Chapter 14

Networks Do Matter: The Socially Motivated Design of a 3D Race Controller Using Cultural Algorithms

Robert G. Reynolds
Wayne State University, USA

Leonard Kinniard-Heether
Wayne State University, USA

ABSTRACT

This article describes a socially motivated evolutionary algorithm, Cultural Algorithms, to design a controller for a 3D racing game for use in a competitive event held at the 2008 IEEE World Congress. The controller was modeled as a state machine and a set of utility functions were associated with actions performed in each state. Cultural Algorithms are used to optimize these functions. Cultural Algorithms consist of a Population Space, a collection of knowledge sources in the Belief Space, and a communication protocol connecting the components together. The knowledge sources in the belief space vie to control individuals in the population through the social fabric influence function. Here the population is a network of chromosomes connected by the LBest topology. This LBest configuration was employed to train the system on an example oval track prior to the contest, but it did not generalize to other tracks. The authors investigated how other topologies performed when learning on each of the contest tracks. The square network (a type of small world network) worked best at distributing the influence of the knowledge sources, and reduced the likelihood of premature convergence for complex tracks.

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INTRODUCTION

This article investigates the use of Computational Intelligence techniques to generate socially motivated behavior in a controller for a 3D racing game. The resultant controller was submitted to the Car Racing Competition at the 2008 World Congress held in Hong Kong China (Loiacono et al., 2008). The goal was to design a controller that can take advantage of the social context in which the race is run. That is, the driver/controller is part of a “pack” of racers during the race as can be seen in the Figure 1.

In order to do this certain aspects of the “individual” were minimized in order to allow for more computational support for the social component. For example, while the controller can get in-race information about the location nearby track edges, if they are aware of the position of the adjacent cars then they can “infer” track boundaries as well as other pieces of information without having to process specific sensory information. This will give the controller more time to aggregate its behavioral experience into its knowledge base in order to make higher-level strategic decisions.

Given this “tabula raza” the intent was to gradually add in higher levels of social knowledge and behavior over time. The key was then to identify a social learning technique that can support learning at a variety of different spatial and temporal scales. Recently, a number of socially motivated algorithms have been used to solve optimization problems. Some of the example algorithms are the Particle Swarm Algorithm (Kennedy & Eberhart, 1995), the Ant Colony Algorithm (Dorigo, Maniezzo, & Colomi, 1996), and the Cultural Algorithm (Reynolds, 1978). These three algorithms all use a population-based model as the backbone of the algorithm, and solve problems by sharing information via social interaction among agents in the population. The difference between them is the diversity of scales over which social learning and interaction can take place.

Since Cultural Algorithms encompass the scale of activities for each of the other social learning systems, we selected that as the learning framework here. In this article we will demon-

Figure 1. Example of the “pack” rounding a turn in close formation during a simulated race
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