Chapter 4.3
Autonomous Specialization in a Multi-Robot System using Evolving Neural Networks

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ABSTRACT

Artificial evolution has been considered as a promising approach for coordinating the controller of an autonomous mobile robot. However, it is not yet established whether artificial evolution is also effective in generating collective behaviour in a multi-robot system (MRS). In this study, two types of evolving artificial neural networks are utilized in an MRS. The first is the evolving continuous time recurrent neural network, which is used in the most conventional method, and the second is the topology and weight evolving artificial neural networks, which is used in the noble method. Several computer simulations are conducted in order to examine how the artificial evolution can be used to coordinate the collective behaviour in an MRS.

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INTRODUCTION

Artificial evolution is one of the emerging approach in the design of controllers for autonomous mobile robots. In general, a robot controller, which is represented as an evolving artificial neural network (EANN), is evolved in a simulated or a physical environment such that it exhibits the behaviour required to perform a certain task. The field of research on autonomous robots with EANNs is called evolutionary robotics (ER) (Cliff, et al., 1993) (Harvey, et al., 2005).

There has been a great deal of interest in EANNs. A good summary of EANNs carried out until 1999 can be found in a study of Yao (1999). Traditionally, EANNs have been classified into the following three categories on the basis of their network structure:

- the network structure is fixed and the connection weights evolve.
- the network structure evolves and the connection weights are trained by learning.
- the network structure and the connection weights evolve simultaneously

The first type of network structure corresponds to the most conventional approach in the field of EANNs.

A typical application is presented in a study of Mondada and Floreano (1995). Recently, continuous time recurrent neural networks (CTRNNs) have been frequently used for evolving autonomous robots (Beer, 1996) (Blynel and Floreano, 2003).

In this chapter, we also consider the network structure of the third type, which are called topology and weight evolving artificial neural networks (TWEANNs) because the evolvability in the corresponding approach is the largest among those of the tree approaches (Stanley and Miikulainen, 2002). Thus far, many TWEANN approaches such as GNARL (Angeline et al., 1994), EPnet (Liu and Yao, 1996), ESP (Gomez and Miikkulainen, 1999) and NEAT (Stanley and Miikulainen, 2002) have been proposed. We are motivated by their work and also developed a robust and efficient approach to EANN design, called MBEANN (Ohkura et al., 2007). In the remainder of this chapter, we deal with the following two approaches: evolving CTRNN (eCTRNN) and MBEANN.

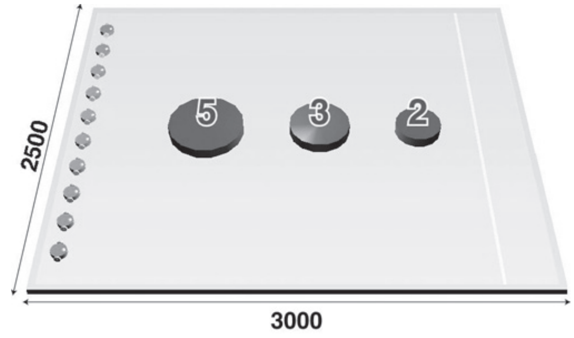
The evolutionary control of multi-robot systems (MRS) has not been well discussed. Only a few papers have been published thus far; however, some basic trail results such as those presented in a study of Triani (2007) or Acerbi (2007) have recently been published. This implies that although artificial evolution is a promising approach in behaviour coordination for a single robot, it is not very easy to evolve an MRS for developing a type of adaptively specialized team play.

Here, we mention two epochal papers. Baldassarre et al. (2003) evolved four simulated Khepera robots to develop a flocking formation and then discussed the variation in the formation patterns with changes in the fitness function. They used simple two-layered feed-forward EANNs as robot controllers and a binary Genetic Algorithms (GA) in which a real value is encoded with eight bits with their original reproduction procedure.

Quinn et al. (2001) evolved a physical robot group by adopting the so-called Sussex approach (Harvey and Husbands, 1997). Specifically, they first evolved the robot controllers in a simulated environment, and then, after achieving sufficiently good performance, they conducted physical experiments on the evolved controllers. They used their original recurrent EANNs as robot controllers and a steady-state real-coded GA.

In this chapter, we solve the task as in Figure1: ten autonomous mobile robots have to push three packages to the goal line, which is drawn on the right side of the floor. The packages are assumed to be too heavy for a single robot to move. In order to move a package, the robot has to cooperate with each other to gather at a certain side of a package and push it in the same direction, as illustrated in Figure 2.

Figure 1. Cooperative package pushing problem



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