Hybrid modelling of crowd simulation

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Abstract

Macroscopic and microscopic modeling have become mainstream methodologies for crowd simulation in dynamic environments. The two models make a trade-off between efficiency and accuracy, but neither of them is able to achieve both goals at the same time. With the aim of achieving both efficiency and accuracy, a hybrid modelling method is proposed in this paper for crowd simulation. This paper illustrates how the two types of models co-exist in a single simulation and work collaboratively. A case study for this method is also conducted, the simulation result of which shows that the proposed method can not only benefit from the macroscopic model by improving the simulation efficiency, but also obtain a fine-grained simulation result by adopting the microscopic model.

Keywords: hybrid modelling, agent-based model, continuum model, aggregation and disaggregation, crowd simulation

1. Introduction

Crowd simulation has become an efficient tool to study the behavior and movement pattern of crowd in real life. Currently, macroscopic and microscopic methods are the two main modelling methods for crowd simulation. The macroscopic method (e.g., methods used in [1, 2]) focuses on the movement features of the whole crowd; whereas microscopic models, such as the methods used in [3], emphasize the issues of individual characteristics, including pedestrian’s psychological and social behaviours, communication among pedestrians, and individual decision making processes. With the ability to describe individual aspects, microscopic models can generate a fine-grain simulation in more detail than the macroscopic method. However, this is achieved at the cost of higher computation complexity. In contrast, macroscopic models offer a higher execution efficiency than microscopic models due to its lack of concerns of individual issues, however, which in turn makes the macroscopic models unable to generate a precise simulation result at individual level. Moreover, macroscopic models cannot cover all the characteristics of crowd behaviour, which further limits its applicability. For example, a typical macroscopic model cannot be easily applied to heterogeneous crowd. In contrast, microscopic models, simulating each individual using an agent, is highly flexible and can be used in the simulation of crowd in dynamic environments.
Existing work has attempted to combine the different models together, with the aim of obtaining both execution efficiency from macroscopic model and the fine-grain simulation result from microscopic model. One typical method (used in [4]) is the layered approach where different layers adopt different models. For example, in [5] the macroscopic model is used at the crowd level to generate simple rules to govern the movement of individuals; while the microscopic model generates the collision avoidance for each individual in the crowd. These methods can decrease the time necessary for model execution to some extent. However, it cannot simulate the scenarios to which the adopted macroscopic model is not applicable. Unlike the above methods, the multi-resolution method, proposed in [6], incorporates both a complete macroscopic model and a microscopic model and executes them inter-changeably. Such an approach can solve the applicability problem of macroscopic model. However, the execution efficiency is achieved on the assumption that the crowd movement is mostly stable (or becomes stable eventually).

This paper proposes a hybrid modelling method for crowd simulation, which combines macroscopic and microscopic models in a single simulation. The simulation environment is partitioned in terms of the crowd characteristic. Each partition is then modelled independently with either a macroscopic or microscopic model. During execution of the simulation, the two types of models work simultaneously on the corresponding partitions. As the models are executed independently, mechanisms are required to transfer data at the boundaries between the partitions. Two types of interaction mechanisms, i.e., aggregation and disaggregation are defined in this paper. The operation of aggregation collects density and velocity information from the simulation result of the agent-based model and then injects them into the macroscopic model as the initial conditions. The operation of disaggregation generates agents at the partition boundary, which is based on the information of crowd density and velocity obtained from the macroscopic model at the boundary. The proposed method makes it possible for macroscopic and microscopic models to work concurrently and hence exploit the advantages from both models. In addition, the method can also avoid the applicability limitation of the macroscopic model, since it can simulate those scenarios where the macroscopic model would otherwise not be applicable by adopting the microscopic model. A case study of the proposed hybrid modelling is conducted, the result of which shows that the proposed method can benefit not only from the macroscopic model by improving the execution efficiency, but also from the microscopic model in terms of simulation accuracy.

The rest of the paper is organized as follows: the existing related work is introduced in Section 2. An overview of the hybrid modelling of crowd simulation is introduced in Section 3. The interactions between the different models are defined in Section 4. A case study of the hybrid modelling is conducted in Section 5. The paper is finally concluded in Section 6.

2. Related Work

One of the typical methods to model and simulate large scale human crowds is agent-based method (a kind of microscopic method), in which each person in the crowd is simulated individually. This is primarily because pedestrians have distinct characteristics and make decisions depending on personal goals. For example, [3] employed a multi-agent based framework to demonstrate emergent human social behaviors, for instance, competing, queueing, and herding. On the other hand, the individual behavior is constrained by the whole movement of the crowd. For instance, following behavior and queue formation are two typical constrained behaviors in real life. The higher the pedestrian density is, the more the individual will follow the average movement of the crowd. Regarding this, macroscopic models, such as those in [1, 2], study the principles of crowd movement and simulate the movement pattern of the whole crowd instead of simulating each individual in a crowd.

In terms of execution efficiency and simulation accuracy, the two different kinds of models are complementary. Aimed at obtaining a high execution efficiency as well as a fine-grain simulation result, there are some existing pieces of work that attempt to combine the two different models together. Methods used in [4] adopt part of modules from both the macroscopic and microscopic model and combine them into a single model. The basic idea is to divide the model into two layers: a set of governing equations are applied from the macroscopic model at the top layer. This performs the role of the cognitive module which results in the overall movement pattern of whole crowd. Based on this result, the movement of each individual is simulated by a simplified microscopic model at the bottom layer. Since the method mentioned above still needs to execute the microscopic model for all the individuals in the crowd, the simulation efficiency definitely decreases as the crowd size increases. In addition, it does not avoid the limitation of the macroscopic model. If the adopted macroscopic model is not applicable for a specified crowd, the whole method will not be applicable.
In contrast to these methods, we have previously proposed a multi-resolution modelling [6] approach, which attempts to combine both macroscopic and microscopic models. The approach of this method is to make the two models work inter-changeable: the macroscopic model governs the simulation when the crowd movement is stabilized; if there is an event which makes the crowd movement unstable, the simulator will switch to microscopic mode and choose the microscopic model to simulate the crowd movement. The simulation will change back to the macroscopic mode when the crowd movement becomes stable again. This method is suitable for simulating crowds whose movement remains mostly stable. It can also avoid the limitation of the macroscopic model, because the part of environment, for which macroscopic model is not applicable, can be simulated by the microscopic model.

3. Overview of Hybrid Modelling

The basic idea of hybrid modelling is to apply both microscopic and macroscopic models in different areas of the simulation environment and execute them simultaneously. In order to implement this, the simulation environment is divided into exclusive partitions, in terms of the crowd composition. Due to the limited applicability of the macroscopic model, it is only applied to those partitions within which only homogeneous crowd exists. The agent-based model is then applied to other partitions, where heterogeneous crowd exists. An illustration of the hybrid modelling deployment is shown in Figure 1.

![Figure 1: Deployment Example of Hybrid Modelling Method](image)

The hybrid modelling of crowd simulation is continuously executed in a time-stepped manner. For each simulation step, the process of the hybrid modelling execution can be divided into two stages: 1) receiving and handling the initial conditions, and 2) the model execution. At the beginning of a simulation step the models need a set of initial conditions as input parameters. After the preparation of the initial conditions, the models are executed in parallel until the end of the current simulation step. With a set of given initial conditions for a simulation step, the crowd can be simulated independently without any communication between different partitions.

The functionality of the first stage of the hybrid modelling execution, i.e., receiving and handling initial conditions, is to prepare the necessary information for the current simulation step. For example, a typical macroscopic model needs the crowd density and crowd velocity on every location of the simulated environment. This information can be generated from the model’s previous time step in the area that is not neighbouring other partitions. The initial conditions at the boundary areas, however, depend not only on the simulation result of last simulation step, but also on the simulation result from the neighboring partitions at last simulation step. Therefore an interaction mechanism is necessary to exchange the crowd/agent information with the neighbouring partitions. The details of the interaction between two neighboured partitions will be discussed in the next section.

4. Interactions

As mentioned in Section 3, agent/crowd may be transferred between the boundary of two partitions. Therefore, an interaction mechanism is needed to help partitions migrate those agents (or crowd) from one partition to the other.
The simulation state and result are quite different for both models. Since the microscopic model focuses on the crowd at the individual level and simulates the behavior and movement of each individual in crowd, its state can be expressed by the position and velocity of each agent in the crowd. The macroscopic model state is expressed as the crowd density and velocity at specified locations over the environment. If two neighboring partitions adopt the same type of simulation model, the interaction mechanism will directly inject the simulation result from one model into the other one. On the other hand, if the types of the two neighbouring models are different, the interaction mechanism first needs to convert the simulation result into the correct format. This conversion is done through two interaction operations, i.e., aggregation and disaggregation. The operation of aggregation collects density and velocity information from the simulation result of the microscopic model at the boundary areas. Conversely, the operation of disaggregation generates agents at the boundary areas based on the information of crowd density and velocity taken from the macroscopic model. Detailed design issues of the two interaction operation are discussed below.

4.1. Aggregation

The execution of aggregation will be triggered if there are agents that cross the boundary from the partition simulated by microscopic model to the one by macroscopic model. The aggregation process converts the simulation result from the microscopic model to the format of macroscopic model. Since only simulation result at the boundary area of the two neighboring partitions needs to be exchanged between the two models, the operation of aggregation only utilizes the simulation result of the microscopic model at the boundary areas.

A typical numerical solution to a macroscopic model needs to divide the environment into finite cells and obtains a result for each cell, which can be considered as the average result for every point inside the cell. In order to generate the same result format from the partition simulated by the microscopic model, the environment near the boundary area at the microscopic model side is also divided into cells (of the same size). An illustration of this process is shown in Figure 2, where the cells at the right side of the boundary are specified by the numerical solution of the macroscopic model, and the cells at the left side of the boundary are defined according to the cell size used in the macroscopic model. Each boundary cell in the macroscopic partition has a counterpart located at the other side of the boundary, simulated by the microscopic model.

![Figure 2: Cell Definition in Microscopic Model for Aggregation Operation](image)

At the beginning of each simulation time step, the aggregation operation will generate the crowd density and velocity in each cell defined in the partition simulated by the microscopic model. The aggregation operation counts the number of individuals inside the cell and then calculates the average density for the cell. As for the crowd velocity for each cell, the operation of aggregation gets the velocities of all the agents inside the cell and calculates the average velocity. Subsequently, the operation of aggregation will inject this information into the neighbouring macroscopic model as the initial conditions.

4.2. Disaggregation

The functionality of disaggregation is to convert and transfer the simulation result from the format of the macroscopic model into the correct format for the microscopic model. If there exists crowd flow leaving from the partition simulated by macroscopic model and entering into the one simulated by microscopic model, the disaggregation will be executed at the boundary of these two partitions. Since the microscopic model needs the location and velocity information for each agent, the operation of disaggregation generates new individuals for the microscopic model based on the crowd density and velocity from the macroscopic model.
In order to generate the new agents for the microscopic model, the area near the boundary in the microscopic partition still must be divided into cells. This is achieved in an equivalent way to the aggregation operation (illustrated in Figure 2). Hence, each cell at the boundary in the partition simulated by macroscopic model will have a corresponding counterpart at the other side of the boundary.

At the beginning of each simulation time step, the operation of disaggregation first fetches the crowd density and velocity from the cells bordering the boundary in the macroscopic model. The method assumes the boundary cells in the microscopic partition share the same crowd characteristics (i.e., crowd density and velocity) as their corresponding cells in the macroscopic partition. Using this information the method generates new agents for the corresponding cells in the microscopic model. The crowd density and cell area determine the number of individuals inside the cell; the velocities of the individuals is directly adopted as the crowd velocity for the cell; finally, these individuals are uniformly distributed in the cell.

5. Case Study

An agent-based model, which is proposed in [7] with the focus being collision-free motion, is adopted as the microscopic model for our case study. The continuum model, proposed in [2], is adopted as the macroscopic model. Based on this continuum model, [8] further proposed a numerical solution to the continuum model, which is also adopted as the solution method for our hybrid model.

5.1. Scenario Description

The scenario adopted for the case study is to simulate agents moving through a corridor. Figure 3 shows the description of the environment. We divide the environment into three sections of different width; an entrance and exit are located at the left and right side of the environment respectively.

Each agent, who comes from the entrance (locating at the left side of Area 1) and leaves the environment through the exit (locating at the right side of Area 3), will pass through a narrow corridor (Area 2 in the middle of the environment). In addition, the movements of all the agents are constrained by the walls located at the top and bottom area of the environment. In this case study, we conducted three experiments by adopting the agent-based, continuum and hybrid modelling to simulate how agent goes through the specified environment, separately. For all the three experiments, the flow rate of agent coming into the environment from the entrance is fixed and set to $1/(m \times s)$.

The executions of the continuum and agent-based model are straightforward by directly applying these models into the adopted scenario. As for the hybrid modelling, we adopt the agent-based model in Area 1 and Area 3, while the continuum model is applied in Area 2. In addition, since the agent’s movement is unidirectional, the interactions between the different models simplifies to: the operation of aggregation between Area 1 and Area 2 and disaggregation between Area 2 and Area 3. In general, where bidirectional flow may be present, both operations may be necessary at a given boundary.
5.2. Simulation Result Comparison

As claimed in [9], the shadow effect should appear for crowd passing through such an environment. It refers to the phenomenon that the pedestrian density in the areas, which is after the narrow corridor and near the edge of the environment, will be kept nearly zero. As for the environment in our case study, there should be few agents near the top and bottom areas in Area3, after the agents pass through Area2. This phenomenon can be verified by the simulation result of the experiment adopting the agent-based model, which is shown in Figure 4.

However, if we use the continuum model to simulate the crowd, this effect does not appear (the simulation results are shown in Figure 5). This is because the continuum model considers all the pedestrians in the crowd as homogeneous, all of which attempt to find and move into lower density areas. As a result, the crowd will fill every location of the environment, including Area3 where the shadow effect is supposed to appear.

We then use the proposed hybrid modelling to simulate agents movement in the given scenario. We do this by adopting the agent-based model in Area1 and Area3, and by applying the continuum model for the crowd in Area2. The simulation result is shown in Figure 6, where the dots in Area1 and Area3 represent the locations of agents in the simulation, and the color in Area2 means the crowd density in the corresponding location. It shows that there are few agents near the top and the bottom of Area3, which is exactly what shadow effect refers to.

In summary, both the hybrid model and the agent-based model can generate similar shadow effect. However, this effect does not appear in the simulation result by the continuum model. This indicates that the adopted continuum model, ignoring some individual characteristics of the crowd, is unable to recreate certain phenomena. On the contrary, the hybrid modelling, combining the two models together, is able to produce a simulation result similar to the agent-based model. This verifies that the hybrid modelling can benefit from the agent-based model, in terms of accuracy of simulation result.

5.3. Performance Comparison

As discussed in Section 1, the hybrid modelling can also benefit from the macroscopic model, in terms of simulation efficiency. The simulation costs for the experiments by the three models are studied in this subsection, and the...
Figure 5: Simulation Result by Continuum Model

Figure 6: Simulation Result by Hybrid Modelling
cost is evaluated by elapsed time per simulation step. The simulation cost is plotted in Figure 7. This compares the agent-based model, the continuum model and hybrid model in same corridor scenario.

At the beginning of the simulation (before the 30th simulation time step), the agent-based model is the most efficient in terms of execution amongst all the three models. At this phase, there are very few agents in the environment and these agents are contained within Area1. The crowd density of Area2 and Area3 is zero. In contrast, both the hybrid model and the continuum model must continually execute for Area2, even in case of zero density in this area. This means both the hybrid and continuum model initially have a higher execution cost than the agent-based model. The hybrid modelling at this stage executes more efficiently than the continuum model, the reason for which lies in the fact that the area handled by the continuum model is smaller in the hybrid model.

As simulation time elapses and more agents come into the environment, the three models show different simulation costs. Since the numerical solution of the continuum model does not depend on the crowd size but rather on the environment size, the simulation cost in the continuum model experiment remains constant (as expected). This is verified by the performance result of the continuum model in this case study, where its simulation cost for each time step is almost constant throughout the whole simulation, with an average value of 230 ms. It is also the most efficient simulation amongst the three models, after the simulation step of 30 (i.e., the number of agents in the environment reaches a certain level).

Between the 40th and 90th simulation time step, the number of agents in Area1 stabilizes and agents begin to come into Area2, while the number of agents in Area3 still keeps zero. The agent-based model has a nearly linear increase in simulation cost. This is because the number of agents increases at a constant incoming rate while no agent leaves the environment. However, the simulation cost of the hybrid modelling for the same period remains almost constant. At this period, the cost in the experiment adopting the hybrid model is composed by two parts, the cost by the agent-based model in Area1, and the cost by the continuum model in Area2. No cost is associated with Area3, since there are no agents there. The cost of the continuum model in Area2 should be constant, since it is not affected by the crowd size. The cost of the agent-based model in Area1 should not change significantly, because after the simulation step 40 the number of agents entering Area1 is more or less the same as the number leaving.

After the 90th simulation time step, agents begin to enter Area3. Since the number of agents inside the whole environment is still increasing, the simulation cost of the agent-based model continues to rise. As for the cost of hybrid modelling, rather than remaining constant, the cost also begins to increase. This is due to more agents now entering Area3.

Finally, after the first agent leaves the environment (after the 140th simulation step), the number of agents simulated in both the hybrid and the agent-based model stops increasing, as the number of agents entering and leaving the whole environment becomes more or less the same. As a result, the cost of both models does not change much. Some cost variations can still be observed during this stage. This is due to the number of agents leaving the environment being not strictly constant, as the agent density is not uniform throughout the environment.

Our simulation results thus have shown that the hybrid modelling can also benefit from the continuum model by improving overall simulation efficiency.
6. Conclusions and Future Work

Hybrid modelling for crowd simulation is proposed in this paper, aiming to exploit advantages from both macroscopic and microscopic models. The two types of models work collaboratively in a single simulation, and are executed over different mutually exclusive partitions. The execution of these models is independent from one another during each simulation step. However, it is possible for the crowd to move from one partition to another, and interactions are used for models to exchange this information. In this paper, two types of interactions are defined, i.e., aggregation and disaggregation, which helps models to communicate at a partition boundary. A case study of the hybrid modelling shows that it not only offers more efficient execution than the microscopic model, but also improves the simulation quality in comparison with the macroscopic model.

In this paper we have shown that combined hybrid modelling can offer significant advantages over traditional approaches to crowd simulation. This is achieved through exchanging simulation state at boundary cells between different models. However, in the current implementation, the exchange of state information is unidirectional. For example, if we consider the case study and examine the boundary from the continuum model to the agent model (Area2 to Area3), the agent model does not affect the calculation of the continuum model in this case. In our case study, only the continuum model provides information for seeding new agents in the microscopic model. For more correct results, there should be an overlapping set of cells (as in overlapping domain decomposition [10]) so that the density of agents (in the microscopic model) should also define an initial boundary condition for the continuum model. In future work we plan to investigate the overlapping boundary for both models, which hopefully helps to further improve the simulation accuracy.

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