Thus,

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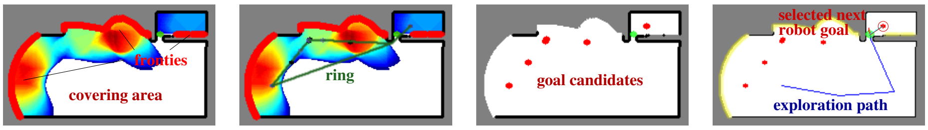
the output layer represents a sequence of straight line segments (ring) which is a shortest path among obstacles connecting the neurons.

During the adaptation, frontiers are presented to the network in a random order and the winner neuron is determined as the closest point of the ring to the presented frontier, i.e., a new neuron is created at the position of the closest point if such a neuron does not exist. At the end of each learning epoch, only winner neurons (representing the current goal candidates) are preserved and all other neurons are removed.



(a) (b) (c) (d)

Fig. 2: SOM based determination of the goal candidates: (**a**) sets $\mathcal{C}_f$ as an intensity map, where blue denote locations covering few frontier cells while red denotes a high number of covered frontier cells; (**b**) a ring connecting the winner neurons; (**c**) determined goal candidates; (**d**) the final selected next robot goal.

The self-adjustment of the number of neurons is important because several frontiers can be covered from a single goal candidate and thus it is not necessary to adapt the network towards all frontiers. Moreover, a coverage of the frontier can be provided from a point that is within ρ' distance from it. Therefore, for each frontier cell f a set of locations $\mathcal{C}_f$ from which f can be covered considering ρ' is determined in advance, see Fig. 2 with visualization of the sets. Then, during the adaptation, the winner ν^* and its neighbors are adapted towards an alternate goal $g \in \mathcal{C}_f$ that is found as the closest point to ν^* (considering a shortest path among obstacles). After the adaptation, all frontiers that can be covered from g are marked as covered and they are not considered for the adaptation in the current learning epoch.

The value of ρ' is set to ρ reduced about a dimension of the squared grid cell of the grid map $\mathcal{M}$ to ensure coverage beyond the frontier. The network starts with one neuron and the adaptation schema can be summarized as follows:

1. Let the current map be $\mathcal{M}$ and the set of frontier cells be $\boldsymbol{F} = \{f_1, \ldots, f_n\}$.
2. Determine the covering area $\mathcal{C}_f$ for each $f \in \boldsymbol{F}$ using ρ'.
3. Create a random permutation of the frontier cells $\Pi(\boldsymbol{F}) \leftarrow \text{permute}(\boldsymbol{F})$ and clear the covered frontiers by the current winners $\boldsymbol{F}_{covered} \leftarrow \emptyset$.
4. Select winner ν^* to a frontier $f \in \boldsymbol{F} \setminus \boldsymbol{F}_{covered}$.
5. Determine the goal g from $\mathcal{C}_f$ that is closest to ν^*.
6. Adapt ν^* and its neighbouring nodes towards g and associate g to ν^*.
7. Mark newly covered frontiers f_i from g; $\boldsymbol{F}_{covered} \leftarrow \boldsymbol{F}_{covered} \cup \{f_i | g \in \mathcal{C}_{f_i}\}$.
8. Remove all covered frontiers from the permutation, $\Pi(\boldsymbol{F}) \leftarrow \Pi(\boldsymbol{F}) \setminus \boldsymbol{F}_{covered}$. and `If` $|\Pi(\boldsymbol{F})| > 0$ go to Step 4.

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9. Remove all neurons that are not winners in the current learning epoch.
10. `If` the winner neurons (the associated goals $\boldsymbol{G}$) provide coverage of all frontiers `Stop` the adaptation; `Otherwise` go to Step 3.
11. Traverse the output layer and use the associated goals to the winners as the required goal candidates $\boldsymbol{G}$.

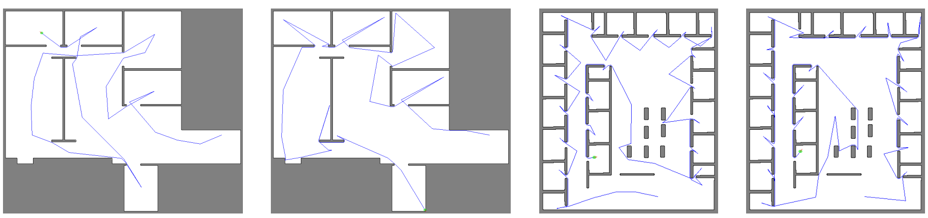
4 Results

The proposed SOM based determination of goal candidates has been validated in three environments: *em*, *autolab*, and *jh*; with dimensions 21 m×24 m, 35 m×30 m, and 21 m×24 m, respectively. The *em* is an environment without obstacles and two other environments are visualized in Fig. 3. Lengths of the final exploration path for the greedy method [1], the TSP distance cost based method with k-means [5] and the proposed goal candidates determination also with the TSP distance cost are depicted in Table 1. The results are average values of 20 trials for each method, problem, and ρ, i.e., 540 trials in total.

Table 1: Average lengths of the exploration path for 20 trials

Environment	*em*			*autolab*			*jh*		
ρ [m]	3	5	7	3	5	7	3	5	7
Greedy [1]	172	97	91	302	269	167	196	204	178
K-means [5]	144	92	73	260	223	175	219	179	174
Proposed SOM	148	76	53	228	177	125	199	175	172

The presented results indicate the proposed formulation is valid and the SOM based determination of the goal candidates provides shorter exploration paths. The proposed approach provides better results in open space like environments for longer sensing ranges, while for the office-like environments better results are for small visibility ranges.



(a) SOM, L=137 m (b) TSP, L=175 m (c) SOM, L=170 m (d) TSP, L=178 m

Fig. 3: An example of the final exploration paths in the *autolab* (**a**, **b**) and *jh* (**c**, **d**) environments for ρ=7 m and ρ=5 m, respectively.

The current implementation of the proposed approach is computationally demanding because of the underlying path planning on a grid, which also limits its real deployment. However, this can be addressed by a polygonal representation of the environment as it is shown in [12].

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5 Conclusion

A new SOM-based algorithm has been proposed for the robotic exploration formulated as the TSPN. It is worth mentioning SOM enables to solve this problem formulation, because other TSPN approaches are restricted to problems without obstacles or non-overlapping neighborhoods, which is not the case of SOM. The main source of the exploration-performance improvement comes from the explicit consideration of the sensor range in determination of the goal candidates. A navigation to the position of a frontier close to obstacles is avoided. Such a movement is not necessary because it will not provide a new information about the unexplored area.

The proposed SOM provides goal candidates that are spatially distributed to guarantee coverage of all frontiers while a cost of visiting all the candidates is also taken into account. Even though, the results do not provide a significant evidence of benefit arising from such a consideration, the SOM benefit is in a straightforward solution of the related TSPN problem. Moreover, the flexibility of SOM allows to consider not only sensing at the goal candidates but also sensing along the path from one candidate to another candidate during the network evolution. This can provide an additional source of performance improvement in the mobile robot exploration task and it is a subject of our future work.

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