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Chapter VI

Evolutionary Learning of a Box-Pushing Controller

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Abstract

In our research we use evolutionary algorithms to evolve robot controllers for executing elementary behaviours. This chapter focuses on the behaviour of pushing a box between two walls. The main research question addressed in this chapter is: how can a neural network learn to control the box-pushing task using evolutionary-computation techniques? In answering this question we study the following three characteristics by means of simulation experiments: (1) the fitness function, (2) the neural network topology and (3) the parameters of the evolutionary algorithm. We find that appropriate choices for these characteristics are: (1) a global external fitness function, (2) a recurrent neural network, and (3) a regular evolutionary algorithm augmented with the doping technique in which the initial population is supplied with a solution to a hard task instance. We conclude by stating that our findings on the relatively simple box-pushing behaviour form a good starting point for the evolutionary learning of more complex behaviours.

Introduction

Imagine a cat on a rooftop. It has just spotted a juicy pigeon sitting on a window sill and is wondering how to catch this prey. The situation is tricky: there are two routes the cat can take, both of them involving walking on narrow ledges and requiring daring tricks of balance. The cat decides to take the shortest route and tries to lower itself onto a ledge beneath. While trying to do so, it notices that the chance of toppling over and falling three stories down onto a busy shopping street is becoming increasingly more realistic. The cat now decides to abandon its plan and sets its senses to something more practical.

From a traditional Artificial Intelligence point of view, this navigation problem is not that difficult. The start and goal positions are known, the possible routes are clear, and apparently, the cat has developed a plan to catch the bird. However, the successful execution of the plan critically depends on the cat's low-level interactions with its environment, rather than its high-level planning capabilities. Hitherto, the Artificial Intelligence community has given little attention to low-level control mechanisms (e.g., equilibrium controllers) as compared to high-level controllers (e.g., symbolic problem-solving systems).

Low-level controllers are typically needed for autonomous systems dealing with elementary tasks in dynamic partially observable environments. They form the foundation of high-level controllers executing more complex tasks in the environment (Brooks, 1986). In this chapter we focus on the elementary task of pushing a box between two walls. The box-pushing task was originally introduced (albeit in a slightly different form) by Lee, Hallam and Lund (1997). Pushing an object is an important aspect of robot soccer, a modern platform for autonomous systems research (Asada & Kitano, 1999), and underlies many more complex behaviours such as target following, navigation and object manipulation. While the deceptively simple task of pushing an object is usually disregarded in favour of the seemingly more challenging task of determining a strategic position, pushing is far from trivial and deserves at least as much attention as the strategic task.

The main research question addressed in this chapter is: how can a neural network learn to control the box-pushing task using evolutionary-computation techniques? In answering this question we study the following three characteristics by means of simulation experiments: (1) the fitness function, (2) the neural network topology and (3) the parameters of the evolutionary algorithm.

The outline of the remainder of this chapter is as follows. First, we discuss some background on the use of neural networks and evolutionary algorithms in learning to control a robot. Then we describe the goal of the research in terms of the three characteristics discussed above (i.e., the fitness function, the neural-network topology and the parameters of the evolutionary algorithm). We give an overview