Chapter 1
Evolutionary Control of Helicopter Hovering Based on Genetic Programming

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ABSTRACT

Computational intelligence techniques such as neural networks, fuzzy logic, and hybrid neuroevolutionary and neuro-fuzzy methods have been successfully applied to complex control problems in the last two decades. Genetic programming, a field under the umbrella of evolutionary computation, has not been applied to a sufficiently large number of challenging and difficult control problems, in order to check its viability as a general methodology to such problems. Helicopter hovering control is considered a challenging control problem in the literature and has been included in the set of benchmarks of recent reinforcement learning competitions for deriving new intelligent controllers. This chapter shows how genetic programming can be applied for the derivation of controllers in this nonlinear, high dimensional, complex control system. The evolved controllers are compared with a neuroevolutionary approach that won the first position in the 2008 helicopter hovering reinforcement learning competition. The two approaches perform similarly (and in some cases GP performs better than the winner of the competition), even in the case where unknown wind is added to the dynamic system and control is based on structures evolved previously, that is, the evolved controllers have good generalization capability.
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INTRODUCTION

Limitations of classical control theory has led to the usage of computational intelligence techniques (neural networks, evolutionary computing, and fuzzy logic) for the control of nonlinear, noisy and other dynamic systems which involve complexities.

Genetic Programming (GP), a field which belongs to evolutionary computing techniques, aims at the automatic discovery (evolution) of computer programs for a given task given minimal or no information about the task. The computer programs are involved based on a fitness function without any other information (the details of the dynamic system, derivatives of the system, etc.) being available. Such a computer program can serve as a control law, if the underlying task for which is evolved for, is the control of a dynamical system. Following this approach, the idea of automatic generation of controllers by GP seems ideal, assuming that it can be proven successful in practice too. In the past, GP has been applied to only a small number of challenging control problems (Dracopoulos & Piccoli 2010), compared with other computational intelligence techniques (Dracopoulos, 1997; Si, Barto, Powell, & Wunch, 2004; Werbos, 2008).

One of the challenging control problems found in the literature is that of helicopter hovering. According to this, a helicopter attempts to hover as close as possible to a fixed position. The dynamics of the helicopter is nonlinear, high dimensional, complex, asymmetric and noisy (Koppejan & Whiteson 2009; Ng, Kim, Jordan, Sastry & Ballianda 2004). The problem has been included in different control competitions (e.g. Reinforcement Learning competition 2009) as a benchmark in developing new more powerful control architectures.

The control of a helicopter in hovering position must take into account the different forces of the main rotor and the tail rotor. While the main rotor rotates clockwise, the air which blows downwards generates upward thrust that keeps the helicopter in the air. Based on this, one could suggest that the balancing of the generated thrust with the force of the weight of the fuselage is sufficient to achieve hovering. However, the clockwise torque of the main rotor has as a consequence an anti-torque force, that tends to spin the main chassis. In order to balance the fuselage, the tail rotor has to blow air rightward to generate the appropriate moment to counteract the spin (Ng, Kim, Jordan, Sastry & Ballianda 2004).

This chapter describes in detail how genetic programming can be applied to the problem of generalized helicopter hovering. The results are compared with the neuroevolutionary approach which won the first position in the 2008 Reinforcement Learning (RL) competition for the same problem (Koppejan & Whiteson 2009; Reinforcement Learning Competition 2009). The problem of generalized hovering includes noise in the form of unknown wind. Wind is added to each generalized version (domain) of the problem, according to some unknown probability distribution. The controller evolved has no knowledge about the amount of the wind which is present in each domain. Any control algorithm attempting to guess the wind in a single domain, will overfit the model for that particular case and it will perform badly in the other domains which include different wind.

THE PROBLEM OF HELICOPTER HOVERING

The state of the dynamic system of a helicopter is described in Box 1: where $P$ is the helicopter position in inertial coordinates and $\Theta = [\phi, \theta, \psi]^T$ are the Euler angles corresponding to the roll, pitch and yaw respectively. $v_p^x$ is the velocity vector: $v_x^p$ is the forward, $v_y^p$ is the