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Agent-based Modelling Using Ensemble Approach with Spatial and Temporal Composition

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Abstract

Crowd behavior and its movement has been an actively studied domain during last three decades. There are microscopic models used for realistic simulation of crowds in different conditions. Such models reproduce pedestrian movement quite well, however, their efficiency can vary depending on the conditions of simulation. For instance, some models show realistic results in high density of pedestrians and vice versa in low density. This work describes an early study aimed at developing an approach to combine several microscopic models using an ensemble approach to overcome individual weaknesses of the models. Possible ways to build hybrid models, as well as the main classes of ensembles are described. A prior calibration procedure was implemented using the evolutionary approach to create an ensemble of the most suitable models using dynamical macro-parameters such as density and speed as the optimization objectives. Several trial experiments and comparisons with single models were carried out for selected types of hybridization.

Keywords: agent-based modeling, collision avoidance, ensemble simulation, social force, calibration

1 Introduction

Today multi-agent systems modeling is actively studied. One of the key problems in this area is the simulation of the realistic movement of pedestrian agents in different conditions. There are many models to simulate the behavior of pedestrians in various environments: both open (stadiums, streets, squares, etc.) and closed (areas, offices, corridors, shopping centers, trains, planes). Goals of the simulation may vary from the implementation of Artificial Intelligence in computer games or training programs to design or prediction of a large flow of people.

The behavior of models is traditionally divided into three classes: macroscopic, mesoscopic, and microscopic. The first class of models considers the crowd as a whole, i.e. collective behavior and dynamics. Mesoscopic models deal with an ensemble of agents in a certain area. Microscopic models describe interaction between particular agents and their individual behavior, which could include various characteristics such as psychological states, physical capabilities, etc. A wide range of

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different approaches is used to implement these classes of models. The most popular among them are force models based on Newtonian dynamics. In the 70s Henderson [1] compared the crowd traffic with the Navier-Stokes equation. Others, taking as a basis the fact that human movements are chaotic, used the gas kinetic equations [2] (the Boltzmann equation). In 1995, Dirk Helbing proposed a social force model [3], which is the form of nonlinear-dependent Langevin equations.

Other type of agent-based models is cellular automata [4], [5], [6] where space and time are discrete, and the space state is also discrete and limited as well. In each moment of time the values of all cells are updated synchronously based on the values of neighboring cells.

In our work, we will be considering force-based and collision-avoidance models, in particular Social Force (SF) and Reciprocal Velocity Obstacles (RVO) [7]. In SF, a velocity vector is computed with using social forces – interaction forces between agents and agents and obstacles. In RVO, the velocity that mostly close to preferential speed of agent is selected from set of velocities which is guaranteed collision-free motion. This set is counted by the way of searching minimal changes of velocity vector. It`s an important fact for this research that the minimal change is bisected because it`s assumed that other agent behaves the same manner. Each approach has its drawbacks. The SF model, as stated in [8], gives good results in high-density crowd, but situations with low density show unrealistic behavior, given the simplicity of their physical nature. RVO in turn creates congestion in narrow areas and crowd can form turbulence.

A natural question arises about the accounting for the heterogeneity and complexity of crowd behavior. One possible way is to compare different models. There are several works [9], [10] in which attempts were made to combine different models. In [9] authors join continuous models that are better suited to simulate situations with a high density of crowds and discrete models for low and medium density agents. Determining the density of the crowd, the paper proposes a mixture of models using weights. In work [10] a hybridization of micro- and macroscopic models are proposed, where they are used simultaneously in different regions of environment which is divided into partitions in heterogeneous areas of agent-based models and macroscopic homogeneous. Operations of disaggregation and aggregation are applied to represent simulation result into correct format when agent goes to partition with another type.

Unlike the above works, in this paper, an attempt will be made to create the ensemble of microscopic models, considered simultaneously, and can be used under different conditions, which will be discussed below.

Several main aspects are considered within the proposed work. The first one is the choice of tools of analysis and evaluation of the quality of the results. The second one is the model calibration procedure which can be implemented in various ways using evolutionary approach. The last part is the creation of an ensemble of models and its application to the hybrid models.

2 Agent-based Modeling Within the Ensemble Approach

2.1 General Approach

The core idea of the proposed approach is focused on the simultaneous use of several models with unified control and aggregation. As stated above, the hybridization is divided into several stages, which are depicted on the diagram in Fig.1. While using one or more different models, the calibration method is selected to optimize models. Then, the resulting set of modes is sent to Ensemble Module (EM). This module performs aggregation of the obtained models using different types of ensemble (PMFE and TME) or a combination of both. Preferential Model Field Ensemble (PFME) stores models that are pegged to a part of environment and Temporal Model Ensemble (TME) stores these models using different times of simulation. The resulting ensemble can vary in time and space; thus, the mapping procedure is defined to adapt the ensemble to the particular condition of the environment.