A Linear Wave Propagation based Simulation Model for Dense and Polarized Crowds

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Abstract

Fluid-like motion and linear wave propagation behavior will emerge when we impose boundary constraints and polarized conditions on crowds. To this end, we present a Lagrangian hydrodynamics method to simulate the fluid-like motion of crowd and a triggering approach to generate the linear stop-and-go wave behavior. Specifically, we impose a self-propulsion force on the leading agents of the crowd to push the crowd to move forward and introduce a Smoothed Particle Hydrodynamics (SPH) based model to simulate the dynamics of dense crowds. Besides, we present a motion signal propagation approach to trigger the rest of the crowd so that they respond to the immediate leaders linearly, which can lead to the linear stop-and-go wave effect of the fluid-like motion for the crowd. Our experiments demonstrate that our model can simulate large-scale dense crowds with linear wave propagation.

Keywords: dense and polarized crowd, fluid-based model, boundary constraints, linear waves, smoothed particle hydrodynamics

1 Introduction

Large-scale virtual crowd simulation is an important research topic in the entertainment industry and social governance, with a wide range of applications such as films, games, sports, and evacuation simulations. For example, individuals have minimum freedom to rotate or stop when congested in a dense crowd flow, but often follow the leaders, especially when the crowd has a unidirectional goal. In such a situation, it is dangerous when people are accumulated at the bottleneck, such as the front of an evacuation crowd. To avoid the potential jamming and clogging, many researchers have investigated simulations to explore the critic parameters charging for the deadlock [1, 2, 3, 4].

In [5], Helbing et al. reported that the stop-and-go waves may lead to disasters. For example, in a marathon contest, often thousands of runners will generate stop-and-go waves when they follow the guidance managers to aim at the start line. However, in the real world, runners in a marathon rarely are jammed. Hughes et al. [6] assumed that the motion of crowd flow is dominated by the hydrodynamics equation. Recently, by studying the fluctuation of density and velocity from the recording videos of several marathons with the hydrodynamics theorem, Bain et al. [7] have shown that the density field and velocity field waves can be formed by linear wave propagation models. However, their models cannot be directly applied to simulate a fluid-like crowd in computer graphics applications, because it ignores agent-agent interaction rules such as collision avoidance.

In this paper, we propose a Lagrangian hydrodynamics based method to simulate the fluid-like motion of polarized and dense crowds. Specifically, we use interaction rules to guide the move of the crowd toward the global directions with linear waves. Generally, fluid-like crowds can be observed in many circumstances, such as dense pedestrians walking through a corridor, passengers evacuating from a train station platform, and so on. These scenarios share the same constraints of density, boundary, and uni-direction, which are key factors for the dynamical crowd simulation with fluid-like motion. Figure 3 shows the simulated marathon by our approach.

The main contributions of this work can be summarized as follows:

- It introduces a new solution for the macro-level movement and the border-triggered propulsion behavior based on Lagrangian hydrodynamics to reproduce the findings of the dynamic response and hydrodynamics model of polarized crowds [7];
- It introduces a new method to simulate the linear wave propagation of dense and polarized crowds by applying local individual interaction rules.

The remainder of this paper is organized as follows. We first discuss the related work in Section 2. The overview of our model is then introduced in Section 3, with the details of our model being presented in Sections 3.1, 3.2, 3.3 and 3.4. With the simulation results of several challenging scenarios, we present the evaluations of our model in Section 4. We finally conclude our work in Section 5.

2 Related Work

While there exist intensive simulation studies on individual behaviors based on local interaction rules [8, 9, 10, 11, 12], researchers have also developed various models for crowd simulation, including force-based [13, 14], velocity-based [15, 16], cell-based [17, 18], vision-based [19, 20], etc. Although the existing microscopic models for crowd simulation have the advantage of describing the agents' realistic behavior, they generally suffer from heavy computation that may lead to local vibrations in dense crowds.

Generally, for dense crowds or flocks, we obtain macroscopic responses with a continuum model [21]. The fluid-based approach has been successfully applied to the simulation of pedestrians [22], robotics [23], insects [24], etc. Many hydrodynamics theories have been developed for the simulation of micro-level groups such as cell tissues, bacterium, and synthetic self-propelled particles [25]. However, macro-level human crowd simulation is mainly based on the continuum assumption proposed by Hughes et al. [6]. With this assumption, Treuille et al. successfully simulate a continuum of pedestrians by constructing a potential field on the discrete floor [21]. Similarly, Narain et al. compute the pressures among the dense crowd with the unilateral incompressibility constraint (UIC) solver [26]. Furthermore, Lagrangian hydrodynamics based methods can be applied for pedestrian simulation [27, 28, 29]. However, they cannot be directly used for linear dense crowd simulation.

The stop-and-go model has been broadly applied to simulate vehicles or human crowd waves [30, 31, 32]. In [30], Aw et al. appllied the stop-and-go model to traffic simulation. Based on Aw et al.'s vehicle simulation model, Pettré et al. explored a follow-the-leader model for the queuing human simulation with stop-and-go waves [31]. Similarly, Cao et al. investigated the dynamics of different aged people [32]. This model could reproduce flow waves mainly for 1D circumstances, where individuals have particular leaders to follow with a safe distance, such as the vehicles in one lane. However, the stop-and-go model cannot simulate linear waves for highly self-aligned dense crowds, in which the agents do not have pre-defined lanes to follow and time/space to react.

3 Our Schema

In [7], Bain et al. have observed the following features of polarized and dense crowds:

- The motion of the crowd complies with a hydrodynamics rule.
- The crowd is driven by a self-propulsion force, $\mathcal{F}(\rho, \mathbf{v}, \mathbf{P})$, which not only influences the fluctuation of the density ρ and

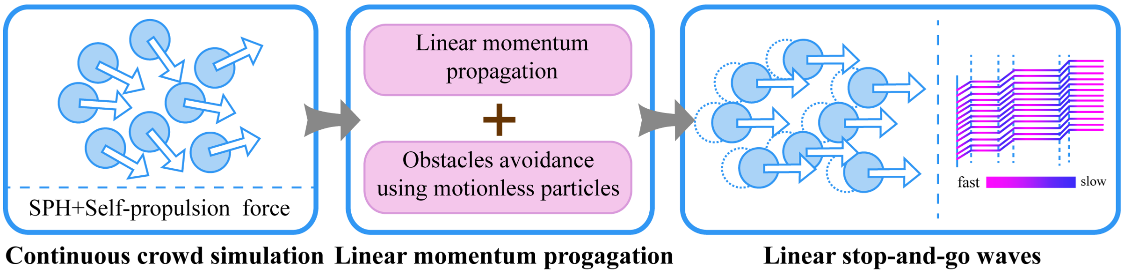


Figure 1: Pipeline overview of our dense and polarized crowd simulation model. First, we use the SPH method to simulate the dynamics of dense crowds and use a self-propulsion force for the tide of the crowds to move towards the destination (left); A trigger approach is used to make the rest of the group respond to the immediate leaders linearly. Meanwhile, we use static particles to prevent the motions of agents from penetrating through the obstacles (middle); we obtain linear stop-and-go waves of the fluid-like motion for the crowd (right).

the velocity $\mathbf{v}$, but also can align individuals to the global direction $\mathbf{P}$.

- The crowd movement is boundary-triggered, and the dynamics of the crowd are linearly propagating from the tides to the tail of the queue.

Based on the above observations, in this work, we simulate the hydrodynamics of the human flow based on Lagrangian hydrodynamics.To simulate the boundary-triggered momentum of dense crowds, we design a linear wave propagation method for fluid-like crowds, which is described below (shown in Figure 1),

1. At the micro level, we simulate the hydrodynamics of dense and polarized crowds based on the Lagrangian hydrodynamics method. Specifically, we interpolate the density, pressure, and viscous force for each agent with kernel functions. Moreover, we discrete the floor into grids to accelerate the search for the interaction neighbors.

2. At the macro level, we solve the mass movement of the crowd by a self-propulsion force. That is, each agent obtains a preferred velocity from the global planner and integrates the preferred velocity as a self-propulsion force into the Smoothed Particles Hydrodynamics (SPH) algorithm.

3. Furthermore, we synthesize the hydrodynamics and border-triggered self-propulsion behavior to generate the wave propagation mass movement for the crowd. The momentum linearly propagates from the tide to the tail of the dense pedestrian queue.

Note that our SPH-based model may not be able to simulate more complex behavior of a sparse crowd than existing methods. However, with the boundary constraints and uni-direction condition, our proposed linear wave model is highly effective for simulating highly self-aligned and dense crowd.

3.1 Hydrodynamics of The Crowd

First, the fluid-like crowd automatically complies with the mass conservation (Equation 1):

$$\frac{\partial \rho}{\partial \mathrm{t}} + \boldsymbol{\nabla} \cdot (\rho \mathbf{v}) = 0, \tag{1}$$

because the total number of agents does not change. In Equation 1, ρ and $\mathbf{v}$ denote the agent's density and velocity, respectively. Then, the momentum equation (Equation 2) can be defined as follows:

$$\rho \frac{\partial \mathbf{v}}{\partial t} = -\nabla p + \mu \nabla^2 \mathbf{v} + \mathcal{F}^{\,\text{external}}, \tag{2}$$

where the pressure force $\mathcal{F}^{\,\text{pressure}} = -\nabla p$ (p is pressure) mainly acts for collision avoidance for agents instead of the mass movement of the crowd. The viscous force $\mathcal{F}^{\,\text{friction}} = \mu \nabla^2 \mathbf{v}$ (μ is the friction coefficient) can be treated as the friction force to slow down the movement of the agents. Moreover, we define the external force $\mathcal{F}^{\,\text{external}}$ as a self-propulsion force involved in

Equation 2 to drive the movements of individuals (Section 3.2).

Furthermore, we apply the SPH algorithm to simulate the hydro-dynamics of dense crowds by interpolating the densities and velocities. The densities, pressures, and viscosities of the particles are interpolated by a smooth kernel function. By inserting the obtained values into the Navier-Stokes equation (Equation 2), the accelerations of the particles can be solved by $a = \frac{\partial \mathbf{v}}{\partial t}$.

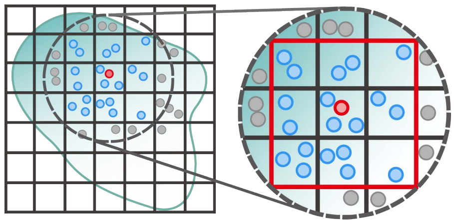


Figure 2: Simulation of the dynamics of dense crowds based on the SPH method. Girds are used to search for interacting neighbors. The red one interacts with neighbors (blue) in adjacent grids.

Based on the fluid simulation model in [33], the evaluation of $A(\vec{r}_i)$ for the density, pressure, and viscosity of the particle at position $\vec{r}_i$ can be computed as follows:

$$A(\vec{r}_i) = \sum_j A_j \frac{m_j}{\rho_j} W\left(\vec{r}_i - \vec{r}_j, h\right), \quad (3)$$

where m_j, $\vec{r}_j$ are the mass and position of neighbor j of the i-th agent, respectively. $W\left(\vec{r}_i - \vec{r}_j, h\right)$ is the kernel function introduced by Monaghan [34], which is designed as follows:

$$W(\cdot) = \frac{15}{7\pi h^2} \cdot \begin{cases} \frac{2}{3} - r^2 + \frac{1}{2} r^3, & \text{if } 0 \leq r < 1 \\ \frac{1}{6}(2-r)^3, & \text{if } 1 \leq r < 2 \\ 0, & \text{if } r \geq 2 \end{cases} \quad (4)$$

where $W(\cdot) = W\left(\vec{r}_i - \vec{r}_j, h\right)$, $r = \frac{|\vec{r}_i - \vec{r}_j|}{h}$.

Specifically, the density of the i-th agent can be computed as follows:

$$\rho(r_i) = \sum_j m_j W(\cdot). \quad (5)$$

The pressure force of the i-th agent is computed by:

$$\mathcal{F}_i^{\text{pressure}} = \begin{cases} -\sum_j m_j \frac{p_i + p_j}{2\rho_j} \nabla W(\cdot), \\ \qquad\qquad\qquad \text{if } d < d_{min}, \\ 0, \quad otherwise. \end{cases} \quad (6)$$

Note that we only compute the pressure force when the distance ($d = |\vec{r}_i - \vec{r}_j|$) between the agent i and its neighbor j is smaller than a threshold d_{min}.

The friction force of the i-th agent is computed as follows:

$$\mathcal{F}_i^{\text{friction}} = \mu \sum_j m_j \frac{\mathbf{v}_j - \mathbf{v}_i}{\rho_j} \nabla^2 W(\cdot). \quad (7)$$

Moreover, we apply the discrete grids to search for the interacting neighbors and set the radius of search larger than the kernel radius h. For instance, the red agent interacts with neighbors (blue) located in adjacent grids (see Figure 2). This helps to obtain a better system equilibrium. Once we obtain the pressure and friction force, the local continuum velocity of the crowd, V_i^{loc}, can be computed by Newton's second law $F = ma$.

3.2 Macro Movements

With the above hydrodynamics based neighborhood interactions, local agents will not automatically present mass movement toward the destination. Thus, an appropriate self-propulsion force is needed for a fluid-like crowd simulation. In our model, we assume that each agent has the knowledge of the global direction and the self-propulsion for the destination. To achieve this, we first apply a roadmap-based algorithm [35] to compute a set of path points $\vec{s}_i (i = 0, 1, ..., n)$ for the crowd through the global planning algorithm. Then, we compute a self-propulsion force $\mathcal{F}^{\text{external}}$ between an agent's current position and the nearest path point, where $\mathcal{F}^{\text{external}}$ will act as an external force involved in the momentum equation (See Equation 2).

In order to integrate the self-propulsion force into the hydrodynamics equation, we apply an analog of social force [5] as the self-propulsion force as follows:

$$\mathcal{F}_i^{\text{external}} = \rho_i \frac{\vec{s}_i - \vec{r}_i}{|\vec{s}_i - \vec{r}_i|} \xi, \quad (8)$$

where $\vec{s}_i$ and $\vec{r}_i$ are the nearest path point and the position of the i-th agent, respectively. ρ_i is the density of the i-th agent. The scalar ξ is a noise to simulate the dynamic speed of the agent. For highly self-aligned behaviors, we make the agents self-aligned to the path direction. The normalized vector $\frac{\vec{s}_i - \vec{r}_i}{|\vec{s}_i - \vec{r}_i|}$ naturally acts as the polar field $P(\cos\theta, \sin\theta)$, which ensures the agents highly self-aligned.

After obtaining the self-propulsion force, we can compute the preferred velocity ${V_i}^{\text{pro}}$ of the i-th agent. However, directly accumulating ${V_i}^{\text{loc}}$ and ${V_i}^{\text{pro}}$ to compute the actual velocity V_i ($V_i = {V_i}^{\text{loc}} + {V_i}^{\text{pro}}$) may enlarge the influence of the external force. To avoid this, we set a constraint of the maximum velocity of the agents to avoid the potential infinite acceleration.

3.3 Motion Synthesis

Although the crowd has knowledge of the global direction, only head line agents in the crowd have the space to move with expected maximal speed under the dense and boundary constraints, such as in marathon scenarios. However, the agents behind the head line have minimum freedom but to follow their immediate leaders. When the tide agents stop because of the guiding information, the highly self-aligned followers should respond correctly to avoid stampede accidents. We design a signal propagation model for the fluid-like crowd with linear waves by the devised self-propulsion force to simulate the safe following behavior.

In our model, the momentum propagates in a 2D queue with a self-propulsion force from the head line to the tail line of the queue. The rest of the agents triggered by the front neighbors will move based on their current states. A person can be in a state of either *active* or *inactive*. For example, the stopped agent is transformed into the *inactive* state. The *inactive* one will be triggered into *active* state when the influence of the motion signal propagated from the leaders exceeds a threshold. Only the active agents will be given a reaction time τ to move with the self-propulsion force. This signal propagation model can be modeled with a vision-based method, because an agent can only sense a finite interaction zone. Based on this observation, the momentum will linearly propagate from the head line to the tail of the queue, which is similar to the Mexican wave traveling in a stadium [36].

The trigger model can be defined as follows:

$$w_{ij} = \begin{cases} \exp\left(\frac{-d}{R}\right), & 0 < d < R \\ & \textit{and } j\textit{-th agent is activated}, \\ 0, & otherwise, \end{cases} \tag{9}$$

where w_{ij} is the influence of the j-th agent on the i-th one. R is the radius of interaction zone. To ensure that the influence propagates along the global path from the head lines of the crowd to the tail line, we revise w_{ij} as follows:

$$w_{ij} = \alpha \, w_{ij} \, \left(r_{ij} \cdot r_i s'_i\right), \tag{10}$$

where $r_{ij} = \vec{r}_i - \vec{r}_j$, $r_i s'_i = \vec{r}_i - \vec{s'}_i$. As shown in Figure 4, s_i is the next path point for the i-th agent and $\overrightarrow{r_i s'_i} = \vec{r_i t} + (t\vec{r}_i + t\vec{s}_i)$, t is the closest position on the path from the i-th agent. Moreover, we define α as follows:

$$\alpha = \begin{cases} 1, & r_{ij} \cdot r_i s'_i > 0, \\ 0, & otherwise, \end{cases} \tag{11}$$

where $r_{ij} \cdot r_i s'_i > 0$ denotes that the j-th agent is positioned in front of the i-th agent.

Additionally, if the force-based crowd simulation mode leads to unnatural drawback behaviors when the crowd flow encounters a bottleneck, we stop updating such agents, inspired by the rule introduced in [14].

3.4 Boundary Interaction with Obstacles

We treat the obstacles as static particles to interact with the boundary agents. Inspired by [37], we discretize the hard boundary (such as walls or the edge of the road) into motionless particles. To save computation, we only sample the surface of the obstacles. When the agents move into the interaction circle of the static particles, the repulsion force is computed similarly as in Equation 3. This approach is also applicable to dynamical obstacles, such as walking staff in the marathon.

4 Experiments and Discussion

We implemented our simulation model in C++ and conducted various simulation experiments

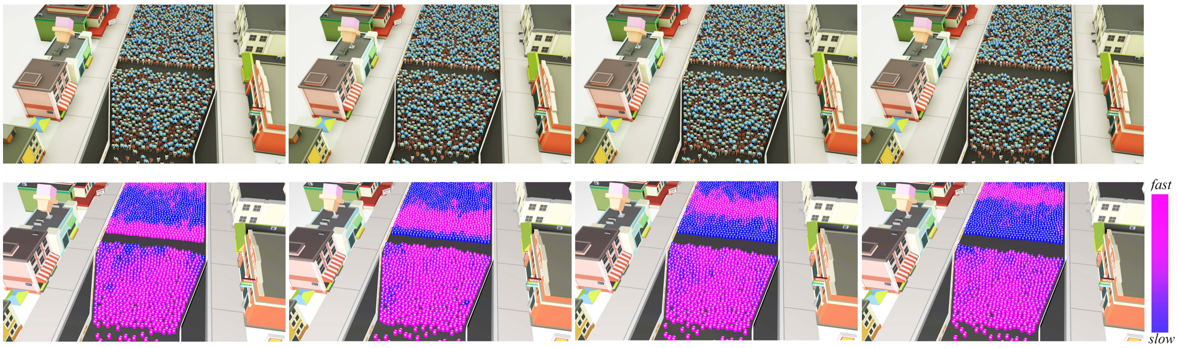
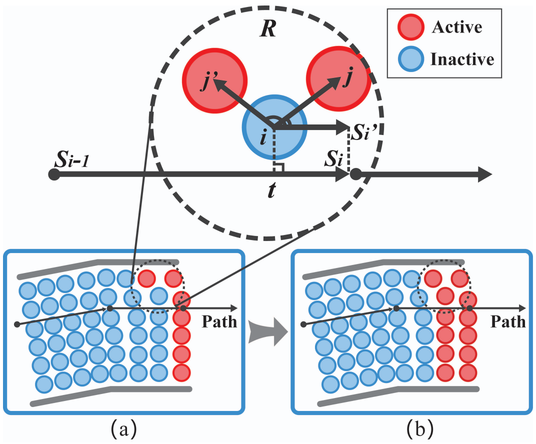


Figure 3: The top row shows simulation results of a marathon at the evacuating point with linear waves. The bottom row shows the corresponding colored visualization of the speeds of the marathon runners. The speeds of the runners are visualized from pink (moving/hill) to blue (stop/valley).



: Figure 4
The influence propagates along the global path from the head line to the tail line of the crowd flow: (a) the i-th agent can be influenced by the activated j-th agent, i.e., $r_{ij} \cdot r_i s_i' > 0$, while the j'-th agent has no influence on the i-th agent, i.e.,

on a PC with Intel (R) Core (TM) i7-7700 CPU and 16GB memory. The output results are rendered with Cinema 4D. Simulated animation results can be found in the supplementary video.

Marathon scenario simulation. As shown in Figure 3, we simulated the evacuation process for marathon runners as recorded in [7]. In this scenario, the runners are guided to move towards the starting line. With dense, polarized, and boundary constraints, the highly self-aligned runners compete to the starting line and present a linear momentum. Our simulation result demonstrates that the dense crowd can be simulated through hydrodynamics, and our triggering approach facilitates to obtain the linear momentum.

Wave diagram analysis. For the sake of simplicity, we only draw the trajectories of 40 individuals in Figure 7. As can be seen from this figure, the dense crowd presents the wave linearly travelling in the queue. Each wave from these trajectories does not show transverse motion, while the dominant longitude waves indicate that the momentum linearly impulses from the border line to the tail of the queue. Furthermore, the average density fluctuation of the flow also propagates upstream from the start line (as shown in Figure 8). Note that, the density of an agent is computed according to Equation 3.

Attacking behavior of army. In this experimental scenario, we present a outside scene of army strike. As can be seen in Figure 5, the dense army presents perceptible collision avoidance behaviors and push each other. The motion of each agent triggered by immediate leaders while starting an attack. Please refer to the simulated animation in our supplementary video.

Comparisons with the state-of-the-art method. In the existing HiDac model [14], individuals can present waiting behavior by applied waiting rules. However, for dense crowd simulations as shown in Figure 6 and the supplementary video, the HiDac model cannot generate linear stop-and-go waves. Moreover, the dense agents in the HiDac model tend to congest when passing a bottleneck because of its queuing rules. In contrast, the crowds simulated by our model can evacuate more

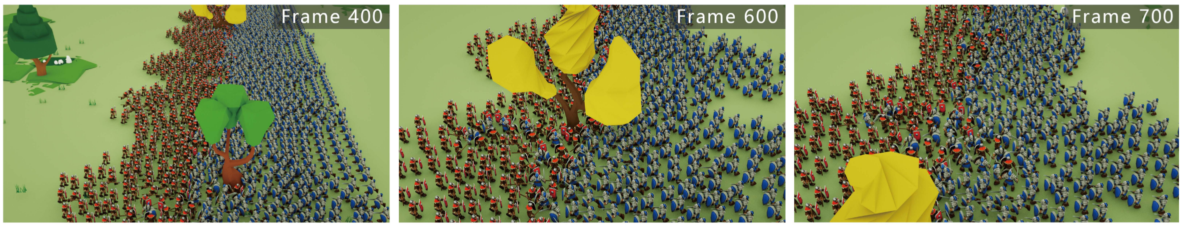


Figure 5: A fluid-like army strike simulation using our model.

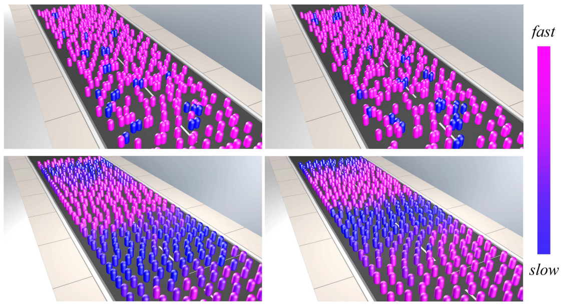


Figure 6: Comparison between the HiDac model and our model: The HiDac model can produce local stops for queuing behaviors but cannot generate linear stop-and-go waves (top), while our model can produce linear stop-and-go waves (bottom). The speed waves of the agents are visualized from pink (moving/hill) to blue (stop/valley).

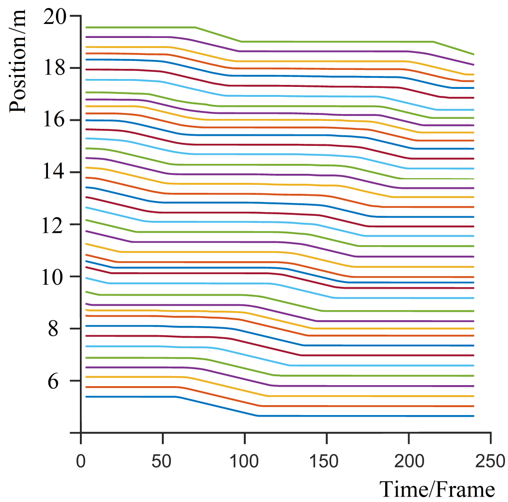


Figure 7: Trajectories of 40 agents in a dense crowd flow.

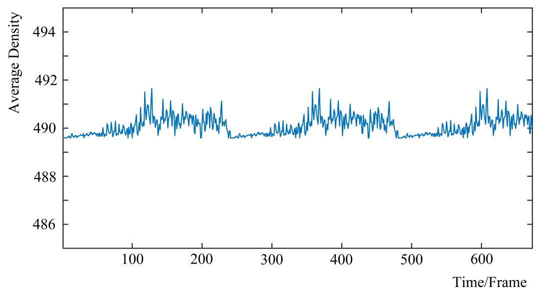


Figure 8: The fluctuation of average density in a dense crowd flow.

smoothly. This is because our model takes the benefit from the equilibrium of pressure force from SPH methods (see Figure 9 and Figure10). In an army strike scenario (Figure 11), by using our model, the agents incline to push each other. In contrast, HiDac model does not show perceptible pushing-each-other behavior because it applies stopping rule to avoid vibrating in a dense crowd.

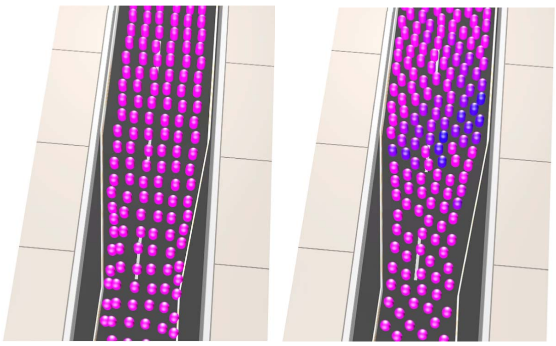
Performance. The computational cost of our model is mainly correlated with the number of the agents, due to the neighbors search through neighboring girds while computing the density, pressure force, and signal influence of each agent. The complexity of the search algorithm can be denoted as $O(m \cdot n)$, where m is the average number of the agents per grid, and n is the total number of agents in the simulation. The computation of the model also includes the update of the density and pressure force for the motionless particles, i.e., the obstacles. The detailed performance statistics of our experiments are reported in Table 1.

5 Conclusion

To simulate the macroscopic response of dense crowds, in this paper we present a Lagrange hydrodynamics based model to simulate local dynamics, and introduce a signal propagation method to simulate the linear macro momentum.

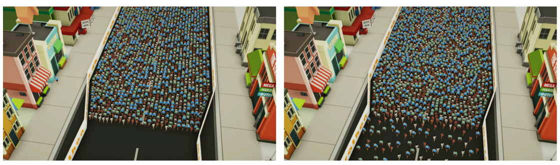
Table 1: Performance statistics of our simulations

Scenarios	Agents	Grid size	FPS (CPU)
Marathon evacuation by our model	2,284	200 $\times$ 15	24.7
	2,688	200 $\times$ 15	24.2
Marathon evacuation by HiDac [14]	2,688	-	0.14
Army strike by our model	1,778	300 $\times$ 300	29.4
Army strike by HiDac	1,778	-	0.45



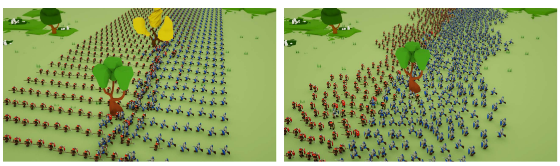
(a) (b)

Figure 9: Simulation results of the crowd evacuation with a bottleneck by using HiDac (a) and our model (b). The speed waves of the agents are visualized from pink (moving/hill) to blue (stop/valley).



(a) (b)

Figure 10: Comparisons on the simulation of marathon at the evacuating point by using HiDac (a) and our model (b).



(a) (b)

Figure 11: Comparisons on the simulation of army strike by using HiDac (a) and our model (b) .

Our experiments demonstrate that dense crowds can be simulated through fluid-based models with boundary constraints. Our model is more computationally efficient, compared to existing rule-based models.

Although our current model can produce stop-and-go waves for dense crowds, it has the two limitations. First, our model needs a small update step for the system equilibrium. Similar to existing fluid simulation models, our model requires small time steps to obtain symmetric forces among agents. Second, as we focus on the macro responses of the dense crowds, our implementation lacks realistic agent behaviors, which can be improved by using a more accurate human walking model. In the future, we plan to integrate more local rules into our model to produce more natural crowd motion.

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