State of the art

March 9, 2020

The exploration of an unknown environment pursued by a team of robots is a complex problem, tackled in different ways across the literature. Looking at it from a conceptual point of view, there can be identified mainly two phases. First one concerns the detection of the best locations to explore next in the partial map built so far. The other one deals with the allocation of robots to these candidate locations. Thus, the whole exploration can be seen as an iterative two step procedure where, once the map is updated, a set of possible points of interest are chosen, based on some criterion, and then to each robot is assigned a goal location. These two steps are repeated until the exploration can be considered finished. The *exploration strategy* is the algorithm which detects the candidate locations, while the *coordination mechanism* is the one allocating the robots to them.

1 Exploration strategy

As previously described, the exploration strategy is an algorithm providing the candidate locations robots should visit to maximize their knowledge about the environment. There are two crucial aspects in this, that are the definition of a candidate location and the metric used to choose the best one.

How a candidate location is defined depends strongly on the representation of the environment. This can be divided into two categories, topological or metric, which turns into graph-based or grid-based representations, even if other data structures are possible, like in [1] where the map is stored as two lists of line segments.

The choice of the next location to explore among the set of candidate ones is done in different ways across literature. An example of this in a metric representation is in [1], where a comparative review of four strategies for single robot exploration is performed, distinguishing among a random approach (used as benchmark), a greedy one and two complex *ad hoc* procedures, testing their performances over different environments. Therefore, the choice can be done according to different metrics and the two main factors affecting it are the expected utility provided by the location and the cost of reaching it. In a topological representation, strategies like a Depth First Search [2] and Breadth First Search [3] are naturally possible algorithms on undirected graphs, while [4] proposes an interesting approach to solve the exploration problem on directed graphs.

In the following, some exploration strategies are presented, distincted into three categories: *information gain-based, frontier-based* and *topological strategies*. Giving particular attention to the second one, being the one used in this work.

1.1 Information gain-based strategies

Prior to the definition of this kind of strategies, it is useful to define occupancy grids and coverage maps. *Occupancy grids* model the environment as a grid where each cell can be marked as *free* or *obstacle*, if already scanned through sensors, or *unknown*, if it has not been scanned yet. Also *coverage maps* are a grid-based representation of the environment, where each cell contains the posterior probability of being covered by an object. This provides different advantages compared to occupancy grids, like for example the possibility to finely model a wall not parallel to x- or y-axis of the grid, without the need of enlarging it to match the discretization.

Information gain-based strategies as presented in [5] are probabilistic strategies usually employed on coverage maps, and consequently extensible to occupancy grids. Candidate locations are chosen among the cells of the grid, according to the expected change in the entropy obtainable by moving a robot there. Given a posterior probability distribution *p(x)* of a cell x, its entropy *H(p(x))* is defined as

$$H\left(p\left(x\right)\right) = -\int_{x} p\left(x\right) \log p\left(x\right) dx.$$

While, the information gain for a given cell c and measurement z taken from the pose x is

$$I\left(c, x, z\right) = H\left(p\left(c\right)\right) - H\left(p\left(c|x, z\right)\right).$$

Then, each cell in the grid is considered as a possible candidate location and the one providing the highest expected entropy reduction, i.e. information gain, is selected. This method provides suitable locations because the information gain for a completely known cell is near zero, thus the approach tends to assign candidate locations in proximity of uncertain cells, increasing the knowledge of the environment.

In [5], besides the basic strategy presented so far, are also introduced two modifications. The first one reduces the number of candidate locations from the whole map to the ones in a local window, which has to be completely explored before moving on. Rather than reducing the set of candidate locations, the second one modifies the way in which the next one to explore is chosen by introducing the cost to reach that location from the robot pose.

In [6], is presented the *A-C-G strategy* which defines a conceptually similar approach but takes explicitly into account the contribution to entropy of the points sensed from the candidate location, discriminating between already sensed points and the ones sensed for the first time. It also includes a factor proportional to the distance from the robot location and the candidate one.

In [7], an information gain strategy is integrated into the localization and mapping phase. This allows to decide which action to perform at each step of the exploration, by taking into account the trajectory and map uncertainty.

1.2 Frontier-based strategies

As presented above, information gain-based strategies mainly focus on the process of deciding the next location to explore, giving less attention to the definition of the set of candidate locations. This is extremely clear by considering the base method, where all the cells in the grid are possible candidate locations and the method implicitly cuts out the ones not providing new knowledge. In frontier-based strategies, the focus is completely shifted to the creation of a good set of candidate locations.

As defined in [8], the paper originally introducing this strategy for single robot exploration, a *frontier* is the boundary region between explored and unexplored space. The idea is that by assigning a robot to its closest frontier as location to explore, the line between explored and unexplored space is pushed continuously, until the whole environment is mapped. In that case, occupancy grids are used to model the environment and with that representation, it is pretty straightforward to find out a frontier, identifiable with the cluster of free cells which neighbors are unknown.

This simple idea works extremely well in practice and for this reason it has been used widely in the literature, producing a lot of extensions and adaptations to the various cases, like [9] where the strategy is extended to multi-robot scenarios.

In [10], the Leader-Follower exploration algorithm is presented. It focuses on the roles assumed by the robots during the exploration, which can be dynamically changed, according to the distance from the assigned location. Candidate locations detection is done by identifying frontiers and, differently from the original strategy, the next to explore is not chosen as the nearest one. Indeed, it looks for the pair of frontiers maximizing the sum of the rewards for the leader and the follower, where the reward function is composed by a utility term and the cost to reach the frontier.

[11] provides an extension of this exploration strategy to the topological map, rather than occupancy grids. An interesting aspect of this is in the definition of *frontier nodes*. They are classified according to geometric information about the environment into free area or a transit area, defined as the area where the robot transits between two spaces (rooms, corridors, and so on). As the environment is progressively mapped, frontiers are detected, classified in one of the two categories stated above, then the next frontier to explore is selected and the topological map is updated. The algorithm proposed is shown to have good performances both in terms of exploration time and traveled distance against some benchmark algorithms.

1.3 Topological strategies

Topological strategies rely on a graph-based representation of the world. This is useful to neglect the geometrical features of the environment and to focus on its structure. As showed in [12], the complexity of using geometric maps grows exponentially as the environment becomes larger and this justifies the use of topological maps. Moreover, the use of a directed graph can also simulate the case of a one-way street, where the robot is allowed to go in one direction and not in the opposite one [13], which would be impossible to describe just relying on geometric maps.

In this kind of strategies, candidate locations are nodes of the graph and the next one to explore is decided in various ways, strongly depending on the type of graph used. In fact, in the literature are used both undirected and directed graphs, with a further distinction whether or not the vertices are identifiable. A vertex is identifiable if it can be recognized by a robot when revisited. This is not always guaranteed because the robot may have limited sensor capabilities or the appearance of vertices may change.

Undirected graphs with distinguishable vertices are the most straightforward case. Each vertex is labeled in a unique way and the robot is allowed to traverse the edges in both ways [2, 14]. In [15] is presented an extension of the Depth-First Search algorithm to the multi-robot scenario both for graphs and trees. A particular aspect of the model used is that edges are considered as opaque, this means that from either end, it is not clear where the edge goes. In [16] is analyzed the problem of piecemeal exploration, this states that the robot can traverse a limited number of edges before going back to the source vertex. It is a realistic context in which the robot has a limited amount of fuel and needs to refill it after a fixed number of steps or traveled distance. The algorithm proposed for this problem is based on Breadth-First Search and another important aspect is the use of the concept of *frontier vertex*, defined as a vertex incident to unexplored edges.

Undirected graphs with anonymous vertices introduce some difficulties and to get rid of them, markers are needed to distinguish between explored and unexplored area [3, 17, 18]. In [17] is shown that one marker is sufficient to allow the robot to build a graph isomorphic to the environment in low-order polynomial time and the use of multiple markers may improve the performance. In [3] are presented two enhancements both to single-robot and multi-robot exploration in such environments, provided by the use of a Breadth-First Search and the exploitation of local neighbors information.

In the case of directed graphs, the robot movement is strongly limited with respect to undirected graphs. Clearly, Depth-First Search is not always possible because backtracking is not guaranteed to be applicable. Different algorithms have been proposed to deal with these models [4, 13, 19]. In [4] is proposed an algorithm to visit all nodes and edges with a sub-exponential upper bound on the number of edge traversals. In [13] is defined an algorithm able to explore a directed graph with anonymous vertices by using two robots through the simultaneous learning of the graph and an homing sequence. This is done by keeping multiple possible maps, updating them through a sequence of movements, then checking their correctness. It also states that it is not possible to efficiently learn the same kind of graph by means of a single robot with a constant number of pebbles without prior knowledge on the number of vertices. Problem which, as stated above, [17] shows to be solvable with one marker in low-order polynomial time in the case of an undirected graph.

2 Coordination mechanisms

In a multi-robot scenario, once candidate locations are detected on the map, it comes out the problem of how the robots in the team have to be assigned to them in order to maximize the knowledge about the environment. The answer to this is provided by the coordination mechanism, which is the algorithm that assigns robots to candidate locations according to some criteria and on the base of these, coordination mechanisms are distinguished into online and offline. Online mechanisms assigns robots to candidate locations by taking into account the actions done by the other members of the team [20, 21, 22]. In offline mechanisms, in contrast, roles are assigned to robots before the exploration starts, they act according to them [23, 24, 25, 26] and eventually they can change them dynamically as the exploration goes on [10].

A coordination based on an online mechanism is weighed down by the need of more communication among the agents. Before an allocation is made, an agent has to know other agents pose and target locations. On one hand, this implies a lot of communication to make proper assignments; on the other hand, this allows to perform choices aimed at maximizing the performances of the system. Through the use of roles, offline mechanisms require little to no communication once the exploration is started, making the robots and the whole system easier. The other side of the coin is that robots move almost freely, with the possibility of interference among them and the redundancy of assignments to the same target location.

The relation between exploration strategy and coordination mechanism is quite tight and the relative impact each one has on the performances is hard to establish. A work in this sense is [27], where different exploration strategies and coordination mechanisms are compared on two different environments. What comes out is that on structured environment, like an office one with a lot of rooms and corridors, the detection of good candidate locations is preferable over a good assignment of robots to them. In an open environment, the contrary holds, being the coordination mechanism able to increase the amount of area explored in the same amount of time, making the impact of the exploration strategy less relevant.

2.1 Online mechanisms

Online coordination mechanisms allocate robots to target locations exploiting information about other robots actions. To achieve this, robots need to communicate each other. This has been done in different ways across literature, using different techniques [20, 21, 22].

In [20] the communication is performed through the use of *bids*. Every time a robot receives a map update from the central mapper, it sends a bid with a list of costs and information gains for each frontier to the central executive. As the central executive gets all the bids, computes the assignment maximizing the difference between information gain and cost for each robot and assigns the frontier to it. Once an assignment is fixed, the other bids are discounted by a certain value to take it into account. This procedure is iterated as long as there are no remaining robots or tasks. The discount factor is fundamental being the main factor introducing the online coordination aspect of this algorithm, in fact if the bid was not discounted, each robot would go towards the frontier with its highest estimated utility, not taking into account other robots assignments. Also [21] and [22] perform coordination by considering the utility of each frontier computed as the difference between the information gain it can provide and the cost to reach it.

In [21] every time a robot is assigned to a certain frontier, the utility of the other target points is discounted by a value proportional to the probability of being in the visibility area from the assigned one. In [22] this approach is extended to limited communication scenarios.

[28] provides an algorithm where the Voronoi Graph of the partial map is computed, then it is segmented and frontiers are detected for each segment. After this step, robots are assigned to the frontiers in a way to minimize the total cost of the assignments.

2.2 Offline mechanisms

Offline coordination mechanisms provide a definition of roles prior to the beginning of the exploration. By sticking to these roles, the coordination among robots needs little to no communication, which is one of the main advantages of this approach. Roles definition may also be modified run-time, like how is done in the Leader-Follower algorithm [10] presented above, where the role depends on the distance from the assigned frontier.

Two major works in this sense for this thesis are represented by [25] and the further extension provided by [29]. In [25] are presented three coordination mechanisms, namely *reserve, buddy system* and *divide and conquer.* The *reserve* mechanism splits the team into two smaller teams where one is left idle in the initial position, the second one is sent to explore frontiers. As new frontiers are found, idle robots are progressively turned into active agents and assigned to them. Once all the initially idle robots are active agents, the exploration is carried out without further coordination. *Buddy system* works in a similar way, with the difference that rather than considering single robots, couples of robots are considered. At the start of the exploration, some couples are sent to explore frontiers, while the others remain idle in the starting position. Once a branching point is found, the couple is split and each robot explores a different branch. If another branching point is found, one branch is explored by the single robot which discovered it, and the other one is assigned to a couple from the idle set, that then turns into active. In *divide and conquer*, at the beginning of the exploration, all the robots move together following a leader, then as a branching point is found, the team splits in a half. A new leader for the second team is decided and each team is assigned to a branch. This splitting approach goes on until a team is composed by more than one robot and after that, they proceed in an uncoordinated way.

[29] modified these mechanisms proposing respectively *proactive reserve, proactive buddy system* and *side follower.* The idea behind the first two is to move the idle set from the starting position, towards a better position, nearer to the possible branching points. This would allow the robots turned into active to reach the target position in less time, once they are called. The waiting position for the idle team is computed as the barycenter of the locations of the active agents. This thesis expands this approach modifying the way in which this waiting position is computed by introducing the topology of the environment into account. Differently from *divide and conquer,* the *side follower* mechanism organizes the agents into groups of three, rather than a single group. The idea is that each robot in the group has a preferred direction for the frontier to explore: the left robot tends to explore frontiers on the left, the right robot prefers the ones on the right and the robot in the center explores the ones in front of it. This modification are shown to have very good performances when compared with the benchmark ones, particularly *proactive reserve* which is usually better than all the other considered strategies. While *proactive buddy system* outperforms the simple *buddy system* mostly on open environments, resulting in even or worst performances on the others. *Side follower* also performs generally better than *divide and conquer*, particularly on the environments reflecting the structure for which it is designed, that is a central corridor with spaces on the sides.

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