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Sensor-Based Probabilistic Roadmaps: Experiments with an Eye-in-Hand System

Yong Yu
yongyu@cs.sfu.ca

Kamal Gupta
kamal@cs.sfu.ca

School of Engineering Science
Simon Fraser University
Burnaby, BC, CANADA, V5A 1S6

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Abstract

We present a real implemented Eye-in-Hand test-bed system for sensor-based collision-free motion planning for articulated robot arms. The system consists of a PUMA 560 with a triangulation-based area-scan laser range finder (the eye) mounted on its wrist. The framework for our planning approach is inspired by recent motion planning research for the classical model-based case (known environment) and incrementally builds a roadmap that represents the connectivity of the free configuration space, as it senses the physical environment. We present some experimental results with our sensor-based planner running on this real test-bed. The robot is started in completely unknown and cluttered environments. Typically, the planner is able to reach (planning as it senses) the goal configuration in about 7 - 25 scans (depending on the scene complexity), while avoiding collisions with the obstacles throughout.

1 Introduction

Our research is concerned with sensor-based motion planning (MP) for articulated robot arms with many degrees of freedom. The arm (called robot from here on), equipped with an "eye" sensor (See Figure 1) that gives distance of the objects from the sensor, is required to plan and execute collision-free motions from a given start configuration to a given goal configuration, in an environment initially unknown to the robot. Note that the planning space (the configuration space) and the sensor space (physical environment) are very different. This is the fundamental distinction from sensor-based planning for a mobile robot (treated as a single point as in [11, 12]), where sensing and planning basically take place in the same (physical) space. Therefore, these sensor-based approaches for point robots may not be directly extended to the case of articulated arms via the standard "convert to C-space" argument, since, the sensor senses in physical space and will not, in general, correspond to sensing in C-space (See [7] for more on this).

Our approach, based on a recent paradigm in solving classical model-based MP[1], is to capture the connectivity of robot's free configuration space ($\mathcal{C}_{free}$) in a finite graph structure (called a roadmap) [1, 2, 9], with each node representing a free robot configuration, and an edge between two nodes representing the fact that a simple local planner can find a collision-free path between the corresponding robot configurations. Since this roadmap is constructed without explicitly representing the C-obstacles, it is particularly useful as a representation for high dimensional configuration spaces. The crux of our methodology is to *incrementally* construct this roadmap as the sensor senses new free space in the physical environment. The (evolving) roadmap reflects the connectivity of known $\mathcal{C}_{free}$ within which the robot carries out its motion to further sense the physical environment. The $\mathcal{C}_{free}$ (and the roadmap) expands as the sensor senses new free space in the physical world. This process is repeated until either the final goal is reachable from one of the nodes in the graph, or the goal is declared unreachable. Our current implementation adapts the PRM approach of [9]. We call our approach sensor-based incremental construction of probabilistic roadmap (SBIC-PRM).

In this paper our main focus is on systems and experimental aspects of our work; the formal and theoretical development of our approach will be subject of a forthcoming paper. In particular, we present a real implemented Eye-in-Hand test-bed system, and experimental results with the SBIC-PRM planner running on this test-bed. A main purpose behind the development of this test-bed is to be able to test different algorithms for sensor-based motion planning for robot manipulators. The details of the test-bed including hardware description and the system architecture are presented in Section 3. Section 4 presents the SBIC-PRM algorithm. Section 4.5 provides representation details buried in the succinct description of the algorithm. Experimental results are detailed in Section 5, followed by a summary in Section 6.

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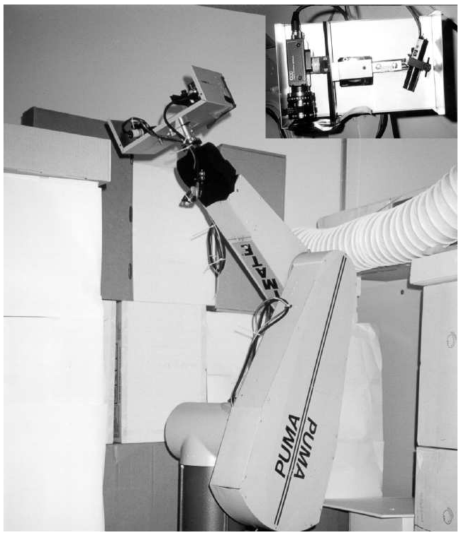
[1] In classical model-based MP, the environment is assumed to be completely known, often in the form of geometric CAD type models of the objects comprising the environment.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