Building Multiagent Behaviors from Observation

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1. Introduction

Multiagent behaviors play a vital role in coordinated robotics, scientific simulations, and surveillance systems. Training applications, for example, require authentic movements from the autonomous agents that work with and compete against the user. Similarly, surveillance systems must develop a model for normal group behaviors before they can identify unusual circumstances. In the case of mobile agents, the behaviors must generate movements for each individual based on its perception of the world. Our system automatically develops behaviors for autonomous mobile agents from the observation of the movements of real multiagent groups. It learns by watching. With these behaviors, we demonstrate a multiagent system that anticipates the future actions of the observed system and retargets behaviors to control different groups in novel circumstances.

2. Learning from Observation

One potential method for modeling and creating multiagent behaviors is to replay prerecorded examples of group movements. While these data-driven methods effectively capture the original performance for a particular instance, the success of these methods for interactive, multiagent applications is limited by the large number of potential agent movements that must be prerecorded. To mitigate the scaling effects of data-driven multiagent behavior algorithms, we propose a behavior model that more effectively uses observed agent movements by first reducing the data dimensionality with a technique inspired by Video Textures [Schodl, SIGGRAPH 2000] and then performing reinforcement learning analyses that were previously infeasible.

The machine learning and computer graphics communities have investigated learning by example and motion capture technologies for single agents, but all data-driven methods like these are confronted with the need to use models to fill gaps in the database, blend incongruous observations, and extrapolate to new circumstances. To be effective and realistic, these behavioral models must possess sufficient degrees of freedom to discriminate between similar, but distinct, observations. However, they cannot become so rigidly defined that the model size and complexity scale uncontrollably to represent the myriad observed interactions between the agents and the dynamic world. Our contribution is to map the high-dimensional data of observed agent movements to a simplified representation that preserves the ability to synthesize and predict agent movements.

3. RoboCup

We have chosen to investigate the multiagent behaviors of soccer players and are able to predict and generate the actions of the simulated players from a popular simulated soccer testbed, RoboCup. In comparisons with systems that use simple physical models to predict future agent positions, our data-driven system produced team behaviors 30% more accurately. The game logs of RoboCup soccer games are widely available and provide our system with the observational data needed to build behavioral models of player actions and team strategies. Although the game logs provide extensive details of the game state, we only use the player positions in our algorithms and thus these algorithms would be compatible with the data generated by future image-based systems for human soccer games.

4. Impact

We are inspired by data-driven techniques like motion capture that have revolutionized the animation of single agents for movies, games, and training environments. Realistic motion is synthesized from nothing more than computerized observations of human actors. Multiagent actions can be observed in a similar manner (during live training exercises) and we propose the development of large multiagent behavior databases. These multiagent databases can be used to accurately simulate the actions of the synthetic participants in virtual training simulations for military operations in urban terrain (MOUT). The autonomous agents could automatically adapt to the actions of the training participants while following the most appropriate samples from the database.

In a related research project funded by DMSO, these behavioral technologies are being paired with *multiresolution modeling* to further improve MOUT training simulations. In this research, we are building tools that permit subject matter experts (SMEs) to identify important functional relationships in multiagent data. For example, particular relationships (temporal or spatial) between a few specific agents may be marked as vital, e.g. agent B reaches checkpoint X ten seconds before agent D. These important relationships are encoded as functional constraints that the multiagent behaviors we develop are designed to preserve, while the actions of unconstrained agents are permitted to adapt to the dynamic runtime conditions. Much as retargeting algorithms permit single-agent motion capture to be adapted to new animated characters, we believe our system will permit multiagent motion capture data from live training exercises to be repackaged to drive the behaviors of agents in novel training environment.