Using GP to Model Contextual Human Behavior

Hans Fernlund and Avelino J. Gonzalez

Intelligent Systems Laboratory
University of Central Florida
Orlando, FL 32816-2450
hfe@du.se, gonzalez@pegasus.cc.ucf.edu

Abstract. This paper describes a new approach that automatically builds human behavior models for simulated agents by observing human performance. This research synergistically combines Context-Based Reasoning, a paradigm especially developed to model tactical human performance within simulated agents, with Genetic Programming that is able to construct the behavior knowledge in accordance to the Context-Based Reasoning paradigm.

1 Introduction

The use of a learning system that could automatically extract knowledge and construct human behavior models could reduce development complexity and cost of building simulated agents with human characteristics. This paper presents an approach to building human behavior models automatically. The approach employs Context-Based Reasoning (CxBR) and Genetic Programming (GP) to implement the learning artifact of a methodology called Learning by Observation, which will learn the behavior of a human merely by observation. The intent is not only to use the observations to learn, but also to learn the behavior of the observed entity. The research described in this paper defines learning by observation as follows: *The agent adopts the behavior of the observed entity only through the use of data collected through observation.*

2 The Genetic Context Learning Approach

CxBR is a modeling technique that can efficiently represent the behavior of humans in software agents [2]. CxBR encapsulates into hierarchically-organized contexts the knowledge about appropriate actions and/or procedures as well as compatible new situations. Mission Contexts define the mission to be undertaken by the agent. While it does not control the agent per se, the Mission Context defines the scope of the mission, its goals, the plan, and the constraints imposed (time, weather, rules of engagement, etc). The Major Context is the primary control element for the agent. It contains functions, rules and a list of compatible next Major Contexts. Identification of a new situation can now be simplified because only a limited number of all situations are possible under the currently active context. Sub-Contexts are

K. Deb et al. (Eds.): GECCO 2004, LNCS 3103, pp. 704–705, 2004.

abstractions of functions performed by the Major Context which may be too complex for one function, or that may be employed by other Major Contexts. This encourages re-usability. Sub-Contexts are activated by rules in the active Major Context. Transitions between contexts are triggered by events in the environment – some planned, others unplanned.

The new learning algorithm presented here by merging CxBR and GP is called Genetic Context Learning (GenCL). Instead of creating the contexts by hand, we use GP to build the contexts. The GP's evolutionary process provides the CxBR frame with appropriate context's action rules and sentinel rules. The individuals in the genetic population are components of the context base and a micro simulator is used to simulate an individual's behavior. The behavior from the micro simulator is then compared with the human performance, and a fitness measure is established to evaluate the models appropriateness. The evolutionary process will strive to minimize the discrepancies between the performances of the contexts created by GP and the human performance. A complete description of GenCL can be found in Fernlund [1].

3 Results

The initial experiments used a full scale automobile driving simulator to collect data used to automatically model personalized human driving behavior by GenCL. Five different drivers were used to collect data and five different agents were evolved with different driver behavior. Further, in order to determine how useful the automatic creation of simulated agents through GenCL is, two agents were developed by an independent source in the traditional, manual way. Here a knowledge engineer interviewed and rode an automobile with two drivers.

The results show that the new GenCL learning algorithm is able to evolve human contextual knowledge in all parts of the CxBR paradigm (i.e. both the actions within a specific context and the context transitions). The agents evolved, show the ability to generalize the behavior and they inhibit long term reliability performance. The performance of the evolved simulated agents showed consistent behavior even after 40 minutes of driving. Further, their performances were competitive with agents developed manually by human developers. To develop this algorithm further, and to apply it in other applications, it could probably ease the future development of human behavior models in simulated agents.

References

1. Fernlund, H. (2004), "Evolving Models from Observed Human Performance", Doctoral dissertation, Department of Electrical and Computer Engineering, University of Central Florida, Spring, 2004.
2. Gonzalez A. J. and Ahlers, R. H. (1998) "Context-Based Representation of Intelligent Behavior in Training Simulations" Transactions of the Society for Computer Simulation International, volume 15, no 4, December 1998.