Information Sciences 471 (2019) 164–184

Contents lists available at ScienceDirect

Information Sciences

journal homepage: www.elsevier.com/locate/ins

Multi-goal motion planning using traveling salesman problem in belief space

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A R T I C L E   I N F O

Article history:
Received 23 January 2018
Revised 25 July 2018
Accepted 25 August 2018
Available online 30 August 2018

Keywords:
Motion planning
Uncertainty
Belief space
Traveling salesman problem
Search and exploration

A B S T R A C T

In this paper, the multi-goal motion planning problem of an environment with some background information about its map is addressed in detail. The motion planning goal is to find a policy in belief space for the robot to traverse through a number of goal points. This problem is modeled as an asymmetric traveling salesman problem (TSP) in the belief space using Partially Observable Markov Decision Process (POMDP) framework. Then, feedback-based information roadmap (FIRM) algorithm is utilized to reduce the computational burden and complexity. By generating a TSP-FIRM graph, the search policy is obtained and an algorithm is proposed for online execution of the policy. Moreover, approaches to cope with challenges such as map updating, large deviations and high uncertainty in localization, which are more troublesome in a real implementation, are carefully addressed. Finally, in order to evaluate applicability and performance of the proposed algorithms, it is implemented in a simulation environment as well as on a physical robot in which some challenges such as kidnapping and discrepancies between real and computational models and map are examined.

1. Introduction

Simultaneous localization and planning is the basis of many robotics applications such as exploration, search and coverage. A proper planning helps a robot to make use of the available information and generate or select right motion commands and actions. Action selection criteria vary with the goals of the application [44]. For example, in an earthquake affected building, motion commands should guide the robot to search and explore the environment in a rapid and successful way using the information such as rough layout of the building [46]. As another example, consider a service mobile robot which operates in an office-like environment and should do a sequence of tasks in different locations, e.g., different rooms. Therefore, a proper action selection and planning, based on the overview-map, is necessary to overcome its tasks successfully and efficiently [28,40]. In this paper, we assume some prior information is available about the environment, e.g., the layout of the environment or an initial map.

In the absence of uncertainty, the planning for search, exploration, and coverage is mainly concerned with investigating the methods to speed up and improve the robot's performance [24,36,47,49]. Xu and Stentz [47] propose a graph based method to find a short path for the coverage of an environment and the problem is modeled as a rural postman problem.

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https://doi.org/10.1016/j.ins.2018.08.062

Additionally, it suggests an algorithm for updating the graph in the case of discrepancy between the actual and the initial map. Pasqualetti et al. [36] use a graph-based solution for patrolling in an environment. Yehoshua et al. [49] study the coverage problem, and the cell decomposition method with high-risk cells is used to find a low-risk path for the robot. A prevalent approach to cope with these kinds of problems is formulating them as a traveling salesman problem (TSP) and exploiting the background information to make a proper plan in order to guide the robot to search the environment faster [7,15,26,35]. Kulich et al. [26] and Faigl et al. [15] model the exploration problem by a single and multi-robot as a TSP which its edges' costs are proportional to the distance between goal points. In the method proposed by Oßwald et al. [35], the robot explores the environment based on a policy obtained by solving a TSP to speed-up the exploration, but there is not a predefined and certain path, and the robot moves between manually selected goal points using a local exploration algorithm. It also suggests a solution for replanning and updating TSP solution in the case of finding a difference between the initial and the actual map.

More importantly, what makes planning more difficult and sophisticated is the presence of motion and observation uncertainties which are usually ignored in most studies. Uncertainty is closely tight to robotics problems and ignoring it may lead to choosing a short path with the low probability of success. Motion and observation uncertainties cause the lack of full state information for decision making and planning. However, a filter (e.g., Kalman and particle filter) can estimate a probability distribution function (PDF) over all possible states, called belief or information state, using the dynamical model of states and measured values by sensors [1,3]. This means the planning and decision making in the aforementioned examples should be done in the belief space. Freundlich et al. [16] study the path planning and the resource allocation for the multi-goal problem, under motion and sensor uncertainties, but it is restricted to the discrete space and is not applicable in large and real environments as well as long-term operations. Faigl et al. [14] study the autonomous multi-goal inspection by adding auxiliary navigation way points around each goal to reduce the uncertainty and applying self-organizing map algorithm to the TSP [13]. In this method, the uncertainty and the probability of colliding obstacles on the path between every two goals are not considered.

Another major challenge in multi-goal motion planning is the necessity of online replanning ability. In situations such as a change in the map or an update in the robot's belief (localization), it is required that the robot make a replanning online which are not considered in [14,16]. This challenge is more evident in a real application where the computational models of the system such as motion, sensor and map differ from real models. Replanning in belief space is more challenging and requires an approach which is suitable for a real application in the sense of time and complexity.

Motion Planning Under Uncertainty (MPUU) is the basis of the multi-goal motion planning, and many studies recently have been done in this area [21,22,37,39]. Pilania and Gupta [37] propose a sampling-based algorithm for motion planning of a mobile manipulator under uncertainty and consider effects of uncertainty on the manipulator motion. Janson et al. [22] present the MCMP (Monte Carlo Motion Planning) approach that considers probabilistic collision avoidance constraints, and is suitable for the real-time implementation. The MPUU problem is extended to the multi-robot belief space planning in unknown environments by Regev and Indelman [39], and a decentralized sampling-based planning is proposed to address this problem. Owing to successful performance of sampling based methods in motion planning problems, they are expanded to motion planning under uncertainty problems [5,10,37]. In LQG-MP algorithm presented by Berg et al. [8], the best path is chosen from a group of path obtained by RRT, based on their performance in the presence of an LQG controller. Bry and Roy [9] also use RRT* to find the nominal optimized path. Prentice and Roy [38] and Huynh and Roy [20] use breadth-first search method on the roadmap constructed by PRM, to find the best path. The aforementioned methods suffer from the lack of optimal substructure property meaning the cost of each edge affects the travel cost of other edges. Consequently, the constructed roadmap depends on the start point and in every query should be reconstructed. In other words, they are single query algorithms. Moreover, in the case of deviation from the nominal path, constructing a new roadmap is necessary which makes mentioned algorithms unsuitable for real applications.

MPUU, i.e., motion and sensor uncertainty, is an instance of sequential decision making under uncertainty. This problem can be formulated as a Partially Observable Markov Decision Process (POMDP) [23]. POMDP is a prevalent framework for modeling the sequential decision process. Many real-world problems in fields such as industry, ubiquitous computing, business, ecology, control and robotics [11,12,25,27,30] can be modeled as a POMDP problem. The curse of dimensionality and history make the POMDP problem arduous and computationally intractable [23]. They are even more troublesome in the continuous state space. Many methods have been proposed for solving POMDP problem [42,45,48]. However, they are mostly restricted to the problems with a small set of states, they are not applicable in the continuous space or they are computationally expensive. In order to mitigate the abovementioned problems and extending the POMDP applications to real-world and long-term operations, methods such as [3,18,41] have been proposed. Agha-mohammadi [2] propose the Feedback-based Information RoadMap (FIRM) algorithm where the optimal substructure property is held. FIRM turns the intractable POMDP problem into a tractable DP on the FIRM graph. The optimal substructure property of FIRM and the ability to solve the POMDP online enable online replanning in FIRM. Furthermore, the FIRM feedback-based structure makes it a robust algorithm. FIRM also considers all possible future observations in decision making, which provides a reliable plan. FIRM algorithm has been used successfully in motion planning problems and has been implemented on a physical robot and results show its efficiency [4,31].

Although much theoretical work exists on the MPUU, the multi-goal MPUU is not well studied, and the uncertainty is omitted in the most of them which may well cause an improper planning and increase the probability of failure. In addition, they have not consider any approach for online replanning to cope with unpredicted events such as finding new