

# Balancing Detail and Abstraction in Belief-Space Planning for Robotics

Dirk Ruiken

College of Information and Computer Sciences  
University of Massachusetts Amherst  
Amherst, MA-01003  
Email: ruiken@cs.umass.edu

Roderic A. Grupen

College of Information and Computer Sciences  
University of Massachusetts Amherst  
Amherst, MA-01003  
Email: grupen@cs.umass.edu

**Abstract**—Belief-space planning (BSP) has limited usage in robotics as methods quickly become computationally intractable with a growing number of states, observations, and actions. On the other hand, the tasks that can be defined and the solutions that can be found depend on the granularity of states, actions, and observations. As a result, the capabilities and performance of planning and reasoning systems for robots using BSP heavily depends on the representation of the world, the robot, and its own capabilities. We contend that robots must represent interactions with the world, use these models to parse runtime feedback, and accumulate belief over subsets of the model space that lead to success in the task. Moreover, we suggest that suitable abstractions are based on the capabilities of the robot. State, action, and observation spaces can then be derived from these models, resulting in compact representations with little limitation to the expressiveness. We propose using a compact, expressive representation for models based on generalization of the aspect graph used in computer vision to describe objects. We extend the models to support multimodal inference of geometrical information needed for motor control.

## I. INTRODUCTION

To perform tasks autonomously in the world, a robot usually perceives its environment, estimates the state of itself and of the world around it, plans a sequence of actions to reach a goal, and then executes this sequence of actions. This process is repeated during execution to update the state estimate and replan as necessary. These steps are difficult in real world scenarios due to partial and uncertain observations, stochastic actions, and state transition uncertainty itself.

A popular method to formulate the general problem is as a partially observable Markov decision process (POMDP) [15, 2, 4]. A POMDP is specified by the tuple

$$\langle S, A, T, R, Z, \Phi, \gamma \rangle, \quad (1)$$

where  $S$  is the set of state,  $A$  is the set of possible actions,  $T : S \times A \times S \rightarrow [0, 1]$  is the set of conditional transition probabilities between states,  $R : S \times A \rightarrow \mathbb{R}$  is the reward function,  $Z$  is the set of possible observations,  $\Phi : A \times S \times Z \rightarrow [0, 1]$  is the observation function, and  $\gamma \in [0, 1]$  is the discount factor. As the state  $S$  in the POMDP is only partially observable, we use the concept of a belief state,  $b$ , to represent the probability distribution over states. All possible belief distributions  $b$  form the set  $B$ . An optimal solution to the problem expressed by such a POMDP is given by the policy  $\pi : B \rightarrow A$  which

maximizes the reward for a possibly infinite horizon. The optimal action at a timestep maximizes the expected future discounted reward  $E[\sum_{t=0}^{\infty} \gamma^t r_t]$ .

There exist many algorithms for solving POMDPs. However, POMDPs quickly become computationally intractable as the number of states, observations, and actions grows. Moreover, the range of tasks and solutions depends on the granularity of states, actions, and observations. As a result, the performance of a planning system for robotic systems heavily depends on the representation of the world, the robot, and control capabilities. A poorly chosen representation can result in high complexity during planning or a lack of expressiveness. High complexity will make even approximate planning intractable for online use on a robot. Lack of expressiveness results in limited capabilities to interact with the environment or to define tasks accurately. For example, the popular grid world domain is simple enough for possibly tractable planning, but it offers almost no usefulness for real robot control.

We contend that suitable abstractions of the world are required that depend on the capabilities of the (specific) robot. State, action, and observation spaces can then be derived from these models, resulting in compact representations with little limitation to the expressiveness.

In the following sections we present a knowledge representation that aims at meeting these requirements to support tractable planning without sacrificing expressiveness.

## II. TECHNICAL APPROACH

We propose a knowledge representation based on object models. For each object a model is built based on the known (learned) interaction capabilities of the robot with the object. The models are equally suitable to model objects and environments [10].

### A. Models

Consider a model that describes an object. The proposed model is based on the concept of Aspect Transition Graphs (ATG) [5, 9, 13]. This representation defines all the features of the object that are detectable from a single, fixed sensor geometry (called an *aspect*) and organizes them in a multi-graph [13, 14, 7, 6, 8]. Nodes in the graph are called *aspect nodes*. Each aspect node is associated with an aspect defining

the set of features that can be perceived together. Edges between aspect nodes represent actions and parameters that transform one aspect nodes into another.

We extend the ATG model with geometric information. Features of aspects and actions are specified and parametrized with respect to an object frame [12, 10]. This improves differentiation of aspects since geometric constellations of features are much richer than matching based on bags-of-features. Additionally, the geometric information in the models can be used to predict sensor geometries for new observations and supports better pose estimation. Actions are much more expressive and robust without increasing the complexity. The impact on the state and action spaces is discussed in Sections II-B1 and II-B2 respectively. Actions are implemented as controllers with parameters, and these parameters along with estimates of the cost of the action are stored in the ATG. ATG models can be hand-built or autonomously learned by the robot [7, 6, 8, 16].

*As aspect nodes are based on perceivable features of the object as well as the interaction possibilities known to the robot, the aspect nodes of an ATG represent the states of an object that matter to the robot.* Using aspect nodes as an abstract state  $x$  reduces the size of the state space (see Section II-B1). The ATG also contains all relevant (known) actions to interact with the object. Therefore, out of all possible action parameterizations, only useful ones provided by the ATG need to be considered. Additionally, the ATG provides forward and observation models for belief update and planning.

### B. Impact on Belief-Space Planning

The choice of representation can have a large impact on the complexity and expressiveness of a planning method. In this context, we discuss the choice of a state, action, and observation representation which is based on ATGs.

1) *State Representation:* When considering general capabilities of a robot to interact with an object, a large number of actions with continuous multi-dimensional parameters have to be considered. Even typical approaches such as discretization still result in too large a state space and too many actions to consider for efficient planning.

Let us consider a state representation for manipulation of an unidentified object. The state of the object consists of the type of the object—one of  $|O|$  known modeled objects. Additionally, an estimate of the pose  $q$  of the object in  $SE(3)$  is required to perform actions. The resulting state space is the cross product of possible object types with all possible poses. Even for a moderate number of known object models and a reasonably well discretized parameter space for poses, this will result in a very large state space and be prohibitive for planners.

In our framework we use an ATG to model the control interactions between the robot and each modeled object. The state space is based on the abstract state of the robot with respect to the object which is represented by aspect node  $x$ . The set of all aspect nodes from every known object is denoted

as  $X$ . The size  $|X|$  can be approximated as the number of known object models  $|O|$  multiplied by the average number of aspect nodes per object. The pose  $q$  of the object is still required to perform actions. The resulting state space is based on the cross product of possible abstract states  $x$  and possible poses  $q$ :  $S = X \times Q$ . In general belief-space planning frameworks, the belief could be spread over a large number of states of  $X \times Q$ . In our framework, based on the structure of the ATGs and the definition of aspect nodes  $x$ , a unique pose  $q$  can be calculated for each aspect node  $x$  from observations. The marginal belief  $bel(x_i)$  in aspect node  $x_i$  is the sum of the belief in that aspect node with all specific poses  $q_j$ :

$$bel(x_i) = \sum_j bel(x_i, q_j) \quad (2)$$

with  $0 < i < |X|$  and  $0 < j < |Q|$ . As a single pose  $q_k$  can be calculated for aspect node  $x_i$ , all belief  $bel(x_i)$  is concentrated in that combination of aspect node and pose resulting in

$$bel(x_i) = bel(x_i, q_k). \quad (3)$$

For all other poses  $q_j$  with  $j \neq k$  the belief is zero and despite not being handled explicitly, is dealt with correctly and completely. As a result, for each aspect node  $x$  there is exactly one pose  $q$  that needs to be considered and the effective size of the state space is reduced to  $|X|$ . All other states of the original state space are still available but have zero probability and do not negatively impact the planner.

2) *Action Space:* All actions  $a$  in set  $A$  are defined by a type and parameters:  $A = types \times parameters$ . The action parameters can be high-dimensional to support complex actions available to robots acting in human environments. For example, a simple controller for bimanual grasps could take 3D positions for two hands. Similar to the state space, any discretization still keeping the expressiveness of the actions intact will result in a large number of parametrizations for each action type and thus in a very large size of  $|A|$ . Some approaches deal with this complexity by using robot-centric descriptions of the actions (e.g. a bimanual grasp is always just happening in a hard-coded position in front of the robot), but this method lacks expressiveness for anything but highly controlled environments. Alternatively, the state description can include that the robot is in the correct pose for such a robot-centric action to work. This would result in a much larger state space.

For belief-space planners, transitions  $T(s, a, s')$  need to be known and are typically enumerated. Each time a belief update is performed, all applicable actions need to be considered. This is especially costly when rolling out belief for several steps into the future as the number of actions determines a branching factor in the search tree.

In our framework, for each abstract state the corresponding ATG stores all available actions together with parametrizations in object frame. At runtime, for a state  $s_1 = (x, q)$  the available actions can be retrieved from the ATG. To apply process updates, a transition model has to be available for all state action pairs. The ATGs provide an easy mechanism to

match an action from a state  $s_1$  to the corresponding action for any other state  $s_2$  based on the pose information of  $s_1$  and  $s_2$ . Despite an action space of theoretically infinite size, only few actions have to be stored. This comes at the cost of having to determine corresponding actions at runtime as pose information is not known *a priori*. When forward planning the effect of actions, the ATG models provide a list of relevant actions with parametrizations. This drastically reduces the branching factor in a search tree for planning without reducing the available actions and thus the expressiveness.

3) *Observation Space*: In order to perform planning steps to simulate the outcome of actions, all possible resulting observations have to be considered. The number of possible expected observations determines another branching factor in the search tree when rolling out belief over several actions and observations and is one of the limiting factors for belief-space planners. As with state and action space, the observation space is very large with several simultaneously observed features with feature types, 2D or 3D location, possibly orientation, and other continuous variables for other parameters.

We use aspects  $z_i$  of an aspect node  $x_i$  as observations. Instead of using geometric constellations of features with continuous variables directly as observations, we use a matching mechanism to generate support for perceptual aspects. This limits the number of possible observations to a finite number and enables proper normalization of  $p(z_i|s)$  for each state  $s$ .

The ATG model provides an efficient way of predicting possible future observations. As a result, only applicable observations can be acquired from the ATG, and only a limited number have to be considered during planning. For each state  $s$  the corresponding ATG provides the expected observation  $z$  and the probabilities  $p(z|s)$  can be precomputed for all states  $s$  and stored in the model. As described above, for each aspect node  $x$  there is one state  $s$ . Therefore, the number of observations  $|Z|$  to be considered is equal to the number of aspect nodes:  $|Z| = |S| = |X|$ .

4) *Representation Conclusion*: While the state of a robot is usually denoted as  $s$ , we use the benefits from our representation in order to simplify our state, action, and observation spaces. Based on this structure, we can refrain from explicitly enumerating some information. We showed above that the probability of  $s = (x, q)$  is equal to the marginal probability  $p(x)$  over aspect node  $x$ . The pose information  $q$  is implicitly contained as well but does not have any impact on the equations. Therefore, instead of  $s$  we use  $x$  as the variable for our abstract state. This changes the observation model to

$$p(z|s, a) = p(z|x, q, a) = p(z|x, a). \quad (4)$$

Additionally, for the applications considered our work, all robot sensors are constantly running. As a result, the observation probability only depends on the state, and we can use

$$p(z|x, a) = p(z|x). \quad (5)$$

For the transition model we use

$$T(s, a, s') = T(x, a, x'), \quad (6)$$

where a lot of the details are implicitly contained as they are updated at runtime. These choices in representation provide a small effective size of the state, action, and observation spaces without restricting the expressiveness of the framework.

Instead of forming a single belief over the state of all objects in the environment, the robot maintains a separate belief for each encountered object similar to Castanon *et al.*[3]. The planning then scales only about linearly with the number of objects.

For real robot applications, transition and observation models are often not available and they are often approximated at runtime by repeatedly sampling from the belief distribution and simulating action outcomes (e.g. [1]). The high cost of the simulation process can severely hinder the planning process. The ATG models provide both the transition and observation model and can accelerate the planning process.

### C. Application

The ATG models have been successfully used in multimodal active perception applications and manipulation applications on a real robot. Even with model set sizes of over 100 and multi-object scenes, a myopic belief-space planner can reliably and quickly (average less than 3 seconds) choose actions to successfully complete tasks [12, 11, 10].

## III. CONCLUSION

We proposed that feasibility of belief-space planning for real robots can be much improved if a suitable knowledge representation is chosen. If the capabilities of the robot are abstracted, much better compactness in state, observation, and action spaces can be achieved without losing expressiveness of tasks or solutions.

We presented a knowledge representation aimed at belief-space planning for robots: the ATG model. It is based on the capabilities of a robot to interact with objects and the environment. We have shown the benefits that can be achieved by using the ATG model with respect to the compactness and expressiveness of state, observation, and action spaces. The models have been successfully used for online planning for various mobile manipulation tasks on a real robot.

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