Task Parametrization through Multi-modal Analysis of Robot Experiences

(Extended Abstract)

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ABSTRACT

With quickly progressing and increasingly complex robot control and reasoning systems, a large gap of practical real-world knowledge for robots needs to be filled. While two prominent directions exist, namely designing all knowledge manually, or completely bootstrapping it, we emphasize the combination of both: Starting with simple heuristics, we let robots explore a task, record memories, interpret their findings, and improve their own multi-modal understanding to better their own performance. In this work, we present a software system for autonomous robots that allows them to learn task nuances, and make informed decisions based on experience. They store these comprehensive probabilistic models of any task they perform in a robot knowledge service, benefiting from a shared knowledge base and centralized, well-maintained reasoning algorithms.

Keywords

Reasoning in agent-based systems; Robot planning; Parameter learning

1. MOTIVATION

Enabling robots to interpret abstract task descriptions has a number of advantages: (1) The same task description works for a wide variety of situations, (2) nested tasks can share action primitives, resulting in synergies between different activities, and (3) generic task descriptions can be augmented with concrete specializations of a task if – even partial – explicit knowledge about this task is available.

To make such abstract task reasoning useful and not introduce exponential amounts of effort for a programmer, the reasoning must be extendable beyond manually specifying new types of knowledge. One existing source for new knowledge are robot episodic memories, which contain both, relevant and (large amounts of) irrelevant data about the tasks a robot performed. Finding the correct correlations from these memories and transforming them into actionable parameters for an autonomous robot is hard and effort-prone in itself due to the sheer amount of data a robot produces, and the often non-obvious relations between intentions and effects.

To ease this process, we propose a novel approach for multi-modal data analysis on the basis of robot episodic memories. In particular, we concentrate on non-deterministic environments and deduce multivariate, mixed Gaussian distributions for parameter ranges to help an autonomous robot in making informed decisions.

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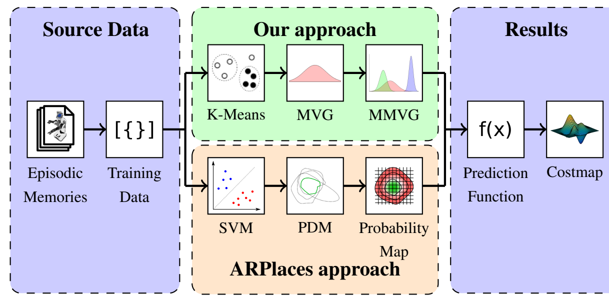

Figure 1: Processing pipeline to generate prediction functions from raw robot experience data. Green shows our approach, compared to the ARPlaces approach in orange.

2. OVERVIEW

We demonstrate our multi-modal, experience-backed learning process on the example of mobile manipulation, and more specifically pick and place tasks in a kitchen environment. The processing pipeline of our approach is shown in Figure 1. More concretely, a PR2 robot parametrizes its own choice of where to position itself for picking up objects based on its own experience data, processed using a Gaussian regression technique.

A similar goal, but with a completely different approach, was pursued by Stulp *et al.* [1]. They used a Support Vector Machine (SVM) based learning approach to generate Point Distribution Models (PDMs), and finally generate a probability map of the regions well-suited for grasping using a Monte Carlo Simulation. We compare our approach to theirs, and show how our approach extends the type and dimensionality of source data that can be used, at the cost of precision.

One of the main advancements of this work over previous approaches is the increase in search space dimensions. While previously the only features used to determine whether a position to perform, say, a grasp action was well-chosen were the numerical relative distances in x and y direction, we introduce Multivariate Gaussian distributions over an arbitrary number of task parameters. Our multi-modal data analysis covers both, real and nominal values: Real values are measured based on their actual numerical value, while nominal values are assigned an index number in their category. This approach is well-formed, as nominal values are not interpolated while querying for probabilities, but their exact indices are used.

We have applied the presented parameterization learning framework to a scenario in which a PR2 robot performs pick and place tasks in a kitchen environment. It picked up objects from three

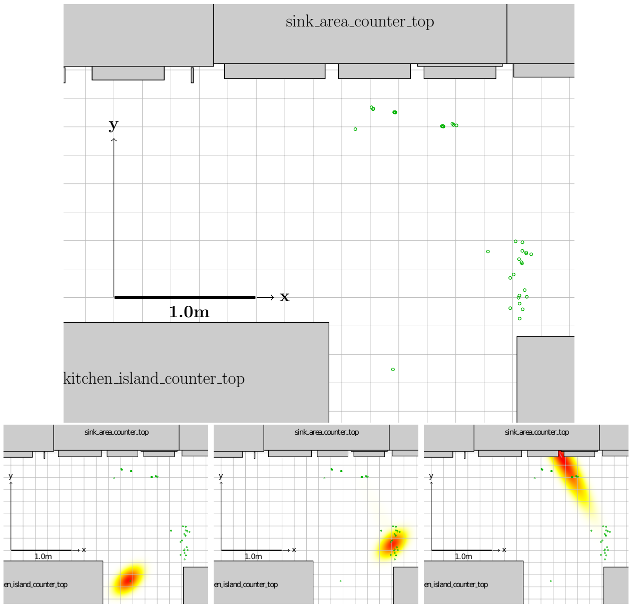

Figure 2: Learned probability distributions for successful grasping, depending on relative distance between robot and object. The three plots show regions of high success probability for grasping the objects on the table near them, as a density function $f := f(\text{relative-position}, \text{relative-orientation})$; chosen relative orientations from left to right: -230Â°, -90Â°, and +300Â°. The pure experience data points are shown in the overarching figure.

tables, multiple times. A manually defined heuristic based on Euclidean robot/object distance was used to collect the training data.

Figure 2 shows the extracted feature points (green) as well as the resulting MMVG distributions (gradient heatmaps) from 40 pick trials. The distributions reflect the probability of success in the given task based on the relative position of the robot w.r.t. the object, as well as their relative orientation to one another. It is important to note here that the learned model does not include characteristics about the environment itself; the coordinates used for training and results retrieved afterwards are purely relative. From left to right, the relative orientations between robot and object in the figures are -230Â°, -90Â° and +300Â°. Except for the rightmost situation, the resulting distributions reflect the source data very well. Our assumption is that the number of data points (given three independent variables, x, y, and θ) in that region is too low (and scattered too much) to generate a properly aligned distribution. A statistically significant amount of source data would mitigate this problem. Besides this, the distributions give a very good prior of where to stand in order to grasp an object, before falling back to the manually designed heuristic.

The episodic memories used in our evaluation were recorded using the robot memory system SemRec [2] and include both, high-volume low-level sensor data and low-volume high-level semantic plan data. Therein included are object descriptions, exact robot motions, grasp details, and kinematic poses at all times. These are the source for our training data.

The maximum expected cluster count depends on the task performed, the size of the environment, and the number of experiences involved. It is safe to say that the number of involved objects (in our example case) gives a hint towards that maximum. We decided to use ten clusters at maximum, while having five objects involved in the pick and place task. Most of the time, this would result in two to three clusters.

3. RELATED WORK

While some cognitive architectures, such as SOAR [3], 3T [4], and ICARUS [5] use planning to solve problems for which an agent knows no solution yet, the usefulness of task planning for agents operating in realistic environments has often been called into question (see [6] for an overview of some history behind a few cognitive architectures). The main arguments against planning are that it is an expensive operation that commits an agent to following a plan, rather than reacting quickly and opportunistically to changes in the environment. Also, classical planning is not well suited to handle situations of incomplete information, stochastic environments and action effects, and quantitative specifications and sub-symbolic, procedural knowledge such as controller parametrizations; although some extensions of PDDL are meant to address this, the corresponding implementations in actual planners are far from mature.

More complex approaches to learning new general plans can be found in explanation-based learning [7], which also attempts to learn quantitative relationships between the actions an agent performs and the state variables describing the world, and the ARPlaces approach [1], which learns probabilities of task success based on parameters such as relative locations of the robot and the objects it needs to grasp. Both explanation-based learning and ARPlaces are particularly interesting in that they consider the sub-symbolic level of action parameters and effects, rather than STRIPS-style abstractions. STRIPS abstractions, while easy to represent propositionally, often fail to capture nuances of environments and actions, such as the existence of a place from which several objects can be grabbed which obviates the need for several navigation actions [1]. Probabilistic representations of locations, in terms of their effects on robots' actions, can then be used in larger knowledge-based systems to parametrize vague actions [8].

4. CONCLUSION

We have demonstrated our framework in the context of mobile manipulation with a PR2 robot performing pick and place actions in a kitchen environment. We compared our approach to a predecessor technique, ARPlaces, and extended the possible dimensionality of the source data compared to that approach. The outcome of our work fully satisfies its expectations by allowing robots to learn arbitrary task parameter distributions from heuristics.

Among possible extensions to the current system, we see automated online learning; as of now, memories of episodes need to be concluded before they can act as training data. Also, the dimensionality up until which learning stays feasible (in terms of amount of training samples) needs to be explored. We have taken into account three dimensions here, but we can easily find many more that seem to be useful (left/right arm used for grasping, other collision objects in the vicinity, etc.). Given that experience data includes both positive and negative task outcomes, we consider adding an additional, negative probability element based on failed task attempts. This would rule out regions that are especially bad for the task at hand and allow the robot to form a more diverse knowledge of non-linear parametrizations. Finally, the learned data needs to be tested across multiple robots/platforms of the same/different morphology to see how well the learned distributions generalize.

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