Chapter 18
Reinforcement Learning in Robotics: A Survey

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Abstract. As most action generation problems of autonomous robots can be phrased in terms of sequential decision problems, robotics offers a tremendously important and interesting application platform for reinforcement learning. Similarly, the real-world challenges of this domain pose a major real-world check for reinforcement learning. Hence, the interplay between both disciplines can be seen as promising as the one between physics and mathematics. Nevertheless, only a fraction of the scientists working on reinforcement learning are sufficiently tied to robotics to oversee most problems encountered in this context. Thus, we will bring the most important challenges faced by robot reinforcement learning to their attention. To achieve this goal, we will attempt to survey most work that has successfully applied reinforcement learning to behavior generation for real robots. We discuss how the presented successful approaches have been made tractable despite the complexity of the domain and will study how representations or the inclusion of prior knowledge can make a significant difference. As a result, a particular focus of our chapter lies on the choice between model-based and model-free as well as between value function-based and policy search methods. As a result, we obtain a fairly complete survey of robot reinforcement learning which should allow a general reinforcement learning researcher to understand this domain.

18.1 Introduction

Robotics has a near infinite amount of interesting learning problems, a large percentage of which can be phrased as reinforcement learning problems. See Figure 18.1 for

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an illustration of the wide variety of robots that have learned tasks using reinforcement learning. However, robotics as a domain differs significantly from well-defined typical reinforcement learning benchmark problems, which usually have discrete states and actions. In contrast, many real-world problems in robotics are best represented with high-dimensional, continuous states and actions. Every single trial run is costly and, as a result, such applications force us to focus on problems that do not arise that frequently in classical reinforcement learning benchmark examples. In this book chapter, we highlight the challenges faced in robot reinforcement learning and bring many of the inherent problems of this domain to the reader's attention.

Robotics is characterized by high dimensionality due to the many degrees of freedom of modern anthropomorphic robots. Experience on the real system is costly and often hard to reproduce. However, it usually cannot be replaced by simulations, at least for highly dynamic tasks, as even small modeling errors accumulate to substantially different dynamic behavior. Another challenge faced in robot reinforcement learning is the generation of appropriate reward functions. Good rewards that lead the systems quickly to success are needed to cope with the cost of real-world experience but are a substantial manual contribution.

Obviously, not every reinforcement learning method is equally suitable for the robotics domain. In fact, many of the methods that scale to more interesting tasks are model-based (Atkeson et al, 1997; Abbeel et al, 2007) and often employ policy search rather than value function-based approaches (Gullapalli et al, 1994; Miyamoto et al, 1996; Kohl and Stone, 2004; Tedrake et al, 2005; Peters and Schaal, 2008a,b; Kober and Peters, 2009). This stands in contrast to much of mainstream reinforcement (Kaelbling et al, 1996; Sutton and Barto, 1998). We attempt to give a fairly complete overview on real robot reinforcement learning citing most original papers while distinguishing mainly on a methodological level.

As none of the presented methods extends to robotics with ease, we discuss how robot reinforcement learning can be made tractable. We present several approaches to this problem such as choosing an appropriate representation for your value function or policy, incorporating prior knowledge, and transfer from simulations.

In this book chapter, we survey real robot reinforcement learning and highlight how these approaches were able to handle the challenges posed by this setting. Less attention is given to results that correspond only to slightly enhanced grid-worlds or that were learned exclusively in simulation. The challenges in applying reinforcement learning in robotics are discussed in Section 18.2.

Standard reinforcement learning methods suffer from the discussed challenges. As already pointed out in the reinforcement learning review paper by Kaelbling et al (1996) "we must give up tabula rasa learning techniques and begin to incorporate bias that will give leverage to the learning process". Hence, we concisely present reinforcement learning techniques in the context of robotics in Section 18.3. Different approaches of making reinforcement learning tractable are treated in Sections 18.4 to 18.6. Finally in Section 18.7, we employ the example of ball-in-a-cup to highlight which of the various approaches discussed in the book chapter have been particularly helpful for us to make such a complex task tractable. In Section 18.8, we give a conclusion and outlook on interesting problems.