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A multi-level density-based crowd simulation architecture

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Abstract. Large-scale crowd phenomena are complex to model as the behaviour of pedestrians needs to be described at both strategic, tactical, and operational levels and is impacted by the density of the crowd. Microscopic models manage to mimic the dynamics at low densities, whereas mesoscopic models achieve better performances in dense situations. This paper proposes and evaluates a novel agent-based architecture to enable agents to dynamically change their operational model based on local density. The ability to combine microscopic and mesoscopic models for multi-scale simulation is studied through a use case of pedestrians at the Festival of Lights, Lyon, France. Simulation results are compared to different models in terms of density map, pedestrian outflow, and computation time. The results demonstrate that our agent-based architecture can effectively simulate pedestrians in diverse-density situations, providing flexibility for incorporating various models, and enhancing runtime performance while achieving comparable pedestrian outflow results to alternative models.

Keywords: Agent-based architecture · Multi-level behaviour · Pedestrian modeling · Multi-scale simulation.

1 Introduction

Pedestrian simulation is an effective tool to model and study the behaviour of pedestrian in various contexts, from optimisation of pedestrian flows to safety issues [1]. Pedestrian behaviour can be modelled into three-layer level architecture [2]:

- **Strategic level:** pedestrians determine a list of activities (or targets) and when they want to perform these activities.
- **Tactical level:** pedestrians choose a path to the predefined destinations based on information about the environment.
- **Operational level:** pedestrians adjust their local movements such as collision avoidance to adapt to the surrounding area.

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In order to build a pedestrian simulation, a modeller has to effectively instantiate one model for each of the three layers, that is to say at least one strategic model (also referred to as *goal selection* model) [3, 4], one tactical level model (also known as *path planning* model) [5, 6], and one operational level model [7, 8]. In this paper, we focus on selecting the proper algorithm for the operational level. Those models are used to compute the velocities and speed of each pedestrian based on local information.

Many types of operational models exist in the literature, each model being built to capture and mimic a specific phenomenon [9]. Therefore, their performance differs if they are put into context for which they have not been designed. Microscopic models are usually suited to simulate pedestrians in low- and medium-density situations, where the density level is less than $2 \text{ ped}/m^2$ [1]. These models encounter specific problems when applied to high-density situations, such as abnormal vibrations with the Social Force Model [10], congestion in dense bidirectional flow with the Velocity Obstacle model [11], unrealistic results in terms of collision metrics with the data-driven models [12]. On the other hand, pedestrian dynamics in high-density situations are similar to fluid flow [13], and fluid-like equation models [13, 14] are particularly appropriate for these scenarios due to their assumption of the continuous of pedestrian flow.

Given that we observe varying performance of pedestrian models in different crowd densities, this contribution proposes and evaluates an agent-based architecture to enable agents to dynamically change their operational model based on local density to adapt to their dynamic environments. Local density estimation is achieved through predefined regions in the environment, which enables contextual and structured adaptation to various environments. Additionally, the use of predefined areas can facilitate the implementation of the model by providing a more intuitive and manageable approach to estimating density.

The paper is organized as follows: In Section 2, a summary of related works is provided. Section 3 describes our proposed agent-based architecture for the multi-level behaviour of pedestrians. Next, Section 4 illustrates the experimental design and presents our simulation results. Finally, the paper ends with a conclusion and discussion in Section 5.

2 Related Work

Helbing et al. introduced the Social Force Model (SFM) [7], which describes pedestrian motion as driven by social forces. These forces result from both internal factors, such as an individual's attraction towards a personal goal, and external factors, like repulsion from neighboring pedestrians and walls. The SFM is formulated based on Newton's second law:

$$m_i \frac{dv_i}{dt} = m_i \frac{v_i^0(t)e_i^0(t) - v_i(t)}{\tau_i} + \sum_{j \neq i} f_{ij} + \sum_W f_{iW} \quad (1)$$

where m_i , v_i , v_i^0 , and e_i^0 represent the mass, current velocity, preferred speed, and desired direction of pedestrian i , respectively. The first term of Equation

1 accounts for the acceleration from current velocity to the preferred velocity within the reaction time τ_i , while f_{ij} and f_{iW} describe interaction forces with other pedestrians and walls, respectively. The SFM has been demonstrated to realistically reproduce self-organization phenomena in low-density situations such as lane formation and arc-shaped clogging at bottlenecks [7].

On the other hand, Treuille et al. [14] proposed the Continuum Crowds (CC) model which treats pedestrian flow similarly as a continuum without taking into account individual differences. Global navigation is managed by dynamic potential field using the eikonal equation (Equation 2):

$$\|\nabla\phi(x)\| = C \quad (2)$$

$$v = -f(x, \theta) \frac{\nabla\phi(x)}{\|\nabla\phi(x)\|} \quad (3)$$

where ϕ , C are potential function and unit cost in the direction $\nabla\phi$, respectively. The cost value to the goals is based on distance, time and discomfort factor. Pedestrian velocity is determined by the direction opposite the gradient of function in Equation 2, with the magnitude dependent on the local area's density field and velocity field. The CC model is suitable for simulating large crowds in extreme-density situations with computational efficiency.

The aforementioned models are only suitable for simulating pedestrians in either low-density or high-density scenarios [10, 14]. To simulate pedestrians in both low-density and high-density situations simultaneously, hybrid modeling is often employed, typically combining macroscopic and microscopic models. Auto-switch models [15, 16] move from a macroscopic model to a microscopic model and vice versa on a trigger condition, while region-based model [17] specifies certain areas for each model. A mechanism for the aggregation and disaggregation of crowds is required for these models to have a consistent transition between the macroscopic and microscopic levels. However, these models normally ignore a higher level of pedestrian behaviour modeling and are therefore only applied in a simple environment with a single infrastructure. Recently, Curtis et al. [18] proposed the Menge framework, a crowd simulator that aggregates different modeling algorithms for each level of pedestrian behaviour. Despite its advancements, this framework only allows for one modeling technique to be implemented at the operational level in the whole simulation.

Currently, there is a lack of a general framework for modeling multi-level pedestrian behaviour that allows agents to dynamically change their operational model. To tackle this challenge, our work focuses on developing an agent-based architecture that models multi-level pedestrian behaviour and is compatible with a variety of modeling algorithms at each level. Moreover, this architecture enables pedestrian agents to switch their operational model in response to changes in local density. A detailed description is provided in the following section.

3 Proposed Model

3.1 General overview

In dynamic environments where the density state of each area changes over time, the environment is divided into several zones either based on expert knowledge or dynamic segmentation according to crowd density. These zones are classified as *high-density zones* (as shown by the red dashed area in Fig. 1) and low-density regions (the region outside of the dashed area in Fig. 1). Each zone is associated with specific triggering rules and transition functions.

The triggering rules evaluate pedestrian and environmental characteristics within the respective zone to select suitable models for pedestrian simulation. Due to the varying performance of pedestrian models across different crowd densities, these rules identify appropriate models to accurately capture the dynamics within each area. When new individuals enter a zone, the transition functions are activated to adapt their information, facilitating a smooth transition from their previous zone to the current one.

When entering a new zone, pedestrians adjust their tactical and operational models to align with the requirements of the corresponding zone. To ensure a generic and extensible approach for various models, an agent-based architecture is proposed in Section 3.2 to model the multi-level behaviour of pedestrians. This agent-based architecture enables pedestrians to dynamically select the appropriate modeling algorithm at each level of behaviour.

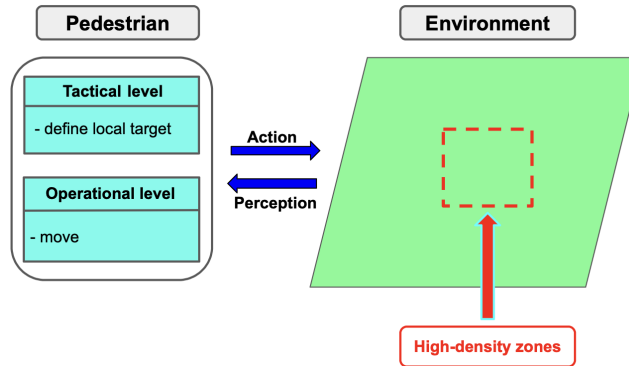


Fig. 1: General overview.

3.2 Agent-based architecture for multi-level behaviour

To develop an agent-based architecture for multi-level pedestrian behaviour, an abstraction is first introduced to describe the problem of pedestrian modeling.

The problem is divided into two subproblems: *tactical* and *operational subproblem*³. Suppose that $S = \{E, A\}$, where E and A are the environment and the set of agents in simulation respectively. The *tactical subproblem* can be formalized by the function T , $T : S \times t \times \mathbb{R}^2 \rightarrow \mathbb{R}^2$, which maps the simulation state, time, and the agents' destination to the local target which is in \mathbb{R}^2 . The *operational subproblem* can be formalized as follows: $O : S \times t \times \mathbb{R}^2 \times [0, 1] \rightarrow \mathbb{R}^2$. The function O maps the local simulation state S , time, local target, and check if agents in *high-density zones* to a feasible velocity, which is then used to update agents' locations in the next simulation step. In general, the problem of pedestrian modeling can be stated by the following mathematical formulation:

$$v_i(t) = O_i(T_i(t)) \quad (4)$$

$$p_i(t+1) = p_i(t) + v_i(t)\Delta t \quad (5)$$

where $v_i(t)$ and $p_i(t)$ are the velocity and the location of agent i in the xy-coordinate system at time t respectively and Δt is the duration of a simulation step.

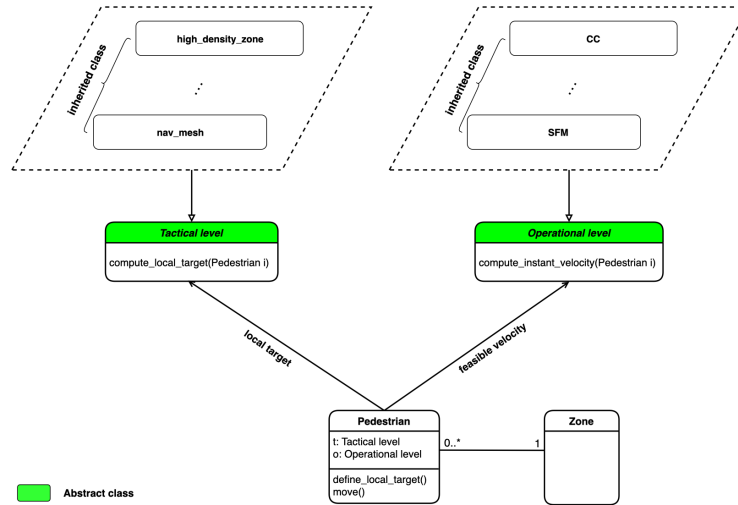


Fig. 2: Agent-based architecture for multi-level pedestrian behaviour.

Given the description above, an agent-based architecture is designed as shown in Fig 2. To include different modeling algorithms, each subproblem is represented by an abstract class. The *tactical subproblem* is presented by the *Tactical level* while the *Operational level* class presents the *operational subproblem*. Each abstract class can contain different inheritance subclasses, where each subclass represents a specific model to simulate various behaviour depending on the situations (strategy pattern). The pedestrian agents are only allowed to present one

³ The integration of *strategic subproblem* is not in the scope of this paper.

model for each level of behaviour at a time, but that model may be changed based on the state of the environment in which the pedestrian agents are operating.

Each modeling algorithm for each level needs to inherit the corresponding abstract class. The *Tactical Level* and *Operational Level* classes return the local target and feasible velocity for pedestrians, respectively. What should be noted here is that in the simulation environment, excluding *Pedestrian* class, only one single instance of each class is created (singleton pattern). Therefore, our architecture does not increase complexity but improves the flexibility of simulation. Furthermore, it is possible to change the modeling algorithm at each level of behaviour by simply updating the variables t and o in *Pedestrian* class.

3.3 Pedestrian activity diagram

Fig. 3 illustrates the activity diagram of pedestrian agents at each simulation step. Initially, the agents perceive their surrounding environment to identify neighboring agents. Subsequently, if the agents have either reached their current local target or do not have a local target, they execute *define local target* behaviour which invokes their corresponding inheritance model from the *Tactical level* class to assign a new local target. Afterward, pedestrian agents perform the *move* behaviour using the returned velocity from their respective inheritance model in the *Operational level*.

After moving to new locations, pedestrians check whether they have arrived at their destination. If yes, their movement is completed. Otherwise, they determine if they have transitioned into a new zone. In such cases, pedestrian agents need to update their states by sending a request to the Zone entity to obtain information about the tactical and operational models employed in this new zone. This query returns the results o_{new} and t_{new} , which represent the operational and tactical in use within the zone, respectively. Pedestrians then update their attributes by setting their operational variable o to o_{new} and their tactical variable t to t_{new} .

This continuous process of perceiving the environment, defining local targets, moving, and updating states based on zone transitions enables pedestrian agents to navigate through the simulation space effectively. This dynamic approach allows for the modeling of complex scenarios and interactions between agents, accounting for varying tactical and operational models across different zones.

4 Experiments and Results

This section presents a set of simulations to demonstrate the capabilities of our proposed architecture. More precisely, the ability to dynamically change the operational model is studied through simulations of crowd exit during the Festival of Lights [19] at the Place des Terreaux, Lyon, France. Simulation results are compared between our model and different other models in terms of density map, pedestrian outflow, and performance.

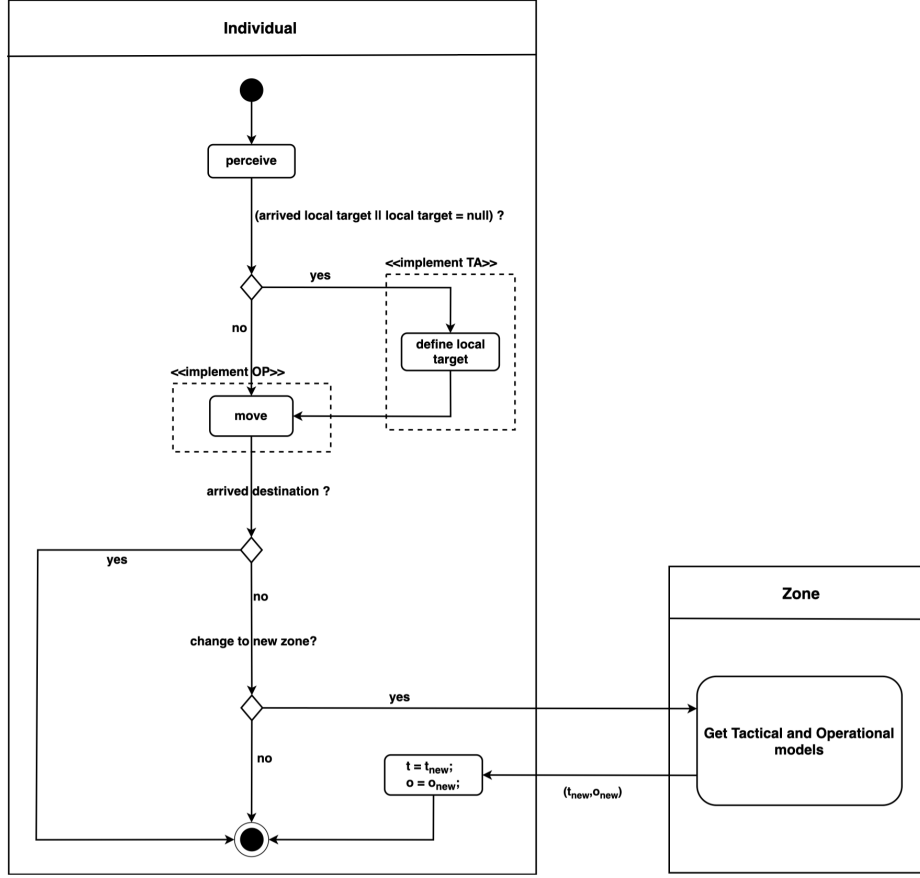


Fig. 3: Pedestrian's activity diagram at each simulation step.

4.1 Experiment design

The simulation area is the Place des Terreaux, a large plaza located in Lyon, France (highlighted by the red dashed rectangle in Fig. 4a) with an area of 7000 m^2 . During the Festival of Lights [19], pedestrians gather at the plaza to watch the show, which is projected onto the walls of the surrounding buildings (see Fig. 4b). After the show ends, pedestrians head towards the two pre-configured exits (as illustrated by the bottom-left blue arrows in Fig. 4a) to explore new attractions. To accommodate these movements, the environment is discretized into three distinct zones (illustrated by the three dashed rectangles in Fig. 4a).

During the pedestrian exit process, the plaza experiences high density, while the two exits exhibit lower density. Our proposed architecture can effectively handle such multi-density situations. The experiment configuration is as follows:

- The simulation is conducted with a time step $\Delta t = 0.1 \text{ s}$, with 6000 agents.



(a) Main circulation of the exiting crowd. (b) Pedestrians watching the show at the Place des Terreaux ⁴.

Fig. 4: Information of the Festival of Lights [19].

- The CC model [14] for a single target cell is used to simulate pedestrians in the plaza (*high-density zones*) due to its effectiveness in dense scenarios. This approach leads to further discretization into cells, each storing information about the environment and the pedestrians, such as average velocity and local density.
- The SFM [7] is applied for those who have exited the plaza as it can realistically simulate pedestrians in low-density situations.
- In the CC model, the minimum and maximum speeds are set to 0.05 m/s and 1.4 m/s respectively.
- The parameters for the SFM are chosen to be consistent with those in [20], where the distribution of the preferred speed is Gaussian with the mean of 1.34 m/s and the standard deviation of 0.26 m/s , with a maximum preferred speed of 1.74 m/s .

The proposed model is compared to three others: SFM-only (which applies the SFM in all three zones), 3-CC-1 model (consisting of three separate CC models, each with one target cell for simulating a single zone), and 1-CC-2 model (using one CC model for simulating the entire environment, with two target cells for two exits in two blue dashed areas in Fig. 4a). These comparisons are based on simulations of crowd exits with 6000 agents. For each simulation, three indicators are computed, and an average is determined from a total of 15 simulations for each model:

- Density map (in ped/m^2) of pedestrian density distribution across the simulation area.
- Outflow (in $\text{ped}/\text{simulation step}$) of pedestrians exiting the plaza to the two exits.
- Computation time (in s) required to calculate one simulation step.

All simulations are conducted using the GAMA platform [21] on a M1 MacBook Pro with 32 GB of memory.

⁴ <https://www.fetedeslumieres.lyon.fr/fr/oeuvre/grand-mix-au-musee-des-beaux-arts-de-lyon>

4.2 Results

Fig. 5a displays the simulation of 6000 agents at Place des Terreaux, with pedestrians in *high-density zones* represented in red and pedestrians in low-density regions shown in blue. In comparison, Fig. 5b presents the histogram of pedestrian speeds for both low-density regions and *high-density zones*. As expected, the speed distribution in the *high-density zones* differs from that in the low-density regions. The mean speed of pedestrians in the *high-density zones* is 0.39 m/s , which is substantially lower than the mean speed of 1.37 m/s in the low-density regions. The observed differences in speed distributions between the two areas suggest that the characteristics of pedestrians in low- and high-density situations can be mimicked by incorporating suitable models at the operational level in our architecture.

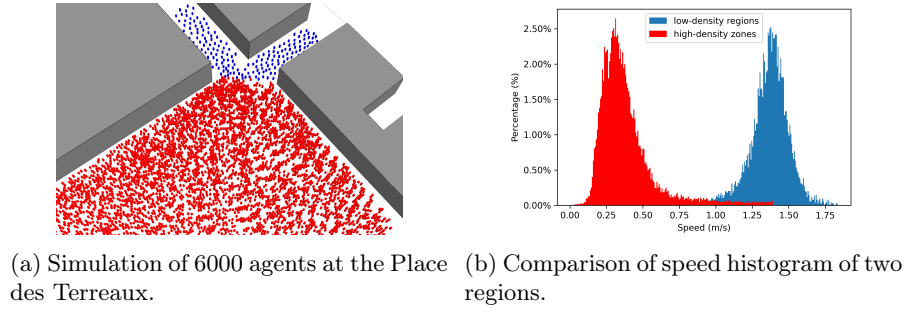


Fig. 5: Simulation results.

Next, comparisons of different models are evaluated in terms of the density map and pedestrian outflow. Fig. 6 presents the density maps of various models over different time steps ($t = 60\text{ s}, 150\text{ s}, 240\text{ s}$). In the SFM-only model, the highest density area, with a maximum density of 3.5 ped/m^2 , is observed in both the plaza and the two exits. Similarly, the 3-CC-1 model and 1-CC-2 model can simulate extremely high densities of $6 - 8\text{ ped/m}^2$, but these extremely high-density areas also appear in both the plaza and the two exits. In contrast, our model exhibits a clear difference in density levels between the plaza and the two exits. Moreover, Fig. 7a, which shows the outflow of pedestrians exiting the plaza for each model over the simulation time, shows that our model's pedestrian outflow results are similar to those of the other models, with a maximum outflow of approximately 1.4 pedestrians per simulation step and a total of approximately 6800 simulation steps. These results indicate that our model can effectively simulate pedestrians in environments with a mix of low- and high-density situations while having similar results of the pedestrian outflow with the other models. Furthermore, a key advantage of this architecture is its generic nature and flexibility, as it can accommodate any combination of zones and models, enabling the modeling of various scenarios and crowd dynamics.

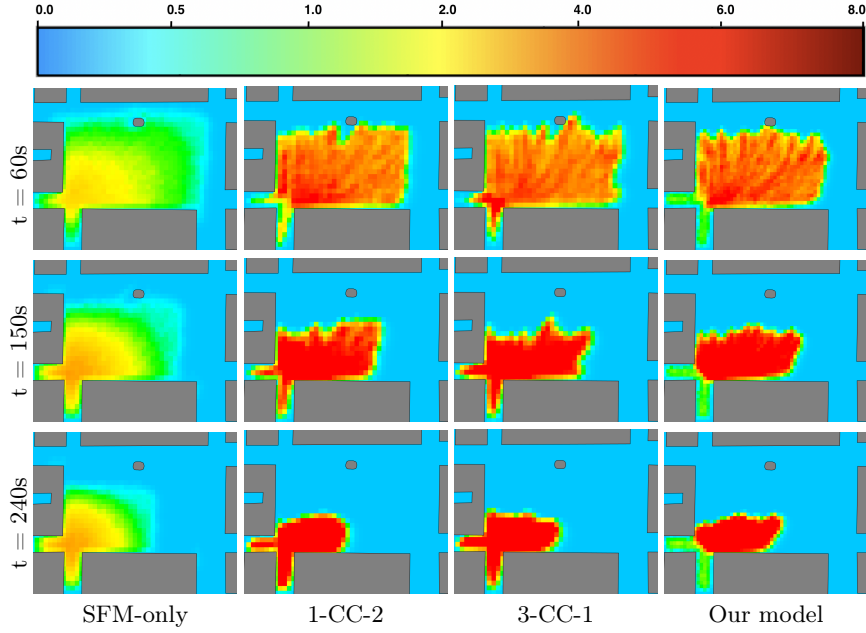


Fig. 6: Density maps among different models with 6000 simulated agents.

Finally, various numbers of pedestrian agents ($3K$ to $15K$) are used to evaluate the simulation time of different models. The results, shown in Fig. 7b, indicate that the SFM-only and 3-CC-1 models have the longest simulation times, which increase significantly as the number of pedestrians grows, while the 1-CC-2 model has a similar simulation time to them at first but drops as the number of agents increases. In contrast, our model demonstrates superior performance in terms of simulation time, with a large difference from the other models observed as the number of pedestrians grows. This finding indicates that using mesoscopic models for low-density regions is unnecessary, and they can be replaced with microscopic models. These results suggest that having different modeling algorithms at each level not only improves the variety of behaviour observed in various scenarios but also enhances overall performance compared to using only microscopic models or multiple mesoscopic models.

5 Conclusion and Discussion

Large-scale crowd phenomena are complex to model as the behaviour of pedestrians needs to be described at both strategic, tactical, and operational levels and it is impacted by the density of the crowd. Particularly in the operational level modeling, each model can only simulate a single type of pedestrian dynamic, while pedestrian dynamics vary significantly depending on the density of

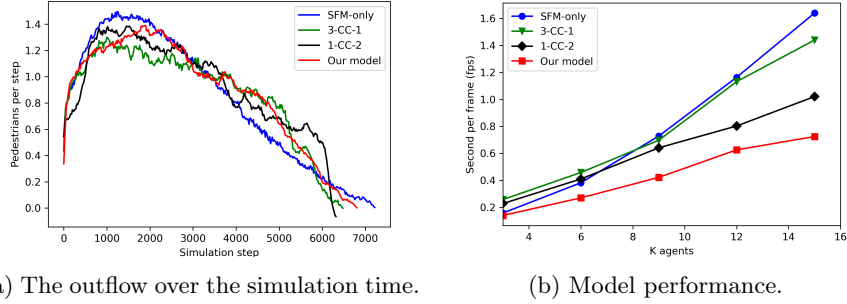


Fig. 7: Comparison results of different models.

the environment. This paper proposes an agent-based architecture for simulating the multi-level behaviour of pedestrians, where agents are able to dynamically change their operational model based on local density. Our architecture is evaluated through a use case of pedestrians at the Festival of Lights, Lyon, France with simulation results compared to different models in terms of density map, pedestrian outflow, and computation time. The results demonstrate that our agent-based architecture can effectively simulate pedestrians in diverse-density situations, providing flexibility for incorporating various models, and enhancing runtime performance while achieving comparable pedestrian outflow results to alternative models. Our architecture is not only generic in the domain of pedestrian modeling but also extensible to other domains such as traffic simulation and social simulation.

Our future work aims to incorporate a greater variety of modeling algorithms for each level of behaviour, particularly at the operational level. Then, the selection of an optimal algorithm at each level of behaviour and the criteria for switching these algorithms need to be defined based on the density of each region. Another promising direction involves applying density-based clustering algorithms to pedestrian coordinates in order to dynamically estimate the local density of environments.

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