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Using direct competition to select for competent controllers in evolutionary robotics

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Abstract

Evolutionary robotics (ER) is a field of research that applies artificial evolution toward the automatic design and synthesis of intelligent robot controllers. The preceding decade saw numerous advances in evolutionary robotics hardware and software systems. However, the sophistication of resulting robot controllers has remained nearly static over this period of time. Here, we make the case that current methods of controller fitness evaluation are primary factors limiting the further development of ER. To address this, we define a form of fitness evaluation that relies on intra-population competition. In this research, complex neural networks were trained to control robots playing a competitive team game. To limit the amount of human bias or know-how injected into the evolving controllers, selection was based on whether controllers won or lost games. The robots relied on video sensing of their environment, and the neural networks required on the order of 150 inputs. This represents an order of magnitude increase in sensor complexity compared to other research in this field. Evolved controllers were tested extensively in real fully-autonomous robots and in simulation. Results and experiments are presented to characterize the training process and the acquisition of controller competency under different evolutionary conditions.

Keywords: Evolutionary robotics; Learning robots; Evolutionary neural networks; Swarm robotics; Developmental robotics

1. Introduction

Evolutionary robotics (ER) is an emerging area of research within the more general field of autonomous robot control. The primary goal of evolutionary robotics is to develop automatic methods for synthesizing intelligent autonomous mobile robot controllers. These methods should not require hand coding or in-depth human knowledge of the particular control tasks for which the controllers are intended.

Typically ER applies population-based artificial evolution to evolve autonomous robot controllers. The process of controller evolution consists of repeating cycles of controller fitness evaluation and selection that are roughly analogous to a generation in natural evolution. During each cycle, or generation, individual controllers taken from a larger population of controllers perform a task or engage in an evaluation period. This involves instantiating each controller into a robot (either real or simulated) and allowing the robot to interact with its environment (which may include other robots) for a period of time. Following this, each controller's performance is evaluated based on a fitness selection function (objective function). In the final step of every cycle, a genetic algorithm (GA) is applied. The GA uses information generated by the fitness selection function to select and propagate the fittest individuals in the current population to the next generation population. During propagation, controllers are altered slightly using stochastic genetic operators such as mutation and crossover to produce offspring that make up the next generation of controllers. Cycles are repeated for many generations to train populations of robot controllers to perform a given task.

Possibly the most important unanswered question within the field of ER is whether the methods used so far to obtain simple proof-of-concept results can be generalized to produce more sophisticated autonomous robot control systems. In turn, a key

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issue related to the successful evolution of autonomous robot controllers is the specification of a fitness selection function.

1.1. Research goals

The development of methods for general fitness selection during evolution of controllers is crucial to the future of ER. This view is reflected in some recent literature [13] and has been noted previously in [11]. As early as the mid-1960s it was pointed out that creating a method of fitness selection capable of selecting for complex behavior was likely to be difficult [15].

One of the main goals of the research presented in this paper is to investigate the application of aggregate success/failure selection in combination with direct intra-population competition to evolve complex neural networks using numerous processed video sensor inputs to perform a non-trivial autonomous control task. In order to address the issue of initial populations having no detectable level of fitness, we also introduce the concept of multi-modal fitness selection. This is discussed in detail in Section 4.

In this work, populations of neural network-based robot controllers were evolved to play a robot version of the competitive team game *Capture the Flag*. In this game, there are two teams of mobile robots and two stationary goal objects. All robots on the first team and one of the goals are of one color (red). The other team members and their goal are another color (green). In the game, robots of each team must try to approach the other team's goal object while protecting their own goal. The robot which first comes in contact with its opponent's goal wins the game for its team. The game is played in maze worlds of varying configurations.

The evolved controllers are tested in competitions of 240 games against hand-coded knowledge-based controllers. Results show that evolved controllers are competitive with the knowledge-based controllers and can win a modest majority of games in a large tournament in a challenging maze world configuration. This work extends research reported on in [38] by applying a new form of fitness selection, producing fitter controllers, and by extensive analysis of the behavior and competence of several populations of controllers evolved under different environmental conditions.

Additional results are presented analyzing the course of evolution and the acquisition of behavior over the course of evolution.

The paper is organized as follows. The remainder of the Introduction presents a review of related research, and a survey of common types of fitness selection functions used in evolutionary robotics. Section 2 presents the physical robot platform used in this research and discusses the video sensors used by the robots. Section 3 presents the evolutionary neural network architecture and Section 4 defines the selection criteria used to drive controller evolution. Sections 5 and 6 present the results and testing of evolved game-playing robot controllers evolved under varying conditions.

1.2. Related work

The field of ER has been reviewed in several publications [20,30,32,43]. Much of the research reported on to date has investigated the evolution of controllers for simple tasks such as phototaxis [19,52] or object avoidance [11,26,36].

Locomotion in combination with obstacle avoidance in legged robots has been the subject of several ER studies [10,18,21,23,26]. In [18] Gruau reports on a cellular encoding scheme for evolvable modular neural networks for legged robot control. Filliat et al. [10] were able to evolve efficient locomotion and object avoidance abilities in a hexapod robot using networks of threshold neurons and IR sensors to detect the robot's environment. There, controllers were evolved in simulation and transferred to real robots for testing. Jakobi [23] described the use of minimal simulation to evolve behaviors in an eight-legged robot with sixteen actuator motors. In [26] Kodjabachian and Meyer describe the incremental evolution of walking, object avoidance and chemotaxis in a simulated six-legged insectoid robot. Finally, in [21] Hornby et al. describe the evolution of ball chasing using an 18-DOF quadruped robot.

Peg-pushing behaviors were evolved in [22,25]. In those works, the task required that two-wheeled robots push pegs (small cylinders) toward a light source. Earlier in [27] Lee et al. investigated a similar box-pushing behavior using genetic programming (GP).

Competitive evolution in which the fitness of one individual may affect the fitness evaluation of another individual represents an important element of the research described in this paper. Several examples of competition in the form of co-competitive evolution have been reported in the literature. Cliff and Miller investigated the co-evolution of competing populations in the form of predator–prey behaviors [6,7]. Other similar works have been reported on in [4,12,20,42]. Direct competitive evolution of controllers within a single population is investigated in [37,38] and is further investigated in the research we report on in this article.

Recently, several somewhat more complex tasks than those mentioned above have been reported. It should be noted that many of these tasks are only marginally more complicated than those achieved in the earliest days of ER. The evolution of robot controllers to perform these relatively complex tasks required using complex hand-formulated fitness functions [40,53].

The most difficult tasks addressed in the literature involve some form of sequential action. Nolfi reports on the evolution of a garbage collection behavior in which a robot must pick up pegs in an arena and deposit them outside the arena [40]. In [53] Ziemke studied the evolution of robot controllers for a task in which a robot must collide with objects ("collect" them) in one zone and avoid them in another. In [14] Floreano and Urzelai report on the evolution of a robot behavior in which robots move to a light and then back to a home zone. Another example of evolving controllers for a more complex task is reported in Tuci et al. [51]. There, robot controllers evolve to produce lifetime learning in order to predict the location of a goal object based on the position of a light source.

Flocking or group movement behaviors have also been investigated. Ashiru describes a simple robot flocking behavior in [1]. A two-robot coordination task in which two robots evolve to move while maintaining mutual proximity is reported by Quinn in [47]. Baldassarre et al. [2] evolved homogeneous